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Does every Tom, Dick and Harry have a similar fuel price elasticity of car travel demand? Micro-level data reveals substantial heterogeneity

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Does every Tom, Dick and Harry have a similar fuel price elasticity of car travel demand? Micro-level data reveals substantial heterogeneity*

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Abstract

This article uses a rich panel dataset of 1,741 Swiss households in order to examine the effect of fuel prices on household car travel demand. Elasticities are estimated for different segments of households, based on their socio-economic and psychological characteristics, on the features of their vehicles, as well as on their driving intensity. Our results, which draw on inter-individual comparisons, yield larger medium- to long-run price elasticity of demand for mileage than previous estimations using aggregate data for Switzerland, and show that there is important heterogeneity in price sensitivity across segments of households. Lower-income households, households living in urban areas, drivers in retirement age and drivers with more efficient vehicles are significantly more price-reactive compared to their respective counterparts. Quantile regression models show that within segments defined on the basis of income, location, age and motor efficiency there is further evidence for price heterogeneity. These results reveal that in addition to a gasoline tax, non-price measures could be tailored to several household segments in order to provide supplementary incentives to reduce mileage and/or avoid penalizing some specific groups.

Keywords: car travel demand, fuel prices, elasticities, households' behavior, heterogeneity, panel data, Switzerland.

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

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1 Introduction

Transport fuels represent 35% of final total energy consumption in Switzerland (OFS, 2020a). Considering that households are responsible for more than 60% of overall gasoline consumption (OFS, 2019a), and that approximately 80% of them own at least one passenger car (OFS, 2017a), reducing the demand for private transportation appears essential for decreasing the country's energy use and its GHG emissions. Towards this end, the first package of measures of Switzerland's *Energy Policy 2050* defines a ceiling for the emissions of new cars imported in the country. Yet, the limit of 130 grams of CO_2/km valid between 2015 and 2019 was exceeded each of these years (OFEN, 2020), thereby raising questions about the effectiveness of this policy. The upper limit for emission levels is moreover decreased to 95 grams of CO_2 from 2020 on, which has refueled the debate on the introduction of a gasoline tax and its impact on different population groups (Parlement Suisse, 2020).

A large body of scientific research is dedicated to the estimation of price elasticities of travel demand. Most studies analyzing aggregate demand point to rather low price-elasticity of roughly -0.1 in the sort 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; West, 2004; Sevigny, 1998). In particular, different segments of consumers could be especially reactive to price variations due to their mobility behaviors and the travel constraints they face. For instance, intensive drivers could easily reduce mileage if they enjoy an important amount of discretionary driving. Car-owning households who live in urban areas are likely to switch to public transportation as a response to higher motor fuel prices, whereas lower-income households could not avoid using their cars even though gasoline and diesel become more expensive (see also Wadud et al., 2010a). 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] Yet, relatively few empirical work investigates how distinct household segments would react to variations in car fuel prices, despite an increased interest in this research topic in the late 2000s and early 2010s (Gillingham, 2014; Wadud et al., 2009). Moreover, the existing analyses in this field focus mainly on the US, investigate a limited number of segmentation criteria, use rather old time periods, employ aggregate demographic and price data, or complex price constructs from different sources in absence of individual prices, and do not reach a consensus about the impact of price variation across households segments.

The present article examines heterogeneity in price elasticity of car travel demand using household-level data from Switzerland between 2018 and 2020. We focus on household segments defined by "traditional" socio-economic, socio-demographic and vehicle characteristics, but also by "less conventional" psychological factors. We also investigate whether the most intensive drivers are indeed the most price-reactive ones, as suggests the fact that private cars in Switzerland are mainly used for leisure activities (OFS, 2017b). To the best of our knowledge, this analysis is the first using data based on revealed behavior to address the effect of price on car travel demand for different household segments in Switzerland.[2]

The remainder of this article is organized as follows. The related literature is discussed in *Section 2*. The dataset used in this article as well as descriptive statistics are presented in *Section 3*, while our econometric approach is discussed in *Section 4*. *Section 5* presents the empirical findings. *Section 6* concludes.

[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] 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 facing the risk of translating fictitious responses to price variations (Tanner, 2012).

2 Literature review

Our paper relates to the wide literature on in price elasticities in transportation. Here, 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
Articles using driving distance or vehicle-miles travelled 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		+				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: "+/-" indicates higher/lower magnitude of price elasticity for the indicated segment (e.g., high income) in comparison to its counterpart; "o" indicates an insignificant difference between the price elasticities of these segments; "U" indicates a U-shaped evolution of the magnitude of price elasticities along the income spectrum.

West (2004) uses state-level price data to investigate the short-run price responsiveness across the income distribution and of US households. She finds that low-income drivers tend to be more responsive than richer ones (-1.51 in the lowest income decile to -0.75 in the highest), presumably because of the constraint imposed by their smaller budgets. The author however notices that it is conceivable that in other contexts poorer households exhibit lower price responsiveness if they hardly have alternative mobility options. Santos & Catchesides (2005), who use data for the UK between 1999 and 2000, also remark that the short-run price elasticity of the demand for mileage declines with higher income levels and increases in urban areas. The price elasticities they estimate for those household segments (between -0.93 and -0.75) are notably higher than those found in the literature. Similar conclusions concerning income and location are

drawn by Blow & Crawford (1997), whose short-run estimates fall in the interval -0.54 to -0.24. However, Gillingham (2014) finds the opposite result using county-level monthly retail fuel prices and vehicle-level data for California between 2000 and 2010. He observes that car owners who are better-off are more price-reactive (elasticity of -0.40) in comparison to low-income ones (elasticity of -0.22) and argues that this could be related to the higher amount of discretionary driving by wealthier households, by their possession of multiple cars, or by the substitution of car with airplane travel. Wang & Chen (2014) find in contrast a U-shape relationship between the demand for vehicle-miles travelled and the price responsiveness among US household segments defined on the base of their income. They show that price elasticities in the upper part of the income ladder are situated in the interval -0.45 to -0.39, those at the bottom of the income spectrum are slightly lower (about -0.24), whereas households in the second and third income quintiles display insignificant price elasticities. With respect to living location, Gillingham & Munk-Nielsen (2019) find that the demand for mileage of Danish households with the longest and the shortest commutes to work exhibit a higher price-responsiveness than the average elasticity of -0.30 over the study period between 1998 and 2011.[3] These two segments of drivers respond to a 10% change in fuel prices by decreasing their vehicle-miles travelled by 6% and 4%, respectively.

