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Heterogeneity in price elasticity of vehicle kilometers traveled: Evidence from micro-level panel data

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Heterogeneity in Price Elasticity of Vehicle Kilometers Traveled: Evidence from Micro-Level Panel Data

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Abstract

This article presents an empirical estimation of the effect of fuel prices on vehicle kilometers traveled (VKT) using a panel dataset of 1,138 Swiss households. Elasticities are estimated for different segments of households, based on their socio-demographic and vehicle characteristics, as well as on their driving intensity. Our results indicate larger price elasticities than previous estimates based on aggregate data for Switzerland and reveal important heterogeneity in price sensitivity across segments. Households who live in urban areas, who live farther from their workplace, and who own more efficient vehicles are significantly more reactive to price variations. The results of a quantile regression model for panel data show that travel-intensive households are responsive to changes in gasoline price, while less intensive drivers do not exhibit statistically significant price elasticities. In addition to gasoline taxes, it therefore appears that non-price measures tailored to household segments would be useful to provide supplementary incentives to reduce distance traveled and/or avoid penalizing some specific groups.

Keywords: vehicle kilometers traveled (VKT), car-travel demand, fuel price, elasticities, household behavior, heterogeneity, quantile regression, panel data, Switzerland.

JEL classifications: Q40; Q41; D12, R41, C21.

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1 Introduction

To what extent do fuel price rises induce people to drive less? The answer to this question is crucial in the context of climate change, where fuel taxes are considered as an important instrument to curb GHG emissions. If price elasticity is weak, such an instrument is doomed to fail. The distributional impacts of fuel price rises are also of primary concern. If reactions differ across individuals and households, some will be more strongly affected than others. Heterogeneous responses to fuel prices may therefore be at the root of serious social questions.

A large body of scientific research is dedicated to the estimation of price elasticities of vehicle kilometers traveled (VKT). Most studies analyze aggregate demand and point to rather low price elasticities of roughly -0.1 in the short run and about -0.3 in the long run (Barla et al., 2009; de Jong & Gunn, 2001; Goodwin et al., 2004; Graham & Glaister, 2004; Johansson & Schipper, 1997), thus suggesting that price-based policy measures are unlikely to significantly reduce mileage, fuel consumption and GHG emissions. When household-level demand is investigated, however, average price elasticities exhibit considerably higher magnitudes (e.g., Frondel & Vance, 2009; Santos & Catchesides, 2005; Sevigny, 1998; West, 2004). Specific segments of consumers seem particularly reactive to price variations because of their mobility behaviors and the presence of transportation alternatives. For instance, households who live in urban areas are likely to switch to public transport as a response to higher motor fuel prices, whereas households living in remote areas such as agglomerations or countryside cannot easily avoid using their cars even when fuel becomes more expensive. An increase in fuel prices could affect low-income drivers disproportionally, pushing them to opt for cheaper means of travel such as public transportation, car sharing or soft mobility. Also, as a response to growing gasoline prices, intensive drivers could more easily reduce mileage if they enjoy an important share of discretionary driving, i.e., driving by choice rather than necessity (see Handy et al., 2010).

The identification of heterogeneous segments of households is essential to assess the distributional and ethical consequences of price interventions, which would obviously affect their acceptability by the population (Mattioli et al., 2018).[1] The heterogeneity in fuel price elasticities has been previously investigated for groups of drivers defined mainly on *observed* socio-demographic segmentation criteria such as income level (e.g., Santos & Catchesides, 2005; Wadud et al., 2009; West, 2004), location (e.g., Gillingham & Munk-Nielsen, 2019; Spiller et al., 2017), multiple-car ownership or household lifecycle (among others Bento et al., 2009; De Borger et al., 2016a; Schmalensee & Stoker, 1999). This literature shows that various driver groups exhibit statistically different price elasticities, so that careful policy design is essential to achieve GHG and energy-reduction goals efficiently and with the lowest social welfare distortion. However, there are important discrepancies between the findings of different studies and the majority focuses on the US. While different empirical methods, temporal horizons and data types could explain such differences, Wadud et al. (2010a) illustrate how plausible real-world scenarios could explain contrasting findings. This provides a motivation for addressing the heterogeneity of price responsiveness in other countries. In Europe, the organization of motorized transportation is very different from that in North America.[2] European countries, and Switzerland in particular, therefore constitute interesting case studies for extending and generalizing knowledge in this domain.[3] Thereby, we follow Gillingham (2014) and Wadud et al. (2009)'s call for further research in this area.

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[1] The violent strikes of the so-called "yellow vests" in France at the end of 2018, which originated after the announcement of an increase in diesel taxes, illustrates dramatically how heterogeneous impacts may matter for the acceptability of policy measures. The discontent originated mainly from rural regions, which often face lower economic development but have to bear a disproportionate fuel tax burden in comparison with large urban centers because the latter are less dependent on private motorized transportation (for anecdotal evidence see *The Economist*, 2018).

[2] For instance, the share of taxes in gasoline prices is particularly important in most European countries (European Commission, 2020; UP, 2018), real fuel prices are significantly higher (World Bannk, 2020) and vehicle fleets consist of cars with notably better motor fuel efficiency (ICCT, 2020). In addition, public transport networks are characterized by a particularly high density not least because of significantly shorter travel distances. National mobility surveys also point to differences in car-travel behaviors: UK and Swiss households use their private cars mainly for leisure trips (NTS, 2018; OFS, 2017b), while the main purpose of vehicle usage in the US is related to professional, non-recreational activities NHTS (2017). More detailed comparisons between the US and European mobility contexts are provided by Buehler (2011), Giuliano & Dargay (2006) and Sprei et al. (2019). Such differences certainly affect price elasticities of driving demand: estimations of price elasticities in European countries are generally higher than in the US (Frondel et al., 2017; Graham & Glaister, 2002).

[3] The number of studies examining heterogeneity of fuel price elasticities in European countries is still limited (e.g., Blow & Crawford, 1997; De Borger et al., 2016a; Manuel Frondel et al., 2012; Gillingham & Munk-Nielsen, 2019; West, 2004).

In addition to observed segmentation criteria, *unobserved* grouping characteristics can be used to investigate heterogeneity in the price elasticity of car-travel demand. VKT could indeed be affected by behaviors or habits, which are often not observed by researchers and of which car drivers themselves might not necessarily be aware. For instance, drivers might not always select the most efficient route, or purposefully drive longer distances to arrive at a certain destination in order to avoid areas with important traffic jams, bad road quality, poor weather conditions or dangerous neighborhoods. It is also possible that some car owners enjoy driving per se. Alternatively, discretionary driving might be related to leisure activities taking place further away from the dwelling or the living region. Other unobserved factors could be the driver's (or a family member's) health, work and household duties, or proximity to facilities, such as a gym or a commercial center. Previous analyses suggest that such factors, which we assume to affect "driving intensity", play an important role in private travel demand (Gardner & Abraham, 2007; Sun et al., 2014; Zhao et al., 2020).

