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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 1560 Swiss households over the period 2018–2021. 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, based on fixed-effect, instrumental variable, and quantile regression models, indicate relatively large price elasticities and reveal heterogeneity in price sensitivity. Single-member households appear significantly more responsive to price than multiple-member households. Travel-intensive households do respond to changes in gasoline price, while less intensive drivers do not exhibit statistically significant price elasticities. For household segments who do not react to price, tailored non-price measures would be a useful complement to fuel taxes in order to reduce distance traveled and/or avoid imposing too strong a financial burden.

1. Introduction

To what extent does travel distance react to fuel price changes? Answering this question is crucial in the context of climate change: fuel taxes are considered as an important instrument to curb GHG emissions. However, if price elasticity is weak, monetary instruments will not be effective. Distributional impacts induced by price rises and fuel taxes are also of primary concern, given that specific individuals and households might be more strongly affected than others. Heterogeneity in fuel price elasticity may therefore be at the root of serious social issues.

A vast body of scientific research is dedicated to price elasticity of vehicle kilometers traveled (VKT). Most studies analyze aggregate data and point to rather low price elasticity around −0.1 in the short run and −0.3 in the long run (Barla et al., 2009; de Jong and Gunn, 2001; Goodwin et al., 2004; Graham and Glaister, 2004; Johansson and Schipper, 1997), suggesting that price-based policy measures are unlikely to reduce significantly mileage, fuel consumption and GHG emissions. When investigated at the household level, however, VKT exhibits considerably higher price elasticity (e.g., Frondel and Vance, 2009; Sevigny, 1998; West, 2004). Specific segments of consumers seem particularly sensitive to price, because of their ability and/or willingness to adapt. For instance, households who live in urban areas are more likely to switch to public transport in response to higher motor fuel prices, whereas households living in remote areas cannot easily avoid using their cars because fewer alternatives are available to them. In case of fuel price rises, low-income households may be constrained to opt for cheaper means of travel such as public transportation, car sharing or soft mobility. Intensive drivers can more easily adjust, provided they enjoy an important share of discretionary driving, i.e., driving by choice rather than necessity (see Handy et al., 2005).

Identifying heterogeneous segments of households is essential to assess the distributional effects of price interventions and their social

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acceptability (Mattioli et al., 2018).[1] Heterogeneity in fuel price elasticities has been previously investigated using mainly *observed* socio-demographic segmentation criteria such as income level (e.g., Santos and Catchesides, 2005; Wadud et al., 2009; West, 2004), geographic location (e.g., Gillingham and Munk-Nielsen, 2019; Spiller et al., 2017), (multiple-)car ownership and household composition (e.g., Bento et al., 2009; De Borger et al., 2016a; Schmalensee and Stoker, 1999). This literature shows that various 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.

In addition to observed segmentation criteria, unobserved factors, such as behaviors or habits that car drivers themselves might not necessarily be aware of, may also cause heterogeneity in price elasticity. For instance, drivers might not always select the most efficient route, or purposefully drive longer distances to avoid congestion, bad road quality or dangerous neighborhoods. It is also possible that some car owners enjoy driving per se. Other unobserved factors could be the driver's (or a family member's) health condition, professional or private duties, or proximity to facilities, such as a gym or a shopping center. Previous analyses suggest that such factors, which we assume to affect driving intensity, play an important role in private travel demand (Gardner and Abraham, 2007; Sun et al., 2014; Zhao et al., 2020). Quantile regressions (QR; see Koenker and Bassett, 1978) offer the possibility to investigate the impact of such unobserved factors. In such models, conditional quantiles can be interpreted as different intensity levels of car-travel demand. Several authors (Frondel et al., 2012; Gillingham, 2014; Gillingham et al., 2015; Gillingham and Munk-Nielsen, 2019) use QR to investigate price elasticities of groups of households characterized by their driving intensity and obtain significant differences across groups.