Using a conditional quantile regression analysis, Gillingham (2014) also finds that the lowest conditional quantile of vehicle-miles-traveled is more price-elastic (elasticity of -0.33) than the highest quantile (-0.17). Frondel et al. (2012) obtain similar findings for Germany. Their analyses show that frugal and intensive drivers are characterized by elasticities of -0.90 and -0.56, respectively. According to these authors, high travel intensity reflects a higher dependency on private mobility, and hence, a lower price responsiveness. However, more driving may also be due non-essential travelling, as suggested by Gillingham et al. (2015). Their study in the state of Pennsylvania shows price elasticities of greater magnitude at the third conditional quartile (-0.15) than at the first one (elasticity non-significantly different

[3] These authors match administrative data at the vehicle-level with weighted household demographic data.

from zero). Another finding of their analysis is that owners of less efficient vehicles are more reactive to price (-0.19) than those with more efficient vehicles (the price elasticity of the latter being not significantly different from zero). This result is attributed to the fact that drivers of inefficient cars already face a more important burden at the pump.

These results have strong implications for policies targeting stricter pollution standards, as they allows forecasts of the evolution of driving across the vehicle fleet. Nevertheless, as summarized in *Table 1*, most studies focus on the North-American context, the number of segmentation criteria is limited, and there is a lack of consensus regarding the impact of price variations across households groups.[4] These comments also apply to the literature exploring price heterogeneity of car fuel demand (rather than distance travelled; second part of *Table 1*). We also observe that none of these studies deals with the Swiss case,[5] so that the patterns of price elasticity heterogeneity in this country remains an empirical open question.

The range of segmentation characteristics used for the analysis of heterogeneity of price elasticities could be extended beyond the socio-economic and demographic features traditionally examined in economic studies by focusing on consumer groups based on psychological features. Notwithstanding the use of such psychological factors in a few studies related to transportation (Abrahamse & Steg, 2009; Anable, 2005; Brand et al., 2017; Klöckner, 2013, 2015; Sütterlin et al., 2011), such "unconventional" segmentation characteristics have so far not been applied to the multivariate economic analysis of price elasticities of car travel demand. The dataset used in this study allows us to integrate such criteria in our analyses.

[4] For instance, Spiller et al. (2017) find that the car fuel demand of urban households in the US is less price-elastic than the price responsiveness of their counterparts. They explain that due to congestion in cities, urban drivers might have optimized their amount of driving, which would make their motor fuel demand less reactive to price variations. With respect to multiple-vehicle ownership, Wadud et al. (2010a, 2010b) find that US households with several cars are more price-elastic, because of the option to switch to more efficient vehicles when driving fuel becomes more expensive. Liu (2015) however obtains the opposite result and argues that switching to the most efficient vehicle could not be the only rational choice. For larger families, especially those with young children, a more convenient option is to continue to use their more spacious vehicle even when fuel prices increase.

[5] An exception is the previously mentioned study by Erath & Axhausen (2010) whose results should be nevertheless taken with a grain of salt, given their reliance on stated preferences.

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 the entire geographical space of 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.[6] We consider only ICE (gasoline and diesel) cars, which represent roughly 97% of the overall car fleet in Switzerland (OFS, 2020e), and exclude other types of vehicles such as electric ones because fuel prices of such vehicles are difficult to compare.