Quantile regression (QR; see Koenker & Bassett, 1978) offers the possibility to investigate the impact of such unobserved factors. In such models, conditional quantiles can be interpreted as different levels of intensity of car-travel demand. Several authors (Frondel et al., 2012; Gillingham, 2014; Gillingham et al., 2015) have used QR to investigate price elasticities of groups of consumers defined on the basis of their driving intensity and have found evidence for statistically significant differences between driver groups. To our knowledge, only Gillingham et al. (2015) use a QR method adapted for panel data.[4]

Most analyzes on heterogeneity of price elasticities of VKT rely on cross-section data, and therefore obtain estimates from geographical differences rather than temporal variations. This distinction is important because the concept of price elasticity is inherently related to *temporal* variations. Nevertheless, panel data applications in this field remain scarce. Also, in absence of micro-level data, many studies use aggregate fuel prices (e.g., Gillingham & Munk-Nielsen, 2019; Mattioli et al., 2018) and prices imputed or assigned

[4] However, this study uses the panel QR method suggested by Canay (2011), which is affected by a severe estimation bias, as outlined by Besstremyannaya & Golovan (2019).

on the basis of geographical location (e.g., Kayser, 2000). Yet, as mentioned by Oum et al., (1992) *"Aggregation "averages out" some of the underlying variabilities of price sensitivity"* (p. 153), suggesting that the differences between the price elasticities of groups of drivers could be also more easily dismissed as statistically insignificant.[5]

The present article contributes to the understanding of heterogeneity in gasoline price elasticity of private car-travel demand. In order to examine the price elasticities of segments of drivers with different levels of driving intensity, we use the panel-data quantile regression approach suggested by Wooldridge (2010) and previously applied in other fields of empirical economic research (Abrevaya & Dahl, 2008; Bache et al., 2013; Tilov et al., 2020). Heterogeneity in price responses is also addressed by using observed socio-demographic and vehicle segmentation criteria and analyzed by including interaction terms in a fixed-effect regression model. We use longitudinal data, which are better suited for the estimation of structural coefficients than cross-section data (see Hsiao, 2007). Also, in contrast to most prior works which consider rather old time periods, aggregate demographic and price data, or complex price constructs from different sources in absence of individual prices, the present article uses household-level data and disaggregate gasoline prices between 2018 and 2020. To the best of our knowledge, this analysis is the first relying on micro-level revealed behavior to address the effect of price on VKT for different household segments in Switzerland.[6]

The remainder of this article is organized as follows. The related literature is reviewed in *Section 2*. The dataset is introduced in *Section 3*, while our econometric approach is discussed in *Section 4*. *Section 5* presents the empirical findings and *Section 6* concludes.

[5] Estimating average price elasticities using macro-level city-, county-, or state-level price data might lead to an important downward bias, as discussed by Levin et al. (2017) and Wadud et al. (2010a). The effect of aggregation in empirical works is also discussed by Blundell & Stoker (2005), Halvorsen & Larsen (2013), Miller & Alberini (2016).

[6] Erath & Axhausen (2010) also investigate heterogeneity for private mobility in Switzerland. Their results show that frequent users of public transportation, the elderly and people living in remote areas are more sensitive to variations in fuel prices. Households owning larger vehicles, with a greater number of adults and with a male respondent are in contrast less price sensitive. The authors also observe that households with high income have larger price elasticities. However, these analyses rely on stated preferences, thus relying on hypothetical responses to price variations (Tanner, 2012).

2 Literature review

Our article relates to the wide literature on price elasticities in transportation. In this section, we focus on the contributions that investigate heterogeneity in price elasticity. *Table 1* provides an overview of the literature's findings with respect to heterogeneity in the price responsiveness of car-travel demand.

Table 1: Price elasticity heterogeneity in previous studies

References	**Country, observation period**	**High income**	**Urban area**	**> 1 car**	**Fuel-efficient car**	**High travel intensity**	**Other segmentation criteria considered**
Articles using driving distance or vehicle kilometers (or miles) traveled as dependent variable							
Blow & Crawford (1997)	UK, 1988-1993	-	+				
De Borger et al. (2016a)	Denmark, 2004-2008			+			
Frondel et al. (2012)	Germany, 1997-2009	o	o	o		-	
Gillingham (2014)	US, 2001-2003	+	+			-	
Gillingham et al. (2015)	US, 2000-2010		+		-	+	vehicle buyer type
Gillingham & Munk-Nielsen (2019)	Denmark, 1998-2011		U				distance to work
Santos & Catchesides (2005)	UK, 1999-2000	-	+				
Wang & Chen (2014)	US, 2009	U					
West (2004)	US, 1997	-	+				
Articles using car fuel demand as dependent variable							
Kayser (2000)	US, 1981	+					
Liu (2015)	US, 1997-2002	-	+	-	-		family size
Mattioli et al. (2018)	UK, 2006-2012	-					
Spiller et al. (2017)	US, 2009	+	-	+	-		distance to urban area
Wadud et al. (2009)	US, 1984-2003	U					
Wadud et al. (2010a)	US, 1997-2002	-	+	+			# of wage earners
Wadud et al., (2010b)	US, 1997-2002	-	+	+			# of wage earners

Notes: "+/-" indicate higher/lower magnitudes of price elasticity for the specific segment (e.g., high income); "o" indicates insignificant differences between the price elasticities; "U" indicates a U-shaped evolution of the magnitude of price elasticities along the distribution of the variable. Cells are left empty when the relationship was not investigated.

Most often, earlier research defines categories of car drivers on the basis of income levels and location. Among others, Blow & Crawford (1997), Wadud et al. (2010a) and West (2004) observe that wealthier households are less reactive to fuel price changes. These studies explain their findings by the possibility that poorer households, who already allocate an important part of their income to car-travel, may respond to increasing gasoline taxes by simply driving less, or by switching to public transportation. Conversely, high-income drivers are less sensitive to price increases because proportionally such changes affect their income only marginally (Wadud et al., 2010a).

In contrast, Gillingham (2014), Hughes et al. (2006), Kayser (2000) and Spiller et al. (2017) reach the opposite conclusion, namely that price elasticity of VKT (or gasoline demand) increases with income. Their analyses suggest it is also conceivable that lower income households who possess a private car do so because they hardly have any cheaper or more convenient mobility alternatives, and as a result might instead reduce other expenditures when fuel prices increase. Likewise, when a drop in motor fuel prices occurs, the first reaction of poorer families might not be to invest in more travel, but rather to acquire basic commodities. On the other hand, more affluent households could be more sensitive to price rises because they have the option of reducing discretionary driving (i.e., leisure or non-work-related trips) or because prices are more salient to drivers with higher motor fuel bills. Yet other studies observe a U-shaped relationship between price elasticity and income (Wadud et al., 2009; West, 2004) or insignificant patterns (Archibald & Gillingham, 1981; Frondel et al., 2012; Yatchew & No, 2001).

Concerning location, there is a general agreement that rural households are less price-reactive than city-dwellers because the former often have little choice over their daily travel distance or the means of transport for commuting (e.g., Gillingham, 2014; Santos & Catchesides, 2005; Wadud et al., 2009). However, Spiller et al. (2017) find the car fuel demand of urban households in the US to be less price-elastic than that rural households. These authors argue that owing to congestion in cities, urban drivers might have optimized their amount of driving, which would make their motor fuel demand less responsive to price variations. Gillingham & Munk-Nielsen (2019) draw a somewhat mixed conclusion with respect to consumer groups defined on living location. They find that both households living in the outskirts of cities (long commutes to work) and city-dwellers (short commutes to work) are particularly responsive to fuel price variations compared to households with intermediate travel distances. The authors assume that drivers in the former category have stronger incentives to consider substitutes because small increases in fuel prices affect driving expenditures substantially, whereas city-dwellers are likely to dispose of more alternatives for commuting.

More recently, the concept of "driving intensity" has been considered in the analysis of heterogeneity in fuel price elasticity of car-travel/gasoline demand. Using quantile regressions, Gillingham (2014) investigates the case of Californian drivers, and finds that the lowest conditional quantiles (low driving intensity) of VKT are more price-elastic than the highest conditional quantiles (high driving intensity). Frondel et al. (2012) obtain similar findings for Germany and notice that higher conditional quantiles reflect stronger dependency on private mobility, and hence, a lower price elasticity.[7] However, more driving may also be related to non-essential (or discretionary) car travel, as suggested by Gillingham et al. (2015). Their study for the state of Pennsylvania shows price elasticities of greater magnitude at the third conditional quartile than at the first one (where elasticity is non-significantly different from zero). The authors explain the difference with the former California study by the fact that it focuses only on new car registrations rather than on the entire vehicle fleet. It is however not clear how this data difference affects the findings of the two studies. Also, in contrast to the two previously mentioned studies,[8] Gillingham et al. (2015) use the panel-data quantile regression approach suggested by Canay (2011). Besstremyannaya & Golovan (2019) criticize this method because it could lead to a severely biased inference in applied works with a large number of observations and a small number of time periods, as is the case in Gillingham et al. (2015). Moreover, this technique conditions quantiles on fixed effects, thus making their interpretation difficult (see Powell, 2016).