The present article adds to the existing literature on heterogeneity in gasoline price elasticity of private car-travel demand in several ways. We use both *observed* and *unobserved* covariates to define household segments, and our analyses employ longitudinal data, which are better suited for the estimation of structural coefficients than cross-sectional data (see Hsiao, 2007). In contrast to prior literature that usually relies on aggregate demographic and price data, or complex price constructs from different sources, the present article uses household-level data and individual gasoline prices between 2018 and 2021. Our estimations rely on *household fixed effects*, whereas most recent studies in this field use a less-intuitive conditioning on *vehicle fixed effects* (e.g., Gillingham et al., 2015; Gillingham and Munk-Nielsen, 2019). To the best of our knowledge, our analysis is the first relying on micro-level revealed behavior to address the effect of price on VKT 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 is presented in Section 3, while our econometric approach is discussed in Section 4. Section 5 presents our empirical findings. Section 6 concludes, outlining the caveats of this article and providing hints for further research.

[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 (see The Economist, 2018).

[2] Erath and Axhausen (2010) also investigate price elasticity heterogeneity for private mobility in Switzerland, but they rely on stated preferences (rather than revealed data).

2. Literature review

Our article belongs to the wide literature on price elasticities in transportation, and more precisely to contributions that investigate heterogeneity in price elasticity. Table 1 provides an overview of the literature's findings, focusing exclusively on studies that investigate explicitly heterogeneity in the price responsiveness of car-travel demand.[3]

Most often, categories of car drivers are defined on the basis of income levels and location. Among others, Blow and Crawford (1997), Wadud et al. (2010a) and West (2004) observe that wealthier households are less responsive 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, presumably because proportionally such changes affect their income only marginally.

In contrast, Gillingham (2014), Hughes et al. (2006), Kayser (2000) and Spiller et al. (2017) reach an 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 fuel prices fall, the first reaction of poorer families might not be to spend more in 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 expenses. Yet other studies observe a U-shaped relationship between price elasticity and income (Wadud et al., 2009; West, 2004) or insignificant patterns (Archibald and Gillingham, 1981; Frondel et al., 2012; Yatchew and No, 2001).

Concerning location, there is a general agreement that rural households are less price-responsive 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 and 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 of 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 and Munk-Nielsen (2019) draw a somewhat mixed conclusion with respect to consumer groups defined on living location. They find both households living in the outskirts of cities (with long commutes to work) and city-dwellers (with short commutes to work) as being 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 (QR), 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

[3] The number of studies investigating price elasticity of travel demand or fuel demand (without considering heterogeneity) is much wider. See for instance Table 1 in Goetzke and Vance (2021), which provides an overview of the price elasticity literature since 2007 focusing on the US.

Table 1
Conclusions of selected studies investigating heterogeneity in price elasticity of car-travel demand.

References	Country and observation period	Data type	Estimation method	Income	Urban area	# cars	Fuel efficiency	Driving intensity	Other segmentation criteria
Articles using driving distance (VMT or VKT) as dependent variable									
Blow and Crawford (1997)	UK, 1988–1993	Pooled	HSM, IV	–	+	–			
De Borger et al. (2016a)	Denmark, 2004–2008	Pooled	OLS, SUR, HSM			+			
Frondel et al. (2012)	Germany, 1997–2009	Panel	RE, FE, QR	∘	∘	∘		–	
Gillingham (2014)	US, 2001–2003	Pooled	OLS, IV, QR	+	+			–	
Gillingham et al. (2015)	US, 2000–2010	Panel	FE, IV, QR		+		–	+	vehicle buyer type
Gillingham and Munk-Nielsen (2019)	Denmark, 1998–2011	Pooled	OLS, IV		∪				distance to work
Goetzke and Vance (2021)	US, 2009, 2017	Cross-section	OLS, IV, QR					∘ (2009) – (2017)	
Santos and Catchesides (2005)	UK, 1988–1993	Pooled	IV	–	+				
Wang and Chen (2014)	US, 2009	Cross-section	SEM	∪					
West (2004)	US, 1997	Cross-section	DCM	–	+				
Articles using fuel consumption as dependent variable									
Kayser (2000)	US, 1981	Cross-section	HSM, DCM	+					
Liu (2015)	US, 1997–2002	Panel	SPM	–	+	–	–		family size
Mattioli et al. (2018)	UK, 2006–2012	Pooled	OLS	–					
Spiller et al. (2017)	US, 2009	Cross-section	DCM	+	–	+	–		distance to urban area
Wadud et al. (2009)	US, 1984–2003	Pooled	OLS, SUR	∪					
Wadud et al. (2010a)	US, 1997–2002	Panel	RE, FE	–	+	+			# wage earners
Wadud et al. (2010b)	US, 1997–2002	Panel	SPM	–	+	+			# wage earners