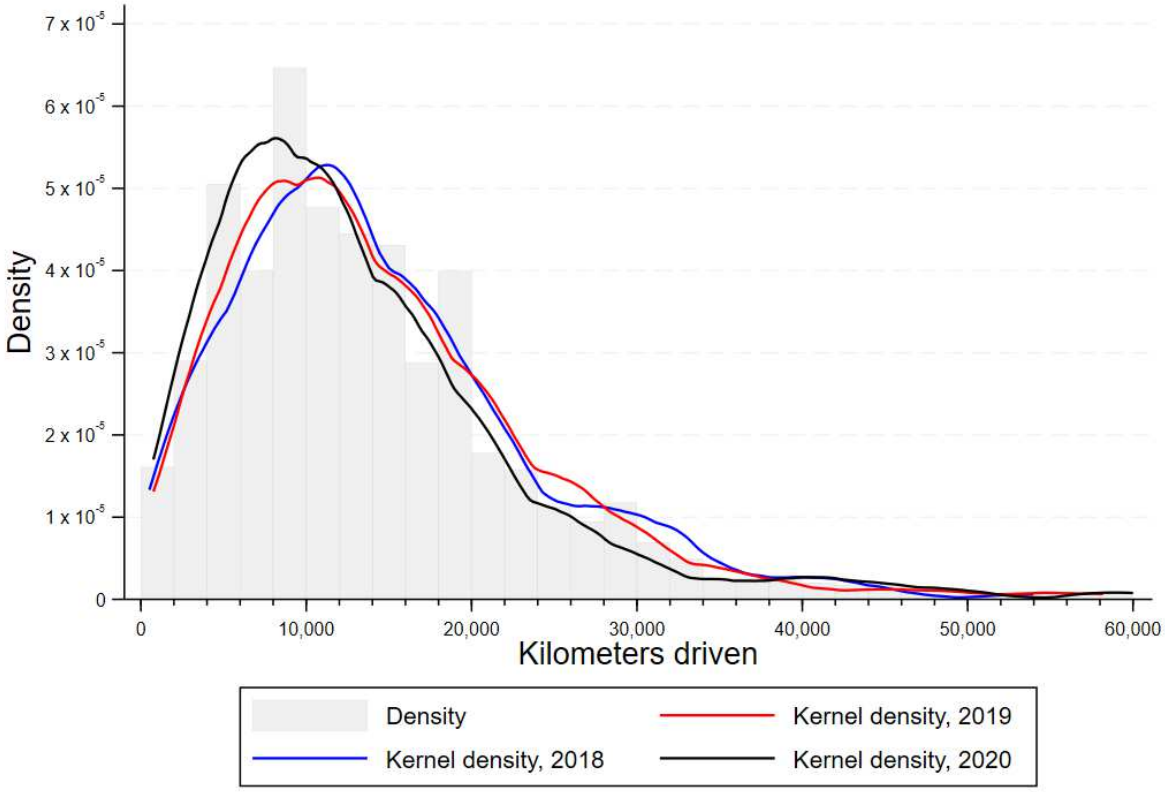
The dependent variable in our analysis is the average annual driving distance of the most used car in the household. It is obtained from the differences in odometer readings, reported in the consecutive waves of the SHEDS questionnaire. We therefore consider only households who do not change their car between two survey waves. Considering car purchased between two waves would force us to extrapolate annual distances from distances traveled during part of the year. Because distance traveled is affected by seasonal factors, this procedure would require strong assumptions. We consider annual driving distances below 500 or above 60,000 kilometers as unlikely and exclude these from the analysis (3% of the observations).

Figure 1 shows the distribution of driving distances in our final dataset. Kernel densities are superimposed to illustrate the evolution of mileage for each year in our observation window. As expected, the density is strongly skewed to the right, with a peak in car travel distance about 10,000 kilometers a year. While the Kernel densities for 2018 and 2019 overlap, it is interesting to note that the mileage distribution shifts to the left in 2020, presumably because of the Covid-19 lockdown.[7]

[6] 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 have corrected 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.

[7] 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



Note: Epanechnikov kernel with optimal width.

Additional information about mileage is displayed in *Table 5* in *Appendix*, which provides descriptive statistics for our sample, separately for each of the three periods covered in our dataset. On average, distance traveled is between 13,000 and 15,000 km/year, but it is characterized by important variability between households. For comparison, statistics from the 2015 *Mobility and Transport Microcensus* (OFS, 2017a) show the "first" car in a typical Swiss household is driven on average 13,441 kilometers per year. In addition, *Touring Club Switzerland* – Switzerland's largest mobility club – uses an annual mileage of 15,000 kilometers for the calculation of the average costs related to a private car in 2020. *Table 5* also mirrors the important drop in average mileage related to the Covid-19 lockdown.

Fuel price is the key independent variable in this article. It is obtained directly from respondents, who are asked the price they paid when they last filled up the tank. Although it does not correspond to an average

price over the year, this information presents the advantage of capturing variability across individuals, thereby presenting a rare opportunity to use individual-level price data.[8]

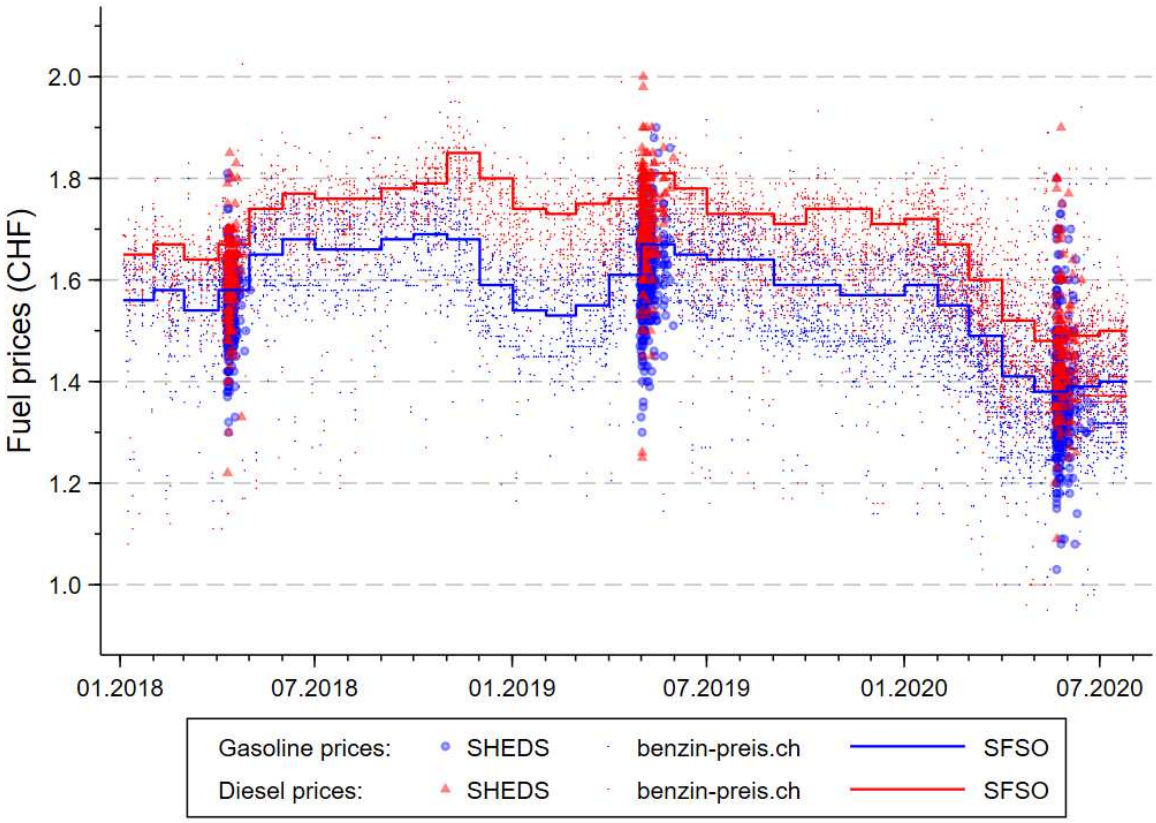
The final sample consists of 1,741 observations from 753 households, each being observed up to three times. *Figure 2* shows the individual fuel prices reported by the SHEDS respondents, and compares them with price data from two other sources: (1) the Swiss federal office of statistics, which provides national average monthly prices for gasoline and diesel (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.[9] *Figure 2* shows there is important variability across prices collected during the survey but the average is close to values observed in other sources. An overall increase in fuel prices is observed between 2018 and 2019, before substantial decrease in 2020. This evolution follows closely both the official average monthly data of the Federal statistical office and the daily prices obtained from www.benzin-preis.ch. Finally, we observe that diesel prices are as expected higher than gasoline prices, as is generally the case in Switzerland (Pock, 2010).