Most studies in this literature still use aggregate price data and rely on cross-section datasets. The application of macro-level price data is likely to be problematic not only for estimating average price elasticities (De Borger et al., 2016a; Levin et al., 2017; Oum et al., 1992), but also for identifying differences in the price reactivities of various segments of drivers, since most of the existing variability in prices is leveled out in such datasets. The interpretation of the temporal dimension of cross-sectional data could

[7] National household travel surveys show indeed that the main purpose of vehicle usage in the US and in Germany is related to professional and non-recreational activities (MOP, 2018; NHTS, 2017).
[8] Despite having panel data at hand, Frondel et al. (2012) prefer to use a pooled quantile regression in their analysis because *"panel quantile methods are fairly new"* (p. 466).

moreover be problematic. Results based on cross-section data are most commonly considered as medium- to long-run responses because they are obtained by comparing different households in different (long-run) equilibria (e.g. Bento et al., 2009; Baltagi & Griffin, 1984; Graham & Glaister, 2002; Wadud et al., 2010). However, there is a debate and some authors such as Espey (1998), Kayser (2000), Mattioli et al. (2018) interpret analyses relying on cross-section data as providing short-run reactions whenever the technology used by individual households (i.e., their car) is controlled for. Moreover, price elasticities estimated with cross-section datasets could be biased because more price sensitive households could be more selective in where they choose to refuel. However, the estimates of gasoline price elasticities should not be affected by self-selection in longitudinal analyses with short panels because in the short run, the choice of a gas station is likely to be determined by routines (see BCG, 2014; GasBuddy, 2021; Kitamura & Sperling, 1987). In contrast, the temporal horizon is clearly defined in panel datasets as the interval between two time periods. The inclusion of time-fixed effects also contributes to mitigate potential biases related to factors affecting households' driving demand.[9]

3 Dataset and descriptive statistics

Our empirical analysis is based on data from the Swiss Household Energy Demand Survey (SHEDS) (Weber et al., 2017), which covers all Switzerland (except the canton of Ticino) and is a rolling panel of 5,000 respondents per wave. We focus on the 2018-2020 waves of the survey, excluding 2016-2017 because information on individual motor fuel prices was not collected in these waves.[10] We consider only gasoline cars, which represent roughly two thirds of the overall car fleet in Switzerland (OFS, 2020c), and exclude

[9] A direct approach to distinguish between the short- and the long-run effects of price variations in the field of car travel is the one used by Batley et al. (2011), Dargay (2007) and Goodwin et al. (2004). These authors use lagged prices in order to exploit the dynamics of price elasticities. Their research also shows that asymmetric model specifications (in which the main explanatory variables are split into monotonic "sub-variables" capturing for instance the cumulating series of income/price rises and falls) can be used if drivers react differently to price increases and price reductions. These methods require nevertheless an important number of observations. In the case of the dynamics of price elasticities in particular, longer panels, usually with data covering more than 5 time periods, as also noted by Wadud et al. (2010), are necessary in order to be able to apply these models.

[10] SHEDS takes place in the second quarter of each year, so that the survey period does not correspond to a calendar year. It is also important to note that we account for the fact that the number of days between two SHEDS waves is not exactly the same from one wave to the next and across respondents. This is done by calculating the number of days between the dates at which respondents filled in two consecutive waves of the survey, so as to obtain an average daily driving distance, and then by multiplying this number by 365.

all other types of vehicles (in particular diesel, electric, hybrid and plug-in hybrid cars) because fuel prices and technologies are difficult to compare.

The dependent variable in our analysis is the annual driving distance (or VKT) of the most used car in the household. It is obtained as the difference in odometer readings reported in two consecutive waves of SHEDS. We therefore exclude observations from households who change their car between two survey waves. Considering car purchased less than a year ago would force us to extrapolate annual distances from distances traveled during part of the year, which would require strong assumptions since distance traveled is affected by seasonal factors. We moreover consider annual driving distances below 1,500 or above 80,000 kilometers[11] as unlikely and exclude these observations (representing about 4% of the sample) from the analysis.

Figure 1 shows the distribution of driving distances in our final dataset. Kernel densities are superimposed to illustrate the evolution of VKT for each year in our observation window. As expected, the density is strongly skewed to the right, with a peak around 10,000 kilometers a year.[12] While the Kernel densities for 2018 and 2019 are similar, it is interesting to note that the distribution shifts to the left in 2020, presumably because of the Covid-19 lockdown.[13]

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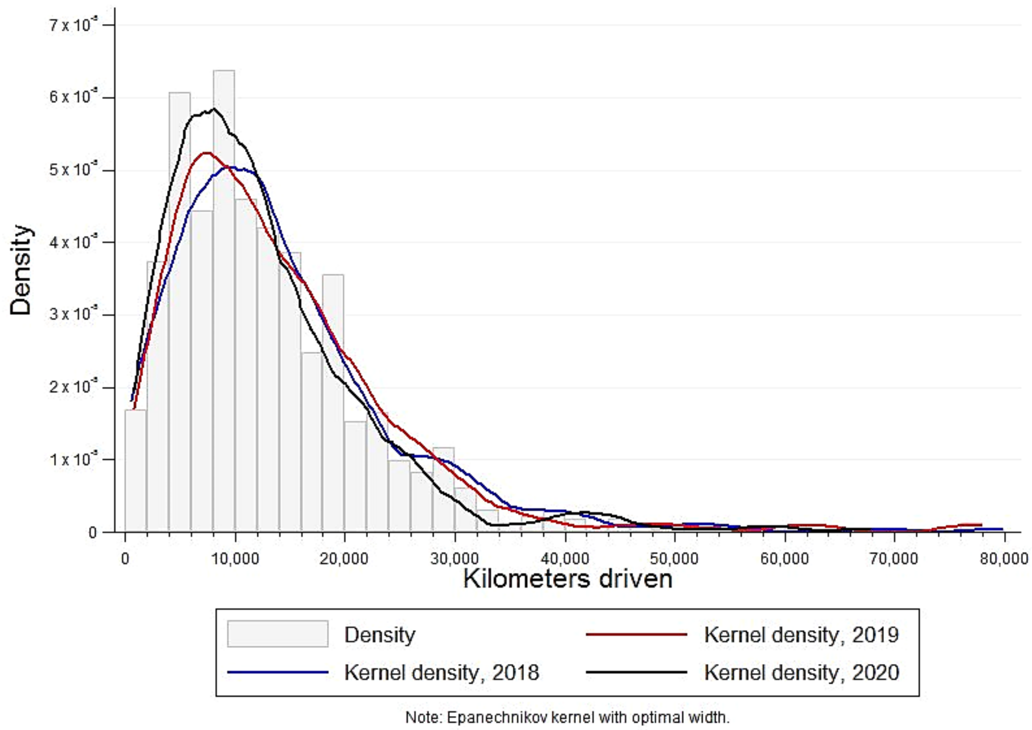
[11] These correspond to daily driving distances below 4 kilometers or above 219 kilometers. Setting limits allows to exclude likely mistakes in odometer readings and also eliminates observations for drivers who have faced very specific circumstances, such as long periods of time spent abroad or health issues, causing very small and unusual observed VKT.

[12] In our models, we take the natural logarithm of the dependent measure (VKT), which makes its distribution close to a Bell curve.

[13] The Swiss government imposed a strict national lockdown from March 16 to June 8, 2020. Given that SHEDS respondents are interviewed from April to June, the lockdown affected distances measured in the 2020 wave.