Notes: "+ / – /∘/∪" indicates that price elasticity increases/decreases/does not change/follows a U-shape along the segmentation criteria (e.g., income). Cells are left empty when the relationship was not investigated. DCM = discrete-continuous model; FE = fixed-effects; HSM = Heckman selection model; IV = instrumental variables; OLS = ordinary least squares; QR = quantile regression; RE = random-effects; SEM = structural equation model; SPM = semiparametric model; SUR = seemingly unrelated regressions.

higher conditional quantiles reflect stronger dependency on private mobility, and hence, a lower price elasticity.[4] 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 not statistically 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, Gillingham et al. (2015), use the panel-data QR approach suggested by Canay (2011).[5] Most recently, Gillingham and Munk-Nielsen (2019), use the same approach and obtain an inverted U-shape in the fuel price elasticity, that is, drivers situated at both ends of the conditional VKT distribution are the most price-sensitive.

Most studies in the literature use aggregate price data and rely on cross-section datasets. However, 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 sensitivity 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 or panel data is also subject to discussion. Results based on such data are most commonly considered as medium- to long-run responses, considering they rely on the comparison of different households in different situations taken as long-run equilibria (e.g., Bento et al., 2009; Baltagi and Griffin, 1984; Graham and Glaister, 2002; Wadud et al., 2010a). However, other authors (e.g., Espey, 1998; Kayser, 2000) interpret models that include some measure of vehicle ownership and/or fuel efficiency as providing short-run to medium-run

[4] National household travel surveys show 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).

[5] Besstremyannaya and 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).

reactions, since responses to a fuel price shock may take up to a decade or more to be reflected in through turnover of the vehicle stock.[6] Moreover, price elasticities obtained with cross-sectional and panel data could be biased because price-sensitive households may select more carefully the gas station where they refuel. In the next section, we nevertheless argue that endogeneity of car fuel prices should not be considered problematic in longitudinal data covering short-time periods.

3. Dataset and descriptive statistics

Our empirical analysis is based on data from the Swiss Household Energy Demand Survey (SHEDS) (Weber et al., 2017), a rolling panel of 5000 respondents from all over Switzerland (except the Italian-speaking canton of Ticino). We focus on the 2018–2021 waves of the survey, excluding 2016–2017 because individual motor fuel prices were not collected in these first two waves. We consider only gasoline cars, which represent roughly two thirds of the overall car fleet in Switzerland (SFSO, 2020a), and exclude 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.[7] Observations from households who change cars between two survey waves are excluded because it is then impossible to compute distance traveled. 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 travelling is affected by seasonal factors. We moreover discard observations with annual driving distances below 100 or above 100′000 km, which corresponds to approximately 2% of our sample.[8]

Fig. 1 shows the distribution of annual driving distances in our final dataset. Kernel densities are superimposed to illustrate the evolution of VKT for each year in our observation window.

Note: Epanechnikov kernel density estimates obtained using optimal width.

As expected, the density is strongly skewed to the right, with a peak around 10,000 km a year.[9] While the Kernel densities for 2018 and 2019 are relatively close, it is interesting to note that the distribution shifts to the left in 2020 and 2021, presumably because of the Covid-19 lockdowns.[10] Additional information about VKT is displayed in Table A.1 in Appendix A, which provides descriptive statistics for each of the four 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* (SFSO, 2017), which show that the “first” car in a typical Swiss household is driven on average 13,880 km per year. In addition, *Touring Club Switzerland* – Switzerland’s largest mobility association – uses an annual mileage of 15,000 km for calculating average costs related to private cars (TCS, 2020). Table A.1 also reveals the important drop in average VKT related to the Covid-19 lockdown, with a decline around 1500 km between 2019 and 2020.