In addition to fuel prices, we account for various socio-economic, socio-demographic, vehicle-related and psychological factors expected to influence distance traveled. The household annual gross income enters the first group of covariates. It 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).

[8] We restrict the prices by using the method suggested by Tukey (1977): for each wave, we exclude prices whose values are lie farther than three times the inter-quartile range below the first or above the third quartile of the price distribution. This excludes 36 additional observations.

[9] We express our gratitude to Marc Wettstein from www.migrol.ch and Michael Möckli from www.benzin-preis.ch for providing us with additional aggregate information regarding fuel prices in Switzerland.

Figure 2: Gasoline and diesel prices



For sociodemographic attributes, like age or education, the respondent's own characteristics are considered as representative of the household. The same approach is adopted for the participants' individual values and attitudes, although complex interactions between household members may determine psychological characteristics of the household as an inseparable entity (Volland, 2017; Zhang & Fujiwara, 2006). Two dummy variables related to residential location (agglomeration and countryside) are also included in the set of socio-demographic variables. Cantonal dummies are also introduced to account for higher level geographical effects.[10]

Following Steg et al. (2014), our model specification includes distinctive measures for biospheric, hedonic, altruistic and egoistic values. These are obtained from a battery of questions, in which participants indicate

[10] Some neighboring cantons are grouped (e.g., Uri, Obwalden, and Nidwalden) when the numbers of observations are very small.

how important they consider different life values, on a scale from 1 (not important) to 5 (extremely important). For each value, an average score is calculated using the multiple relevant items.

Engine efficiency, car vintage and engine type (gasoline or diesel) constitute the subset of vehicle-related determinants. The coefficient of efficiency and other car-related variables may be affected by endogeneity, because drivers who (intend to) travel longer distances might choose to buy newer, more efficient cars, or alternatively bigger and more comfortable cars. Three different ways to address this issue exist in the literature: (1) instrumental variable approaches, although finding relevant and strong instruments has proven challenging;[11] (2) excluding engine efficiency from the set of determinants of fuel demand based on theoretical considerations related to consumer behavior;[12] (3) simultaneous equations models (e.g., Small & Dender, 2007; Weber & Farsi, 2014; Mannering, 1986). In this article, we do not pretend to provide an unbiased energy efficiency coefficient, but we simply introduce efficiency among the covariate to determine whether it affects price elasticity.[13]

The substitutability between public and private transportation is captured by two controls for the number of regional or general travel cards per household member. Multiple-car households are also identified by a dummy indicator in the model specification, because occasional usage of other cars could reduce driving with the first car, even though overall travel demand by the household is not lower. Finally, we control for unobserved time-variant factors, by including year dummies.

[11] 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).

[12] According to economic theory, a rational consumer will treat the variation in the cost of driving in the same manner, regardless of 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) and 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 unexpected and usually temporary, while improvements of engine fuel efficiency are permanent (Linn, 2016). Also, 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 a further discussion of the theoretical non-equivalence between the cost effect of fuel prices and fuel efficiency, see Weber & Farsi (2014).

[13] Frondel et al. (2012) suggest that if fuel prices and engine efficiency are orthogonal, the price coefficient will not be biased. In our dataset, we observe an empirical Pearson correlation coefficient of 0.011 between engine efficiency and fuel price, and -0.067 between car's age and fuel price, as well as a polychoric correlation of about 0.34 between engine type and fuel prices.

4 Econometric approach

In order to evaluate the effect of fuel prices and socio-demographic, vehicle and psychological factors on the demand for car mobility, we use the following multivariate regression model:

$$ln(D_{it}) = \alpha + \beta\, ln(P_{it}) + \sum_{k=1}^{K} (\delta_k\, X_{kit}) + \nu_i + \varepsilon_{it} \qquad (1)$$

where D_{it} is annual mileage of the main car of household i and P_{it} is the self-reported fuel price that household i paid the last time it filled the tank. Other socio-demographic, psychological, lifestyle or vehicle characteristics are captured by the terms $X_{1it}, \dots, X_{Kit}$. Because the dependent measure D_{it} and the main regressor of interest P_{it} are in logarithmic form, coefficient β can be directly interpreted as a price elasticity.[14] The terms ν_i are random components which capture household-specific stochastic residuals and ε_{it} are idiosyncratic residuals.