Figure 1: Annual driving distance



Additional information about VKT is displayed in *Table A.1* in *Appendix*, which provides descriptive statistics for our sample, separately for each of the three years covered in our dataset. On average, distance traveled is between 12,000 and 15,000 km/year, but it is characterized by important variability between households. Our values are consistent with statistics from the 2015 *Mobility and Transport Microcensus* (OFS, 2017a), which show that the "first" car in a typical Swiss household is driven on average 13,880 kilometers per year. In addition, *Touring Club Switzerland* – Switzerland's largest mobility association – uses an annual mileage of 15,000 kilometers for the calculation of the average costs related to a private car in 2020. *Table A.1* also reveals the important drop in average VKT related to the Covid-19 lockdown, with a decline around 1,500 kilometers between 2019 and 2020.

Gasoline price, the key independent variable in this article, is obtained directly from respondents, who are asked the price they paid when they last filled up the tank.[14] We emphasize the originality and the

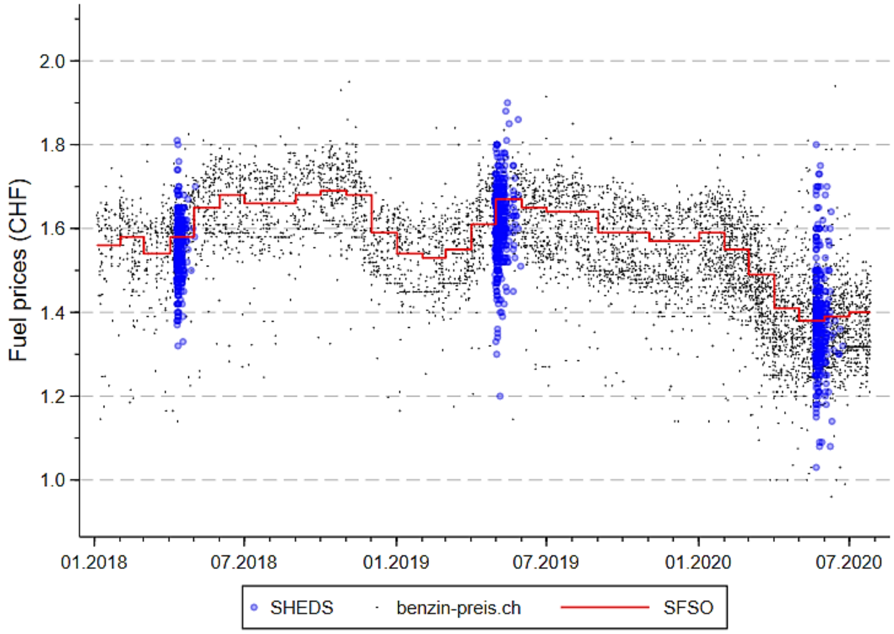
[14] We apply Tukey's (1977) method to identify outliers: for each wave, observations with prices farther than three times the inter-quartile range below the first or above the third quartile of the price distribution are discarded (21 additional observations).

importance of how this information is collected. We observe a specific price for each household and each year, while most of the existing literature uses regional of even national average prices. Two major forces determine the price of car fuel in Switzerland: taxes and other non-energy related costs. Fuel taxation being defined at the federal level, it explains little of the within country variations in car fuel prices. On the other hand, the Swiss oil importers association (*AvenergySuisse*) points out that the main differences in car fuel prices originate from the costs of storage, transport, logistics, marketing, building depreciation or non-fuel-related local taxation regimes faced by gas stations (AvenergySuisse, 2021). In 2019, ABE (2019) found that the price of the most common gasoline type (unleaded with 95 RON) could differ up to 65 Swiss Cents between gas stations in the French-speaking part of Switzerland. This once again shows the importance of factors such as the storage capacity of retailers or the distribution costs they pay. For instance, gas stations located close to the sole Swiss oil refinery (Cressier, canton of Neuchâtel) benefit from low distribution costs. On the other hand, in large cities such as Geneva, high rental costs are associated with higher fuel prices.[15]

Figure 2 shows the individual fuel prices reported by SHEDS respondents, and compares them with price data from two other sources: (1) the Swiss Federal Statistical Office, which provides national average monthly prices (OFS, 2020b) and (2) the private consumer website *www.benzin-preis.ch*, where drivers can enter daily information about the type of fuel they use, its price, as well as the location of the gas station where they filled the tank. *Figure 2* shows there is important variability across prices collected during the survey as well as in prices available from *www.benzin-preis.ch*, but the averages and their evolution are close in all sources. A moderate increase is observed between 2018 and 2019, before a substantial decrease in 2020.

[15] It is also important to mention that *ABE*'s investigation does not cover the German-speaking (eastern) part of Switzerland and does not consider gas stations located on highways, where prices are generally higher and consumers more captive.

Figure 2: Gasoline prices, from different sources



In addition to gasoline price, we account for various socio-demographic and vehicle-related factors expected to influence distance traveled. Household annual gross income is calculated as the mid-point of income intervals and using the Pareto-curve-based procedure for open-ended income categories, as suggested by Celeste et al. (2013). Engine efficiency and car vintage constitute the subset of vehicle-related determinants. The coefficient of car-related variables may be affected by endogeneity because drivers who (intend to) travel more might choose to buy newer, more efficient cars, or alternatively larger and more comfortable cars. This issue has been addressed in various ways in the existing literature: (1) instrumental variable approaches, although finding relevant and strong instruments has proven challenging;[16] (2) simultaneous equations models (Mannering, 1986; Small & Dender, 2007; Weber & Farsi, 2014a); (3) excluding engine efficiency from the set of determinants based on theoretical considerations related to

[16] Such instruments could be the characteristics of the replaced car relative to the average car in the economy (De Borger et al., 2016b) or the fuel price at the time a vehicle was bought (Linn, 2016).

consumer behavior.[17] In this article, however, we consider only households who have not changed cars during the observation period.

Various socio-demographic attributes are also included in our model specifications. The respondent's age, considered as representative for the household as a whole, is expected to affect VKT because mobility patterns and needs vary according to life stages. The number of general (GA) travel cards hold by the household members are included as they indicate the extent of substitutability between private and public transportation for each household. With respect to the necessity of using private transportation, we moreover use a set of dummy variables designating if the households lives in an urban, agglomeration or countryside area as well as an additional "distance" variable capturing the kilometers between home and workplace.[18] For retired and unemployed respondents, and for individuals working from home, this distance does not exist, but we replace the log-transformed distance between home and work for these individuals and flag them using a dummy variable.[19] Finally, we include year dummies to control for unobserved time-varying factors. The final sample consists of 1,138 observations from 490 unique households, among which 332 are observed twice and 158 are observed three times.

4 Econometric approach

In order to evaluate the effect of fuel prices, socio-demographic, and vehicle factors on households' VKT, we use the following multivariate regression model:

[17] According to economic theory, a rational consumer should consider a variation in the cost of driving in the same manner whether it results from a change in fuel prices or from a change in fuel economy (De Borger et al., 2016a; Gillingham, 2014; Sorrell et al., 2009). This has led some authors to exclude engine efficiency from the set of determinants of fuel demand and to interpret (the negative of) price elasticities as a rebound effect instead (e.g. Frondel et al., 2012; Gillingham et al., 2015). However, it is unlikely that households react in the same manner to the two sources of variation in driving costs: price changes are usually unexpected and temporary, while improvements of engine fuel efficiency are permanent (Linn, 2016), and consumers might have different levels of awareness of these two measures (Gillingham et al., 2016). In addition, excluding important vehicle characteristics from modelling fuel demand could lead to an omitted variable bias, as outlined by Spiller et al. (2017). For further discussion of the theoretical non-equivalence between the cost effect of fuel prices and fuel efficiency, see Weber & Farsi (2014).