Gasoline price, the key independent variable in this article, is obtained directly from respondents, who are asked to report the price they paid when they last filled up the tank.[11] We emphasize the originality and the importance of how this information is collected, which makes it possible to observe a specific price for each household and each year, while most of the existing literature uses regional or even national average prices.

Our dataset is characterized by important variability in the individual gasoline prices (see Fig. 2 discussed below). While it is impossible to exclude that some respondents report inaccurate gasoline prices, there is strong evidence that gasoline price differences observed in our dataset are genuine. Two major forces determine the price of car fuel in Switzerland: taxes and costs related to the distribution of fuel. Fuel taxation being defined at the federal (country) level, it cannot explain regional variations. On the other hand, major 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 (Avenergy Avenergy Suisse, 2021).[12] The storage capacity of retailers or the distribution costs are the main drivers of fuel price differences. 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.

To further examine the quality of prices available in our dataset, we compare them with data from: (1) the Swiss Federal Statistical Office, which provides national average monthly gasoline prices (SFSO, 2020b), and (2) the private consumer website www.benzin-preis.ch, where drivers can record 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.

Fig. 2 shows there is important variability in prices collected in SHEDS. Similar variability is also present in data from www.benzin

[6] A direct approach to distinguish between the short- and the long-run effects of price variations in the field of car travel is provided by Batley et al. (2011), Dargay (2007) and Goodwin et al. (2004). Lagged prices are used 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 cumulative series of income/price rises and falls) can be used if drivers react differently to price increases and decreases. These methods nevertheless require important number of observations. Panels with more than five time periods are necessary to investigate the dynamics of price elasticity (Wadud et al., 2010a).

[7] 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. We account for this by calculating the number of days between the dates when respondents filled in consecutive waves of the survey, so as to obtain an average daily VKT and then multiply this number by 365.

[8] Setting these limits allows to exclude probable 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.

[9] In our models, we take the natural logarithm of the dependent measure (VKT), which gives a distribution close to normal.

[10] The Swiss government imposed strict national lockdowns from March 16 to June 19, 2020, and from January 18 to April 19, 2021. Given that SHEDS respondents are interviewed from April to June, the lockdown affected distances measured in the 2020 and the 2021 waves.

[11] The exact formulation of the question is *“How much was the price of fuel last time you filled up the gas tank?”*. It was introduced in the 2018 wave of the survey. 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.

[12] An investigation by ABE (2019) shows that the price of the most common gasoline type (unleaded with 95 RON) can differ up to 65 Swiss cents between gas stations in the French-speaking part of Switzerland. ABE’s does not consider the German-speaking (eastern) part of Switzerland nor gas stations located on highways, where prices are generally higher and consumers more captive.

-preis.ch.[13] National average monthly prices, computed by SFSO, are located around the middle of the cloud of individual prices. All series follow an equivalent evolution over time. Prices were relatively stable between 2018 and 2019, before a substantial decrease at the beginning of 2020 followed by a steep increase in 2021. Overall, these comparisons suggest that our price variable is of good quality and can be reliably used in our analysis.

Beside gasoline price, we control for vehicle-related factors (engine efficiency and car vintage), which are expected to influence distance traveled. The coefficient of efficiency may be affected by endogeneity because drivers who (intend to) travel more might choose to buy more efficient cars or, conversely, larger and more comfortable cars. This issue has been addressed in various ways in the literature: (1) instrumental variable approaches, although finding relevant and strong instruments has proven challenging[14]; (2) simultaneous equations models (Mannering, 1986; Small and Van Dender, 2007); (3) excluding engine efficiency from the set of determinants based on theoretical considerations related to consumer behavior.[15] In this article, we do not attempt to tackle efficiency's endogeneity explicitly because this variable is not central to our analysis. Nevertheless, we run different types of models, some of which exclude fuel efficiency and include fixed effects instead. If endogeneity was a major issue, we expect large discrepancies between RE and FE estimates of gasoline price elasticity.