The investigation of heterogeneity in the sensitivity to fuel price is addressed by introducing a series of interactions between fuel price and the observable population characteristics in equation (1). Similarly to Frondel et al. (2012), we estimate model specifications that include interaction terms either jointly or separately and obtain similar results with both methods.[15]

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

[15] 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

Equation (1) is first estimated by random-effect (RE) and fixed-effect (FE) methods. Prior analyses of car fuel demand (e.g., Filippini & Heimsch, 2016; Frondel et al., 2012; Wadud et al., 2010a) consider the RE model to be better adapted for short panels. We also favor RE models for two additional reasons: (1) time-invariant factors cannot be introduced in FE models but are of interest for our heterogeneity analyses, because they provide additional information on the driving behaviors of various population segments; (2) as argued in *Section 3*, given the nature of our price measure we focus on variations between observations. Thus, our models, delivering coefficients mostly based on inter-household comparisons, should be interpreted as providing estimates of the effects in the median- to long-run.

We moreover use conditional quantile regressions (QR) to estimate (1) and further investigate the presence of heterogeneous price responses. Initially developed by Koenker & Bassett (1978), QR is an important complement to the estimation of the *average* price elasticities 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 qth 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 asymmetric penalties attributed to observations, depending on their position with respect to the best line of fit, and $\theta_{it} = \nu_i + \varepsilon_{it}$ as defined in equation (1) above. Although various extensions of QR for longitudinal data exist in the literature,[16] we use pooled QR, which is consistent with our focus on inter-household variations to investigate heterogeneous price responses among household segments.

5 Results and discussion

The empirical estimations of RE and FE models explaining distance traveled are displayed in *Table 2*. Our RE model yields a price elasticity of -1.05, implying that a change in fuel price would lead to an

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.

[16] These methods are however applied in the context of fixed effect estimations. See Canay (2011), Machado & Santos Silva (2019), Powell (2016) and Wooldridge (2010) for more details.

approximately proportional decrease in travel demand. The estimated fuel responsiveness in our FE model is smaller, yet close in magnitude (-0.85). Former studies on car fuel demand for Switzerland have typically estimated much lower price elasticities in the interval from -0.25 to -0.4 (see Carlevaro et al., 1992; Peter et al., 2002; Schleiniger, 1995; Wasserfallen & Güntensperger, 1988; Baranzini & Weber, 2013; Filippini & Heimsch, 2016). However, we note that these studies examine fuel demand rather than mileage demand, and they apply aggregate country-level time-series data which cover rather old time spans, and are thus likely to be characterized by a downward bias in the estimated price coefficients (Levin et al., 2017).[17] Frondel et al. (2012) and De Borger et al. (2016a), who use more recent disaggregate data for Germany and Denmark, find price elasticities of household driving demand between -0.6 and -0.8. The rapidly growing demand for electric and hybrids cars (OFS, 2020d) in Switzerland due to their decreasing prices, lower driving costs and higher range (TCS, 2020), as well as the increasing environmental awareness of Swiss citizens (OFS, 2019b) are also likely to contribute to an overall higher price-sensitivity.

Results in *Table 2* also confirm several well-documented phenomena related to fuel demand. To start with, a change of 1% in gross household income is related to an approximate increase in mileage of 0.8%. This is in line with the positive but low income elasticities estimated by Frondel et al. (2012) for Germany and Weber & Farsi (2014) for Switzerland. Car travel therefore classifies as a necessity good.

The small positive effect (+4%) of additional household members on mileage is in line with the majority of earlier studies (e.g., De Borger et al., 2016a; Yatchew & No, 2001) and reveals large scale economies in private transportation. Considering the increasing trend in the number of single-member households in Switzerland (OFS, 2020c), this result suggests that any possible scale economies obtained via within-household car sharing will be lost. Next, the age of household members affects the demand for private mobility, with elderly households being less mobile, probably due their more settled lifestyles or because

[17] The sources of bias can 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. Thus, price elasticities might *"differ by magnitudes large enough to substantially impact subsequent policy evaluation or market analysis."* (Levin et al., 2017, p. 344).

of health-related reasons (see Schmalensee & Stoker, 1999; Wadud et al., 2010).

Expectedly, the geographic location of the household has a significant impact on the kilometers driven. The mileage of households living in the countryside (in agglomerations) is on average 19% (16%) higher than the driving distance of urban dwellers, other things being equal. As explained by Yatchew & No (2001), living in non-urban areas is a synonym for longer travel distances between the home and various places such as workplace, city center and public transport stops. The possibilities of substitution between private and public transport increase when the household holds public transportation tickets, so that the demand for mileage decreases substantially for the latter households.

Several additional coefficients displayed in *Table 2* deserve some attention. First, our results indicate that households with diesel cars travel 18% longer distances than drivers of gasoline cars, which could be expected considering that diesel cars typically consume less fuel and are therefore well-adapted for long distances. The year fixed effects show that the Covid-19 lockdown in 2020 had a strong impact on the travel behavior of Swiss households. Finally, *Table 2* also reveals that none of the psychological factors used in our analysis plays a significant role in shaping car travel demand.

The picture of the typical, or average, situation discussed so far could conceal important differences between households. In order to examine the possibility of heterogeneous price responsiveness between various segments of car-owners, we pursue our analysis by interacting the socio-economic, socio-demographic, psychological and vehicle characteristics with fuel price. In particular, we define binary groups of households,[18] such as low- and high-income households, drivers with efficient or inefficient vehicles, retired and working car-owners. The results of these interactions are displayed in *Table 3*, where each line relates to a separate RE model including the interaction between price and the indicated variable,

[18] Interactions between fuel price and the continuous versions of the variables at hand yield insignificant results, like in Frondel et al. (2012). For this reason, we dichotomize the continuous variables to create binary variables. For continuous variables without natural threshold (such as income, car age and the psychological values presented in *Table 3)*, we use the average as the threshold and therefore create groups of below- or above-average households.

in addition to all covariates discussed in previous section. For a more concise representation, only the estimate of the price elasticity for each household segment is displayed (column (4)).