[18] This distance is calculated by using the zip codes at home and at work, We use Stata's user-written command GEOROUTE for calculating (optimal) travel distances (Weber & Péclat, 2017). This variable should nevertheless be considered as a proxy of the real distance between the dwelling and the workplace both because we use distances between zip codes rather than distances to exact locations and because we do not know the exact route taken by the respondents.

[19] Considering that the log-transformed distance is 0 amounts to considering the distance itself as being 1 kilometer. Anyways, because we include a binary control for these observations, the choice of the imputed value as no impact on the results.

$$ln(VKT_{it}) = \alpha + \beta \cdot ln(P_{it}) + \sum_{k=1}^{K}(\delta_k \cdot X_{kit}) + \nu_i + \varepsilon_{it} \quad (1)$$

where VKT_{it} is vehicle kilometers traveled by household i in year t using the main car and P_{it} is the self-reported fuel price that household i paid the last time it filled the tank. Because both VKT_{it} and P_{it} are in logarithmic form, coefficient β can be directly interpreted as a price elasticity. Other socio-demographic and vehicle characteristics are denoted $X_{1it}, \ldots, X_{Kit}$.[20] The terms ν_i capture household-specific stochastic residuals and ε_{it} are idiosyncratic residuals.

With panel data, random effects (RE) and fixed effects (FE) methods can be used to estimate equation (1). Technically, the choice between a RE and a FE model is essentially a *"choice about how to balance variance and bias"* (Clark & Linzer, 2015). Some analyses in the field of car-travel demand have favored RE for short panel datasets (e.g., Filippini & Heimsch, 2016; Frondel et al., 2012). Yet, FE models have the advantage of relying on within- rather than between-observations variation, thereby providing a clearer interpretation of the estimated gasoline price coefficients as short-run price elasticities, and controlling for endogeneity related to the existence of unobserved time-invariant determinants. In addition to RE and FE, we also estimate correlated random-effects (CRE) models (Mundlak, 1978), in which coefficients of independent variables with sufficient within variation (e.g. gasoline price) are estimated using the within-variation in the data, while the coefficients of controls with no or little within-variation (e.g., fuel efficiency) are estimated from between-variation. CRE is implemented by adding the time averages of the time-varying covariates in equation (1), and by applying a random-effect regression to this extended model specification (Schunck, 2013).

The investigation of heterogeneity in the sensitivity to fuel price is first addressed by introducing a series of interactions between gasoline price and observable characteristics in equation (1). To obtain clearly defined consumer segments, we dichotomize the continuous variables and create binary controls (like in

[20] Binary variable coefficients represent semi-elasticities after the transformation $exp(\delta_k) - 1$ (Halvorsen & Palmquist, 1980).

Gillingham (2014) and Gillingham et al. (2015)). We use the median value to separate households, unless there is a natural threshold.[21] Thus, equation (1) is modified as follows (considering income in this example):

$$ln(VKT_{it}) = \alpha + \beta_1 \cdot ln(P_{it}) \cdot \mathbf{1}\{I_{it} < \overline{I_{it}}\} + \beta_2 \cdot ln(P_{it}) \cdot \mathbf{1}\{I_{it} \geq \overline{I_{it}}\} + \gamma \cdot ln(I_{it}) + \sum_{k=1}^{K} (\delta_k X_{kit}) + \nu_i + \varepsilon_{it} \quad (2)$$

where $\mathbf{1}\{\cdot\}$ is an indicator function taking the value 1 when the condition in brackets is true and $\overline{I_{it}}$ denotes the threshold value (or the median) used to split the sample according to income I_{it}. This procedure allows to obtain two separate price elasticities β_1 and β_2, for households respectively below and above the median. When the continuous variable used to split the sample is time invariant (e.g., fuel efficiency), the variable itself is obviously dropped from equation (2). For each segmentation variable, we run a separate estimation in order to avoid multicollinearity issues and an important loss of degrees of freedom.[22]

Second, we use conditional quantile regressions (QR) to further investigate the presence of heterogeneous price responses. Initially developed by Koenker & Bassett (1978), QR is an important complement to the

[21] For age, we use 65 years as the natural threshold, as this corresponds to retirement age. For the number of GA travelcards, we use 0 as the threshold, since most households do not have any. For all other variables, we use the median and implement robustness checks using the first and/or third quartiles as alternative thresholds.

[22] In this context, different authors argue that in presence of multiple hypotheses, p-values associated with testing the statistical difference between coefficients should be adjusted (Chen et al., 2017). The reason for this correction is that implementing multiple tests leads to a higher probability of finding statistically significant results incidentally. This makes it difficult to tell which differences between groups are actually true, and which are merely due to chance. This problem has given rise to a specific field in the econometric literature focusing on various adjustment procedures. Such methods are the classical Bonferroni correction, which in presence of many tests can be rather conservative (Nakagawa, 2004), or the gaining in popularity sharpened False Discovery Rate (FDR) q-values (Anderson, 2008). However, as noted by Streiner (2015), *"The discussion of how to correct for multiplicity has made the implicit assumption that we should correct for it, but this is by no means a position accepted by everyone."* (p. 724). The uncertainty of how many and which tests should be chosen, and whether reducing Type I error should come at the expense of increasing Type II error are arguments against such adjustments (Perneger, 1998). For instance, a researcher could choose the type and the number of hypotheses to be finally tested and presented in a final analysis based on the result of *an ex-ante* FDR correction. Thus, instead of solving it, this could perpetuate the "p-value fiddling" problem. Rothman (1990) even argues that the *"…theoretical basis for advocating a routine adjustment for multiple comparisons […] undermines the basic premises of empirical research, which holds that nature follows regular laws that may be studied through observations."* (p. 43). Other arguments against such adjustments, which we do not address here, are provided by Schulz & Grimes (2005), Moran (2003), O'Keefe (2003) and most recently by Parker & Weir (2020). Perhaps partly for such reasons none of the earlier studies on households' driving demand corrects for multiple hypothesis testing (e.g., Gillingham et al., 2015; Spiller et al., 2017; Wadud et al., 2010a). Based on these considerations and following prior analyses, in this article we also refrain from adjustments for multiple hypotheses testing.

estimation of the *average* price elasticity of a *typical* car fuel consumer, in the sense that it provides a broader picture of the relationship between the dependent measure and the set of covariates. More precisely, the regression coefficients of the q^{th} conditional percentile of the dependent variable ($q \in (0;1)$), are estimated by minimizing the function $\sum_i^N q|\theta_{it}| + \sum_i^N (1-q)|\theta_{it}|$, where q are penalties attributed to observations, depending on their position with respect to the best line of fit, and θ_{it} are model residuals. Quantiles are defined with respect to residuals, so that QR also constitutes an important complement to the previously discussed method based on *observed* segmentation characteristics. Unobserved behaviors, such as driving behaviors or route choices, will then be captured by different quantiles.

We follow Wooldridge (2010) and implement QR for panel data by including the time averages of the basic time-varying covariates in equation (1), and by then applying a pooled quantile regression to this extended model specification. Although various extensions of QR for longitudinal data exist in the literature, we use a CRE QR method for three reasons. First, this model is adapted to datasets with a limited number of periods (T), but a large number of observations (N), unlike the models suggested by Canay (2011) and Machado & Santos Silva (2019). Second, in contrast to these QR techniques for longitudinal data, quantiles are not estimated conditional on fixed effects, thereby allowing their direct interpretation as "driving intensities". Third, Powell's (2016) model with non-additive fixed effects and valid with a small T proved extremely sensitive to our model specifications, whereas CRE QR is robust to alternative model specifications.

5 Results and discussion

We present our empirical findings in two parts. First, we discuss the estimations of average price elasticity of VKT. The picture of the average household is in fact a useful starting point for the later analysis of heterogeneity in price elasticities. These results also allow us to discuss the role of the determinants of VKT. Second, and most importantly, we present and discuss our analyses of heterogeneity in price elasticities.