Various socio-demographic attributes are also included in our model specifications. Household income should certainly influence VKT and price sensitivity.[16] 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 travel cards (GA) 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 use a set of dummy variables indicating if the household lives in an urban, agglomeration or countryside area. Finally, we include year fixed effects to control for unobserved time-varying factors. The final sample consists of 1560 observations from 646 unique households, among which 409/206/31 are observed over two/three/four consecutive periods.

4. Econometric approach

4.1. Estimation strategy

The first stage of our analysis is dedicated to the evaluation of the average effect of fuel prices, socio-demographic, and vehicle factors on households' VKT. To this end, we use the following multivariate regression model:

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

where VKT_{it} is vehicle kilometers traveled by household i in year t using its main car and P_{it} is the self-reported fuel price that household i paid the last time it filled the tank. Both VKT_{it} and P_{it} are in logarithmic form, so that the coefficient β can be directly interpreted as a price elasticity. Other socio-demographic and vehicle characteristics are denoted $X_{1it}, \dots, X_{Kit}$.[17] The terms ν_i capture household-specific stochastic residuals and ε_{it} are idiosyncratic residuals.

We apply both random effects (RE) and fixed effects (FE) methods to estimate eq. (1). Technically, the choice between a RE and a FE model is essentially a *"choice about how to balance variance and bias"* (Clark and Linzer, 2015). Some analyses in the field of car-travel demand have favored RE for short panel datasets (e.g., Filippini and 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 eq. (1), and by applying a random-effect regression to this extended model (Schunck, 2013).

In the second stage of our analysis, we investigate the heterogeneity in the sensitivity to fuel price. We first address this question by introducing a series of interactions between gasoline price and observable characteristics in eq. (1). To obtain clearly defined consumer segments, we discretize the continuous variables and create binary controls (like in Wadud et al., 2010a; Gillingham, 2014; Gillingham et al., 2015). We use the median to separate households, unless there is a natural threshold.[18] We thus estimate an equation of the following form (here considering income as the segmentation variable):

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

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 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 threshold. When the continuous variable used to split the sample is time invariant (e.g., fuel efficiency), the variable itself is dropped from eq. (2). We run a separate estimation for each variable

[13] We exclude prices below 0.9 CHF and above 3 CHF per liter, which are obviously misreported.

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

[15] According to economic theory, a rational consumer should always consider a given variation in the cost of driving in the same manner, disregarding if 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 leads 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 (e.g. Frondel et al., 2012; Gillingham et al., 2015). Yet, 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). For further discussion of the theoretical non-equivalence between the cost effect of fuel prices and fuel efficiency, see Weber and Farsi (2014).

[16] Household annual gross income is originally coded in intervals. We create a continuous variable by assigning the mid-point of closed income intervals and use the Pareto-curve-based procedure for open-ended income categories, as suggested by Celeste et al. (2013).

[17] Binary variable coefficients are interpreted as semi-elasticities after the transformation $exp(\delta_k) - 1$ (Halvorsen and Palmquist, 1980).

[18] For age, we use 65 years as the natural threshold, as this corresponds to retirement age. For the number of GA travel cards, we use 0 as the threshold, since most households do not have any.