Table 2: Determinants of distance traveled

	RE	FE
	Distance driven (ln)	
Fuel price CHF (ln)	-1.046***	-0.851**
	(0.289)	(0.366)
Gross HH income CHF (ln)	0.075**	0.068
	(0.038)	(0.067)
Fuel efficiency km/L (ln)	0.116	0.099
	(0.090)	(0.141)
Engine type: diesel	0.162***	0.149
	(0.046)	(0.180)
SHEDS 2019 (ref.: SHEDS 2018)	0.058*	0.072
	(0.035)	(0.074)
SHEDS 2020 (ref.: SHEDS 2018)	-0.206***	-0.143
	(0.049)	(0.127)
Age of car (years)	-0.004	0.002
	(0.005)	(0.010)
HH with a single car	-0.006	
	(0.049)	
# HH members	0.035**	-0.013
	(0.017)	(0.031)
Age of reference person (years)	-0.008***	-0.026
	(0.002)	(0.060)
Tertiary education: yes	-0.037	
	(0.044)	
Biospheric values	-0.013	
	(0.031)	
Altruistic values	0.042	
	(0.033)	
Hedonic values	0.012	
	(0.028)	
Egoistic values	0.0001	
	(0.027)	
# general public transport tickets (AG) per HH capita	-0.257***	0.044
	(0.074)	(0.138)
# regional public transport tickets per HH capita	-0.206**	-0.053
	(0.093)	(0.175)
Living location: agglomeration (ref.: city)	0.145***	
	(0.053)	
Living location: countryside (ref.: city)	0.176***	
	(0.055)	
Constant	8.922***	10.138***
	(0.503)	(3.172)
Canton fixed effects	Yes	No
Observations	1741	1741
Households	753	753
Min obs. per household	2	2
Average obs. per household	2.3	2.3
Max. obs. per household	3	3
Within R^2	0.016	0.023
Between R^2	0.178	0.067
Overall R^2	0.131	0.050

Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

We also observe that households owning vehicles with better engine efficiency exhibit a significantly higher price elasticity of mileage demand in comparison to drivers of more energy-intensive cars. Gillingham et al. (2015) find the opposite result, arguing that owners of fuel-inefficient cars face a higher burden at the pump, which could make them more price-reactive. Nevertheless, it is also conceivable that households 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 more complex than expected. Also, drivers of less efficient vehicles might continue using them despite their higher operating cost, simply because they do not have cheaper or more convenient mobility option. In addition, our findings reveal that households in retirement age are more price-elastic than those below 65 years old. The latter group is indeed likely to be more dependent on car transportation, not only for work-related purposes, but also due to their more active lifestyles. Thus, the aging pattern of the Swiss population could contribute to the higher price elasticity of travel demand in the future, in addition to a drop in mileage. In this context, the impact of a gasoline tax on the more sensitive group of retired household should be considered and additional policy interventions compensating their welfare loss could be designed on top of the rebates they already receive when purchasing public transport tickets (e.g., elderly households could be offered special subsidies for apartments with facilitated access to public transportation).[19]

Finally, in line with previous findings in the existing literature (e.g., Blow & Crawford, 1997; Gillingham et al., 2015; West, 2004), we find that people living in countryside or agglomerations areas exhibit lower price elasticities, most probably because of the less-developed public transportation, its limited frequency and the more important distance to various facilities, such as grocery stores. This makes rural households, who are more dependent on private mobility (and moreover obtain lower incomes), more vulnerable to price variations of car fuel. The development of public transport in rural regions, the encouragement of car-

[19] On the importance of the proximity between home place and public transport stops for the elderly, see Shrestha et al. (2017). In its advice on retirement planning, one large Swiss insurance company (Generali, 2020) puts forward the crucial importance of proximity to public transportation services. Anecdotal evidence is also provided by the NYT (2014).

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 populations.

Table 3: Price elasticities of various sub-groups

(1)	(2)	(3)	(4)	(5)	(6)
Grouping characteristic	Sub-groups	Number of observations by sub-group	Price elasticity by sub-group	Std. error (clustered by household)	p-value from Wald test for differences between the price elasticities of sub-groups
1. Gross household income:	**≤ 9,600 CHF**	**920**	**-0.925*** **	**0.289**	**0.014**
	> 9,600 CHF	**821**	**-0.656** **	**0.291**	
2. Engine efficiency:	**≤ 14.48 km/L**	**931**	**-0.862*** **	**0.294**	**0.002**
	> 14.48 km/L	**810**	**-1.226*** **	**0.289**	
3. Engine type	Gasoline	1,170	-1.091***	0.318	0.700
	Diesel	571	-0.958***	0.364	
4. Car age:	≤ 8 year	1,116	-1.009***	0.298	0.521
	> 8 year	625	-1.103***	0.298	
5. Number of cars:	1	1,208	-1.093***	0.308	0.615
	2+	533	-0.928**	0.365	
6. Number of persons per HH:	1	382	-1.231***	0.321	0.137
	2+	1,359	-1.012***	0.289	
7. Age of reference person:	**< 65 years**	**1,285**	**-0.967*** **	**0.290**	**0.066**
	≥ 65 years	**456**	**-1.288*** **	**0.325**	
8. Education:	Secondary/less	876	-1.239***	0.330	0.207
	Tertiary	865	-0.848***	0.324	
9. Biospheric values:	Weak	873	-1.074***	0.296	0.598
	Strong	868	-1.014***	0.295	
10. Altruistic values:	Weak	829	-1.048***	0.295	0.963
	Strong	913	-1.043***	0.294	
11. Hedonic values:	Weak	841	-1.079***	0.299	0.574
	Strong	900	-1.013***	0.291	
12. Egoistic values:	Weak	891	-0.989***	0.292	0.275
	Strong	850	-1.113***	0.299	
13. # of travel cards per HH head:	0	1,345	-1.050***	0.292	0.896
	1+	396	-1.022***	0.336	
14. Place of residence:	**City**	**720**	**-1.432*** **	**0.356**	**0.0525**
	Outside city	**1,021**	**-0.800*** **	**0.307**	

* p<0.10, ** p<0.05, *** p<0.010. Bold font indicate that there is a significant difference (p-value < 10%) between the two sub-groups.