Table 2 displays the estimations obtained with random effects (RE), fixed effects (FE) and correlated random effects (CRE). The first column of each of the three estimation blocks presents a basic model, whereas the second column encompasses a larger set of determinants.[23]

Table 2: Determinants of VKT: random effects (RE), fixed effects (FE) and correlated random effects (CRE) models

	RE1	RE2	FE2	FE2	CRE1	CRE2
Gasoline price CHF (ln)	-1.068***	-0.919***	-0.838*	-0.846*	-0.865**	-0.867**
	(0.345)	(0.345)	(0.431)	(0.434)	(0.413)	(0.414)
Gross HH income CHF (ln)	0.144***	0.060	0.141*	0.142*	0.134*	0.133*
	(0.042)	(0.044)	(0.074)	(0.076)	(0.075)	(0.076)
Fuel efficiency km/L (ln)	0.199	0.105			0.094	0.085
	(0.128)	(0.122)			(0.121)	(0.121)
SHEDS 2019 (ref.: SHEDS 2018)	0.026	0.032	0.020	0.019	0.020	0.020
	(0.041)	(0.041)	(0.043)	(0.044)	(0.043)	(0.043)
SHEDS 2020 (ref.: SHEDS 2018)	-0.251***	-0.209***	-0.223***	-0.228***	-0.225***	-0.224***
	(0.055)	(0.056)	(0.063)	(0.064)	(0.060)	(0.060)
Age of car (years)		0.001				0.001
		(0.005)				(0.005)
# HH members		0.043*		0.011		0.009
		(0.022)		(0.038)		(0.038)
Age of reference person (years)		-0.005**				-0.003
		(0.002)				(0.002)
# GA travelcards per HH capita		-0.250***		0.041		0.041
		(0.080)		(0.131)		(0.132)
Driving distance home-work km (ln)		0.026***		-0.005	0.003	0.002
		(0.007)		(0.008)	(0.009)	(0.009)
Living location: agglomeration (ref.: city)		0.105*		-0.058	0.074	-0.053
		(0.060)		(0.151)	(0.059)	(0.150)
Living location: countryside (ref.: city)		0.169***		-0.019	0.154**	-0.031
		(0.060)		(0.170)	(0.061)	(0.170)
Average gasoline price (by household)	No	No	No	No	Yes	Yes
Average gross HH income (by household)	No	No	No	No	Yes	Yes
Average # GA per HH capita (by household)	No	No	No	No	Yes	Yes
Average # HH members (by household)	No	No	No	No	Yes	Yes
Average home-work km (by household)	No	No	No	No	Yes	Yes
Average living location: agglomeration (by household)	No	No	No	No	No	Yes
Average living location: countryside (by household)	No	No	No	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Imputed driving distance home-place: yes	No	Yes	No	No	Yes	Yes
Observations	1138	1138	1138	1138	1138	1138
Households	490	490	490	490	490	490
Overall R^2	0.034	0.131	0.027	0.008	0.148	0.150
Between R^2	0.039	0.175	0.030	0.005	0.182	0.185
Within R^2	0.029	0.016	0.030	0.031	0.027	0.029
Adjusted R^2	.	.	0.026	0.023	.	.
AIC (RE estimation via ML)	2216	2173	.	.	2154	2164

Clustered standard errors (by household id) in parentheses

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

[23] We also tried specifications including additional sets of covariates, e.g. psychological determinants, number of vehicles owned by the household, or region fixed effects. The inclusion of these variables does not affect the estimated price elasticities even though it yields higher information criteria (AIC). Therefore, we display only two specifications: a "basic" one and a "preferred" one.

In all models presented in *Table 2*, the estimated price elasticities are significant (at least at the 10% level) and are of non-negligible magnitude. RE models yield estimates close to unity and slightly larger (in absolute value) than those obtained through FE and CRE models. A robust version of the Hausman test (Arellano, 1993) shows that FE estimations are preferable to RE estimations (Sargan-Hansen statistic: 30.16; χ^2=13; p-value = 0.005). The larger elasticity obtained with RE may also be due to an upward bias caused by unobserved time-invariant factors.

FE and CRE models yield price elasticities of approximately -0.85, implying that a 1% change in fuel price would lead to a 0.85% decrease in VKT. This result suggests that price-based policies trying to reduce GHG emissions and energy consumption might have a much more important impact than previously thought. Former studies on car fuel demand for Switzerland indeed estimate much lower price responsiveness in the interval from -0.25 to -0.4 (see Baranzini & Weber, 2013; Carlevaro et al., 1992; Filippini & Heimsch, 2016; Peter et al., 2002; Schleiniger, 1995; Wasserfallen & Güntensperger, 1988). However, we note that these studies examine fuel demand rather than travel demand and consider country-level time-series data, and are thus likely to be characterized by a downward bias in the estimated price coefficients (Levin et al., 2017).[24] De Borger et al. (2016a), Frondel et al. (2012) and Santos & Catchesides (2005) who use disaggregate data for the UK, Germany and Denmark, respectively, find price elasticities of household driving demand between -0.6 and -0.9.

Several reasons may explain the relatively strong elasticities of VKT in the Swiss case. First, the public transport network of this country is characterized by a particularly high density and quality, thus providing a very good substitute for private transportation. The relatively high fuel prices (at least compared to US

[24] Potential sources of bias relate to the weighting of city-specific price responses, the omission of time and location fixed effects, and correlations between within-month variations in nationwide gasoline usage and national average prices. According to Levin et al. (2017, p. 344), such price elasticities might *"differ by magnitudes large enough to substantially impact subsequent policy evaluation or market analysis."*

prices, where gasoline price is about half that in Switzerland[25]) may themselves contribute to increase consumers' reactions. An additional reason is related to the use of vehicles, which seems to differ from country to country. National car-travel surveys indeed show that Swiss and UK households use their private cars mainly for leisure trips, while the main purpose of vehicle usage in the US and Germany is related to professional and non-recreational activities.[26] Nevertheless, we acknowledge that if more price-sensitive drivers or households with higher gasoline bills are better informed about the gasoline price they face, this would lead to a measurement error in the price variable that is correlated with price sensitivity.

Results in *Table 2* also show that income elasticity of VKT is about 0.14. This is in line with previous estimations by Frondel et al. (2012) for Germany and Weber & Farsi (2014) for Switzerland. Car travel therefore classifies as a necessity good. This estimate is however much lower in comparison to the existing literature, where income elasticities are most often situated between 0.3 and 0.8. A possible explanation for the low income elasticity observed in *Table 2* lies in the way income is measured. Because households report their income in an interval, we derive income as the mid-point of each interval and this measure only captures limited variations in households' revenues. Nevertheless, we expect income elasticities in Switzerland to be low because of the high standards of living which make fuel costs easily affordable. TCS (2020) measures that expenditures for motor fuel represent on average only 15% of the total annual car spending (120 CHF per month), with a substantial share being attributable to insurances and garage costs. The last available Swiss household budget survey 2017 (OFS, 2020a) reveals monthly gasoline expenditures of about 100 CHF per month, which represents less than 2% of households' monthly disposable income.

Another remarkable result obtained in *Table 2* is that the distance traveled by the respondents of the 2020 wave of SHEDS is about 25% lower than in the reference year 2018. The strict national lockdown related to the Covid-19 pandemic between mid-March and June is included in the period covered by wave 2020 of

[25] For instance, see Bloomberg (2021).
[26] MTMC for Switzerland (OFS, 2017a), NHTS (2017) for the US, NTS (2018) in the UK, and MOP (2018) for Germany.

the survey, which was fielded in May-June 2020. It is also interesting to note that while the FE and CRE show that the impact of socio-demographic and vehicle characteristics on driving distance is statistically insignificant (as should be expected in the short run),[27] we obtain the expected coefficients for most covariates in RE2.[28]

The picture of the "typical", or "average" consumer discussed so far could conceal important differences between households. In order to examine the possibility of heterogeneous price elasticities between various segments of drivers, we pursue our analysis by interacting the socio-demographic and vehicle characteristics with gasoline price in model FE2.[29] As showed in equation (2), we define binary groups of households, such as low- and high-income households, drivers with efficient or inefficient vehicles, retired and working households. The results of these interactions are displayed in *Table 3*, where each model is estimated through FE, and where p-values related to Wald tests of the difference between the gasoline price coefficients in each model are displayed at the bottom of the table. Statistically significant differences at commonly accepted significance levels are highlighted by indicating the reported p-value in a bold font.