Lastly, we further examine heterogeneity in price elasticity of travel demand using a quantile regression approach. This strategy allows to investigate which of the sub-groups defined above are more price-reactive when an additional grouping criterion, namely the intensity of travel demand within each sub-group, is considered. Such an analysis goes one step further and makes it possible to answer more intricate questions. For instance, among elderly households, are the most frugal drivers also the most reactive to price changes? Or, conversely, are the most travel-intensive young households more price-sensitive than their older counterparts? Are there specific differences between sub-groups based on *both* age and intensity criteria? To answer such questions, a series of QR including the previously discussed interaction terms are estimated. In particular, we focus on the interactions of price with household income, price with engine efficiency, price with household age, as well as price with living location across the conditional distribution of travel demand. Estimations for three conditional quartiles of mileage demand estimated via QR are shown in *Table 4*. We display the results related to the previously discussed interaction terms and omit the rest of the output for a more concise representation.

Table 4 shows that groups defined according to income and living location exhibit significant price elasticities only at the high-end of the spectrum of the conditional demand for mileage. Although the difference in magnitudes between the coefficients within the third quantile confirms the results presented in *Table 3*, the difference between them is not statistically significant. More generally, our estimations suggest that for the two aforementioned household segments, only drivers who can be defined as intensive, or wasteful, react in a significant way to variations in prices. This result is intuitive, considering that private cars in Switzerland are mainly used for leisure activities (OFS, 2017a), implying that intensive drivers dispose of an important amount of discretionary driving which can be reduced when fuel prices increase. This effect is desirable for price-based policies, such as fuel taxes, since these would trigger reduction of car usage among the most wasteful drivers.

Table 4: QR with interactions

Grouping characteristic	Sub-groups	q0.25 Price elasticity	q0.25 p-value from Wald test of difference	q0.50 Price elasticity	q0.50 p-value from Wald test of difference	q0.75 Price elasticity	q0.75 p-value from Wald test of difference
Gross household income:	≤ 9,600 CHF	-0.784 (0.646)	0.600	-0.543 (0.412)	0.398	-0.861** (0.356)	0.855
	> 9,600 CHF	-0.663 (0.652)		-0.389 (0.415)		-0.837** (0.339)	
Engine efficiency:	≤ 14.48 km/L	**-0.600 (0.553)**	**0.008**	**-0.283 (0.427)**	**0.077**	**-0.616 (0.382)**	**0.049**
	> 14.48 km/L	**-1.171** (0.562)**		**-0.601 (0.429)**		**-0.873** (0.371)**	
Age of reference person:	< 65 years	**-0.733 (0.539)**	**0.084**	**-0.396 (0.449)**	**0.056**	**-0.708** (0.298)**	**0.026**
	≥ 65 years	**-1.274** (0.601)**		**-0.809* (0.489)**		**-1.100*** (0.328)**	
Place of residence:	City	-0.466 (0.588)	0.642	-0.763 (0.527)	0.294	-1.132** (0.497)	0.191
	Outside city	-0.830 (0.819)		-0.258 (0.482)		-0.544 (0.344)	

Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.010

Table 4 also shows that elderly households are significantly more price-sensitive in comparison to younger drivers, regardless of their driving intensity. This implies that a fuel tax would affect the least and the most intensive drivers over 65 years old similarly. In line with our estimations in *Table 3*, we also observe that the magnitude of the price coefficient is higher for households with more efficient vehicles across all conditional quartiles. Significant results are nevertheless observed for the least and the most intensive drivers, but not for the median. The differences between the estimated magnitudes within each quartile suggest that there is little difference between the price elasticities of efficient and inefficient vehicles with different travel intensities.

Several remarks considering our analyses are in order. As noted by Wadud et al. (2010a), the use of interactions is likely to further affect the precision of model estimates, due to possible multicollinearity. Larger datasets, as those used in Gillingham (2011) and Gillingham & Munk-Nielsen (2019) would provide

the best remedy for this issue. Another caveat is that our price measure captures fuel prices obtained at the end of the driving period, rather than average prices over the entire period. Although the obtained price variable still allows capturing variations between households, we carry out several robustness checks by excluding the last wave of SHEDS from our analyses, having in mind that the gap between our price measure in 2020 and the average price over the previous 12 months is certainly wider due to the sharp drop in fuel prices caused by the global Covid-19 pandemic. After excluding year 2020 from our RE model, we obtain an average price elasticity of travel demand of about -0.75, which is somewhat lower than the elasticity obtained for the entire 2018-2020 period. Yet, it remains much higher than previous estimates obtained for Switzerland and other countries. The statistical differences between household segments is further confirmed, apart from the result related to segments of car owners in urban and non-urban locations. However, the difference in the magnitudes of these coefficient still confirms the results discussed in this article. We believe that the large price elasticity, as well as our finding regarding heterogeneous price responses are therefore not driven only by the variations in fuel prices present in the last wave of our survey.

6 Conclusion

This article examines the fuel price elasticity of car travel demand in Switzerland. In particular, we investigate the differences in the price responsiveness of various segments of households, defined according to a number of socio-economic, socio-demographic, vehicle, psychological and lifestyle characteristics. A series of panel regression models including interaction terms are estimated using 1,741 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, thereby suggesting that fuel taxes could have a more important effect than previously assumed. We also find that the average elasticity conceals important heterogeneity between households. In particular, low-income households, households with more efficient vehicles, elderly drivers and city-dwellers exhibit significantly higher price elasticities in comparison to their respective counterparts. We further observe that within household groups defined on

the basis of income and location, intensive drivers exhibit higher price responsiveness, whereas no difference is observed for groups of households defined on the basis of age.

We acknowledge that our analysis suffers some caveats. First, we do not correct for endogeneity related to vehicle-related characteristics. Although we assume that this does not affect our price coefficient, future research could collect and use more detailed data on vehicle acquisition decisions and thus apply the continuous-discrete framework suggested by Dubin & McFadden (1984) and Mannering (1986) to correct for endogeneity. Second, our point estimates are characterized by large confidence intervals, and are also likely influenced by multicollinearity between interaction terms and their components in our models. Thus, bigger datasets are required in order to verify if statistically significant differences between the price responsiveness of the household segments discussed in this article could be confirmed, as well as to investigate whether evidence of heterogeneity in price-responsiveness between other groups of drivers could be found as well. It is also possible that in reality travel price elasticities are asymmetric. Frondel & Vance (2013) find that households' driving demand is more responsive to price increases than to price decreases. Finally, in order to control for endogeneity due to time-invariant factors, future research could focus on within panel variations, but this would require a longer panel than the one we have at hand.

From a policy perspective, the results of the present article suggest that in Switzerland non-price measures could provide an important complement to fuel taxes. Low-income households could be offered special rebates for public transport tickets, or subsidies for using car-sharing services in order to avoid imposing an additional welfare burden on this already vulnerable population. Drivers with less fuel-efficient vehicles could be targeted more intensely by information campaigns about the advantage of acquiring more efficient cars and they could be offered special car-exchange or car purchase advantages provided they purchase a more efficient vehicle. Financial advantages could also be designed in order to facilitate relocation of elderly households in urban regions. Because elderly people are identified as highly sensitive to price, fuel taxation could have a very strong impact on their overall traveling and hence on their well-being. 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 are strongly dependent on private transportation. In addition, our findings from a conditional quantile regression model show that it is overall the highest conditional quartiles of travel demand that are the most responsive to price variations. Because the higher end of the spectrum of driving demand is likely to represent higher amounts of leisure-related travel, an increase of gasoline prices will thus have a desired negative effect on the discretionary driving of the most wasteful groups of households.

Appendix

Table 5: Descriptive statistics, per year

	2018		2019		2020	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Annual driving distance (km)	14,398.10	9,125.69	14,267.87	9,218.47	13,190.58	9,456.22
Annual driving distance, gasoline cars (km)	13,440.35	9,095.14	13,356.45	8,762.52	12,783.77	9,467,41
Annual driving distance, diesel cars (km)	16,302.90	8,909.16	16,082.55	9,836,36	14,081.22	9,398.11
Gasoline price CHF	1.55	0.07	1.61	0.09	1.38	0.12
Diesel price CHF	1.60	0.09	1.71	0.10	1.46	0.12
Gross HH income CHF	9,607.72	4,516.94	9,717.57	4,559.49	9,574.58	4,593.42
Fuel efficiency km/L, gasoline cars	14.23	3.37	14.58	3.73	14.47	3.63
Fuel efficiency km/L, diesel cars	15.57	3.39	15.59	3.14	16.15	3.05
Age of car (years)	7.17	4.45	7.56	4.41	8.04	4.59
# HH members	2.38	1.20	2.43	1.18	2.41	1.19
Age of reference person (years)	51.80	14.94	52.37	14.92	53.17	14.81
# general public transport tickets per HH capita	0.16	0.34	0.14	0.30	0.14	0.30
# regional public transport tickets per HH capita	0.14	0.29	0.12	0.25	0.11	0.24
Biospheric values	3.97	0.74	4.02	0.72	4.02	0.71
Altruistic values	3.89	0.68	3.91	0.67	3.97	0.67
Hedonic values	3.80	0.70	3.76	0.74	3.68	0.74
Egoistic values	2.75	0.72	2.63	0.74	2.66	0.72
Discrete variables	Mean		Mean		Mean	
Engine type: diesel	0.33		0.33		0.31	
HH with a single car	0.70		0.69		0.70	
Tertiary education: yes	0.49		0.50		0.50	
Living location: city (ref. category)	0.40		0.42		0.41	
Living location: agglomeration	0.33		0.33		0.34	
Living location: countryside	0.26		0.25		0.25	
Canton fixed effect: ZH (ref. category)	0.17		0.16		0.15	
Canton fixed effect: BE	0.14		0.14		0.14	
Canton fixed effect: LU	0.07		0.06		0.06	
Canton fixed effect: UR, SZ, OW, NW, GL, ZG	0.06		0.06		0.05	
Canton fixed effect: FR	0.03		0.04		0.03	
Canton fixed effect: SO	0.03		0.02		0.03	
Canton fixed effect: BL, BS	0.05		0.05		0.04	
Canton fixed effect: SH, TG	0.03		0.03		0.04	
Canton fixed effect: AR, AI, SG	0.09		0.08		0.07	
Canton fixed effect: GR	0.02		0.03		0.03	
Canton fixed effect: AG	0.09		0.09		0.10	
Canton fixed effect: VD	0.13		0.14		0.14	
Canton fixed effect: VS	0.03		0.03		0.03	
Canton fixed effect: NE, JU	0.02		0.03		0.03	
Canton fixed effect: GE	0.04		0.04		0.04	
Observations	535		667		539	

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