We observe evidence for statistically different price elasticities for three segments of drivers. Households with more efficient cars (with respect to the median efficiency of the sample), households living in cities, as well as respondents who live farther from the workplace (with respect to median distance between home and work places) exhibit higher price elasticities. Our result concerning the price responsiveness of households with more efficient vehicles is in contrast with previous findings (e.g., Liu, 2015; Spiller et al., 2017), but it robust to alternative definitions of the two group. It holds even if we choose the third quartile of the distribution of car's engine fuel efficiency as a limit to define the two groups of drivers.

[27] Age of the respondent and car vintage are excluded from FE, whereas the panel-means of those two covariates are excluded from the CRE models. Like in Tilov et al. (2020), this is done in order to avoid collinearity with year dummies.
[28] Part of the income effect in model RE2 is likely to be captured by the number of household members and the number of GA travel cards. Excluding these variables does not alter the estimated price elasticity, but increases the magnitude of the observed income coefficient, which also becomes statistically significant at the 99% confidence level. However, we find no evidence of a direct rebound effect, the coefficient of fuel efficiency being insignificant in all estimations.
[29] Goodness-of-fit measures point to relatively small differences between FE, and between CRE models. We use the parsimonious model FE1 (and CRE1 in CRE QR) in order to test the robustness of our findings at the end of this section.

Table 3: Price elasticities of various sub-groups (FE estimation)

	Segmentation criteria							
	Income	Fuel efficiency	Car vintage	HH members	HH age	GA travel cards	Driving distance home-work	Location
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-income HHs	-0.935**							
	(0.472)							
High-income HHs	-0.821*							
	(0.437)							
HH with an inefficient car		-0.659						
		(0.427)						
HH with an efficient car		-1.129***						
		(0.436)						
HH with a more recent car			-0.802*					
			(0.447)					
HH with an older car			-0.913**					
			(0.442)					
Single-member HH				-0.974**				
				(0.487)				
Multiple-member HH				-0.827*				
				(0.436)				
HH ≤ 65 years					-0.839*			
					(0.441)			
HH > 65 years					-0.875			
					(0.552)			
HH with 0 public transp. Tickets / HH head						-0.899**		
						(0.447)		
HH with > 0 public transp. Tickets / HH head						-0.718		
						(0.499)		
HHs with short driving distance home-work							-0.543	
							(0.453)	
HHs with long driving distance home-work							-1.138***	
							(0.430)	
Urban HH								-1.070**
								(0.495)
Non-urban HH								-0.688
								(0.466)
Gross HH income CHF (ln)	0.121	0.153**	0.140*	0.133*	0.143*	0.143*	0.147**	0.143*
	(0.090)	(0.075)	(0.076)	(0.078)	(0.076)	(0.076)	(0.074)	(0.076)
SHEDS 2019 (ref. SHEDS 2018)	0.019	0.020	0.021	0.018	0.019	0.019	0.075*	0.019
	(0.044)	(0.043)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
SHEDS 2020 (ref. SHEDS 2018)	-0.228***	-0.233***	-0.222***	-0.232***	-0.227***	-0.231***	-0.186***	-0.226***
	(0.064)	(0.064)	(0.065)	(0.065)	(0.064)	(0.064)	(0.063)	(0.064)
# HH members	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# GA travel cards per HH capita	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Driving distance home-work km (ln)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Living location: agglomeration (ref.: city)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Living location: countryside (ref.: city)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1138	1138	1138	1138	1138	1138	1138	1138
Adjusted R^2	0.022	0.033	0.022	0.022	0.022	0.022	0.028	0.023
Wald test between model's price coefficients: p-value	0.608	**0.005**	0.593	0.535	0.931	0.622	**0.015**	**0.097**

Clustered standard errors (by household id) in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Gillingham et al. (2015) also find a result opposite to ours and argue that owners of fuel-inefficient cars face a higher burden at the pump, which could make them more price-reactive. Nevertheless, households could acquire more efficient cars precisely because they are more sensitive to fluctuations in fuel prices in the first place (Liu, 2015). Indeed, Turrentine & Kurani (2007) suggest that consumers' attitude towards fuel efficiency is likely to be more complex than expected. Also, drivers of less efficient vehicles might continue using them despite higher operating costs simply because they do not have cheaper or more convenient mobility options. If this is the case, policies targeting reductions in GHG emissions and fuel consumption should rely on more stringent standards in order to influence and support drivers of inefficient cars. Special subsidies for the acquisition of vehicles with lower gasoline consumption could in addition be offered to these households, especially if they are also characterized by modest income levels. They could be also targeted by information campaigns about the financial advantages of driving an efficient car.

In line with previous findings in the existing literature (e.g., Blow & Crawford, 1997; Gillingham et al., 2015; West, 2004), we observe that people living in countryside or agglomerations areas exhibit lower price elasticities most probably because of the less developed public transportation system in those regions and because of the longer distance to various facilities, such as grocery stores. This makes rural households, who are also more dependent on private mobility, more vulnerable to gasoline price variations. The development of public transportation in rural regions, the encouragement of car-sharing schemes or efficient vehicle acquisition via subsidies could be used as complementary policy instruments to car fuel tax in order to limit the impacts on non-urban residents.

Finally, the estimations displayed in *Table 3* show that survey participants with longer driving distances between the home and the workplace are more price-elastic than drivers whose commutes are shorter. The difference in the magnitude remains even when we exclude individuals who do not work or work from home. It is possible that many drivers who use their car in order to get to a distant work location do so because of the convenience provided by private transportation: it is generally faster, more flexible, and more comfortable. They might prefer commuting to work by car as long as the benefit of this perceived convenience outweighs the monetary costs related to it. Another conceivable scenario is that many long-distance commuters have the option and/or are encouraged to work from home, especially if the driving costs from the dwelling to the workplace are borne by the employer.

We further examine heterogeneity in price elasticity of VKT using a quantile regression approach, adapted for panel data (CRE QR). This strategy allows to focus on segments of drivers defined on unobserved factors, which we interpret as translating households' "driving intensity". *Table 4* shows that only the upper end of the conditional car-travel demand, i.e., travel-intensive households, reacts significantly to changes in gasoline prices, while less intensive drivers do not exhibit statistically significant price elasticities. Most likely, households situated at the seventh and ninth conditional deciles have an important amount of discretionary driving (e.g., driving related to leisure activities) which they can adjust easily whenever gasoline prices increase. This effect is desirable for price-based policies since it suggests that higher gasoline prices lead to a reduction in car usage among the most travel-intensive drivers. This finding is similar to Gillingham et al. (2015) who rely on an alternative panel QR method, but contrasts with findings in Frondel et al. (2012) and Gillingham (2014) who apply QR to pooled datasets.

Table 4: Quantile regression with correlated random effects (QR CRE)

	Q.10	Q.30	Q.50	Q.70	Q.90
Gasoline price CHF (ln)	-0.385	-0.801	-0.824	-0.973*	-1.355**
	(0.845)	(0.680)	(0.582)	(0.523)	(0.686)
Gross HH income CHF (ln)	0.330*	0.071	0.099	0.140	0.259**
	(0.185)	(0.139)	(0.117)	(0.100)	(0.129)
Fuel efficiency km/L (ln)	0.304	0.102	0.003	-0.137	0.041
	(0.208)	(0.156)	(0.181)	(0.172)	(0.184)
SHEDS 2019 (ref.: SHEDS 2018)	0.079	0.018	-0.033	0.018	0.024
	(0.091)	(0.069)	(0.056)	(0.058)	(0.075)
SHEDS 2020 (ref.: SHEDS 2018)	-0.129	-0.279***	-0.230**	-0.250***	-0.260**
	(0.108)	(0.104)	(0.096)	(0.072)	(0.131)
Age of car (years)	-0.015	-0.005	0.002	0.003	0.007
	(0.014)	(0.006)	(0.008)	(0.007)	(0.008)
# HH members	-0.090	0.077	-0.027	0.025	0.109
	(0.126)	(0.056)	(0.059)	(0.056)	(0.074)
Age of reference person (years)	0.000	-0.001	-0.001	-0.002	-0.006**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
# GA travelcards per HH capita	-0.252	0.224	-0.051	0.085	0.187
	(0.307)	(0.241)	(0.241)	(0.202)	(0.362)
Driving distance home-workplace km (ln)	-0.003	-0.000	0.003	0.009	0.015
	(0.027)	(0.017)	(0.016)	(0.010)	(0.019)
Living location: agglomeration (ref.: city)	-0.134	0.090	-0.089	-0.037	-0.220
	(0.203)	(0.209)	(0.300)	(0.268)	(0.412)
Living location: countryside (ref.: city)	-0.604	0.273	0.075	-0.112	-0.352
	(0.675)	(0.344)	(0.278)	(0.269)	(0.228)
Average gasoline price (by household)	Yes	Yes	Yes	Yes	Yes
Average gross HH income (by household)	Yes	Yes	Yes	Yes	Yes
Average # GA per HH capita (by household)	Yes	Yes	Yes	Yes	Yes
Average # HH members (by household)	Yes	Yes	Yes	Yes	Yes
Average home-work km (by household)	Yes	Yes	Yes	Yes	Yes
Average living location: agglomeration (by household)	Yes	Yes	Yes	Yes	Yes
Average living location: countryside (by household)	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Imputed driving distance home-workplace: yes	Yes	Yes	Yes	Yes	Yes
Observations	1138	1138	1138	1138	1138
Households	490	490	490	490	490
Pseudo R^2	0.119	0.145	0.145	0.139	0.126

Clustered standard errors (by household id) in parentheses
* p<0.10, ** p<0.05, *** p<0.01

We investigate the robustness of our findings by first defining alternative threshold limits for the definition of binary segments of drivers. As mentioned previously, instead of taking the median of the distribution of continuous variables such as income, fuel efficiency, driving distance home-work or car vintage, we define household segments with respect to the first or the last quartiles of their distributions. Second, we estimate price elasticities in different model specifications, such as FE1 in *Table 2*, which includes only gasoline price, household income and year dummies as independent variables. Third, we define alternative limits for excluding extreme observations for VKT and gasoline prices. The findings presented in this article are robust to such sensitivity checks.[30]

6 Conclusion

This article examines the fuel price elasticity of Swiss households' car-travel demand. In particular, we investigate the differences in the price responsiveness of various segments of households, defined according to various observed and unobserved characteristics. One important strength of our study is to rely on longitudinal household-level data, not only for vehicle kilometers traveled – measured as the difference between two odometer readings – but more originally for gasoline prices – as observed at the gas station by each household on its last fill-up. A series of panel regression models including interaction terms are estimated using 1,138 observations from the Swiss Household Energy Demand Survey (SHEDS) 2018-2020. Results show a considerably higher price elasticity in comparison to prior estimates for Switzerland (or elsewhere), thus suggesting that fuel taxes could have a more substantial effect on driving than previously assumed. We also find that the average elasticity conceals important heterogeneity between households. In particular, households with more efficient vehicles, city-dwellers and respondents who live farther from their workplace exhibit significantly higher price elasticities. We further observe that households who can be qualified as travel-intensive, presumably because of non-essential (or discretionary) driving, are more price-elastic than less-intensive drivers.

[30] These results are available upon request.

From a policy perspective, our results suggest that in Switzerland non-price measures could provide an important complement to gasoline taxes. Drivers with fuel-inefficient vehicles could be targeted by information campaigns promoting the advantage of acquiring more efficient cars and could be offered special car-swap conditions. The development of public transportation, car-sharing or car-pooling in rural regions should be considered as well, in order to avoid penalizing non-urban dwellers who depend more heavily on their vehicles. Our results also show that a gasoline tax will induce a desired VKT-reduction effect on households driving long distances between their dwelling and their workplace. In addition, findings from a conditional quantile regression model for panel data reveal the highest conditional quantiles of travel demand are the most price-elastic. Because the highest portion of the distribution of driving demand is likely to represent higher amounts of leisure-related travel, an increase of gasoline prices will have a desired negative effect on the discretionary driving of the most travel-intensive groups of households.

We acknowledge that our analysis suffers from some caveats. First, we use a three-year panel dataset which does not consider changes in vehicle ownership and is too short to capture variation related to socio-demographic variables such as the number of household members or household age. Datasets with longer panels would make it possible to investigate the effect of evolving technology, and can thus allow researchers to apply the continuous-discrete framework suggested by Dubin & McFadden (1984) and Mannering (1986) to correct for endogeneity related to vehicle characteristics, such as fuel efficiency or vehicle age. Second, our dataset is relatively small so that some of our point estimates are characterized by wide confidence intervals, which prevents us from drawing any conclusions about the effect of several variables. Larger datasets would be required to verify if statistically significant differences between the price elasticities of the household segments defined in this article could be confirmed, as well as to investigate whether evidence of heterogeneity between other groups of drivers could be found as well. Third, it is possible that in reality travel price elasticities are asymmetric. For instance, Frondel & Vance (2013) find that on average households' driving demand is more sensitive to price increases than to price decreases, and an interesting topic for future research would be to explore weather different segments of households react differently to price increases or decreases. It is for instance conceivable that in comparison to rich households, low-income households exhibit greater price elasticity when gasoline prices decrease because their car-travel demand is probably not satiated. On the other hand, when fuel prices increase, it might be more difficult for poorer households to reduce their already minimal driving demand, if it is related to essential travel. In comparison, high-income households could more easily cut off leisure-related driving. uch questions could be addressed through the asymmetric model specifications applied by Batley et al. (2011) and Giuliano & Dargay (2006). Finally, future research could also focus on various combinations of segmentation criteria, such as rural households with different income levels, or households with intensive VKT and inefficient vehicles. As shown by Gillingham & Munk-Nielsen (2019) and Mattioli et al. (2018), the study of more precise segments of drivers can provide further details about the effects of car fuel taxation across the population.

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Appendix

Table A.1: Descriptive statistics, per year

	SHEDS 2018		SHEDS 2019		SHEDS 2020	
Continuous variables	Average	Std. dev.	Average	Std. dev.	Average	Std. dev.
Kilometers driven	14,446.90	10,400.30	14,353.40	10,874.10	12,838.40	9,803.40
Gasoline price CHF	1.55	0.07	1.61	0.09	1.38	0.12
Gross HH income CHF	9,233.00	4,455.65	9,221.10	4,461.75	8,931.70	4,497.70
Fuel efficiency km/L	14.20	3.19	14.43	3.09	14.37	3.16
Age of car (years)	7.52	4.66	7.90	4.76	8.52	4.96
# HH members	2.21	1.11	2.25	1.11	2.23	1.12
Age of reference person (years)	52.59	15.05	53.26	15.00	54.22	15.11
# GA travel cards per HH capita	0.17	0.36	0.14	0.31	0.14	0.32
Binary variables	Average		Average		Average	
Living location: city	0.42		0.43		0.44	
Living location: agglomeration	0.34		0.34		0.32	
Living location: countryside	0.24		0.23		0.24	
Driving distance home-workplace km	14.85		10.58		11.11	
Imputed driving distance: yes	0.10		0.07		0.07	
Observations	345		436		357	