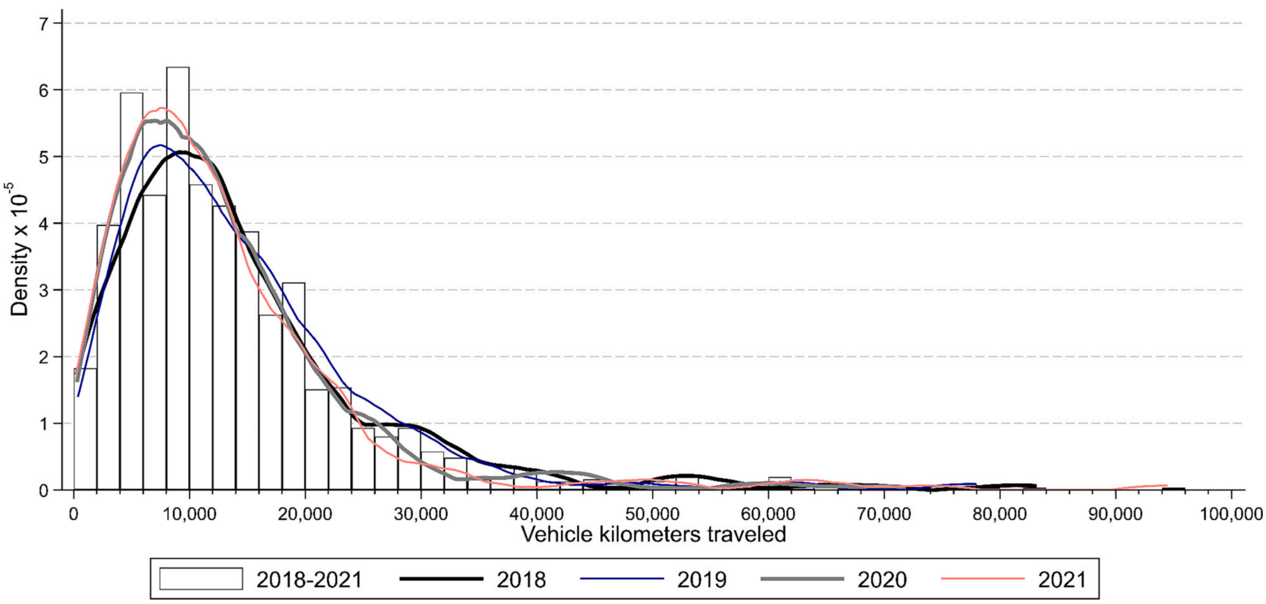

Fig. 1. Annual driving distance.

used to create different segments of households in order to avoid multicollinearity issues and an important loss of degrees of freedom.[19]

To further investigate heterogeneous price responses, we additionally apply conditional quantile regressions (QR). Initially developed by Koenker and Bassett (1978), QR is an important complement to the 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 $\sum_i^N q|\upsilon_{it}| + \sum_i^N (1-q)|\upsilon_{it}|$, where q are penalties attributed to observations, depending on their position with respect to the best line of fit, and υ_{it} are model residuals. QR also constitutes an important complement to the previously discussed method based on *observed* segmentation characteristics, because unobserved factors such as driving behaviors or route choices cannot be controlled for explicitly in estimations.

We follow Wooldridge (2010) and implement QR for panel data (the so-called Mundlak correlated random effects approach) by adding the time averages of the time-varying covariates in eq. (2), and by then applying a pooled quantile regression to this extended model specification. We use a CRE QR method (rather than other QR for longitudinal data) 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 and 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 (2022) model with non-additive fixed effects proved extremely sensitive to our model specifications, whereas CRE QR is robust to alternative model specifications.

4.2. Gasoline price and endogeneity

An issue to consider carefully in the estimation of gasoline price elasticities is price endogeneity, which could arise because of various spatial and temporal factors. For instance, drivers’ decisions regarding where to refuel may create spatial endogeneity. Individuals may indeed drive longer distances in an attempt to find a cheaper gas station. However, several earlier analyses (see BCG, 2014; GasBuddy, 2021; Kitamura and Sperling, 1987) show that the choice of a gas station is more likely to be determined by routines, habits and convenience (e.g., refueling on the way home). Also, it appears that the financial aspect of looking for cheaper gasoline station is unlikely to push consumers to drive more. When comparing an “optimizing” consumer (i.e., a driver who seeks to minimize his fuel costs) in Illinois (US) with one who buys gasoline at random, Highfill and McAsey (2007) observe that optimizers save only about 4% of their annual gasoline bill. The authors therefore conclude that *“…the consumer is often better off saving time rather than money in buying gasoline”* (p. 442). Making detours in order to find cheaper gasoline is in fact not recommended by Switzerland’s the largest mobility club (TCS), for this behavior is usually not profitable as long as the refilled amount is <50 l (a full tank for a large car) because of the

[19] 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 multiple hypothesis testing leads to a higher probability of finding statistically significant results incidentally. This makes it more difficult to tell which differences between groups are genuine, 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 as the classical Bonferroni correction, which is 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 and Grimes (2005), Moran (2003), O’Keefe (2003), and most recently by Parker and 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, we also refrain from adjustments for multiple hypotheses testing in the present article.

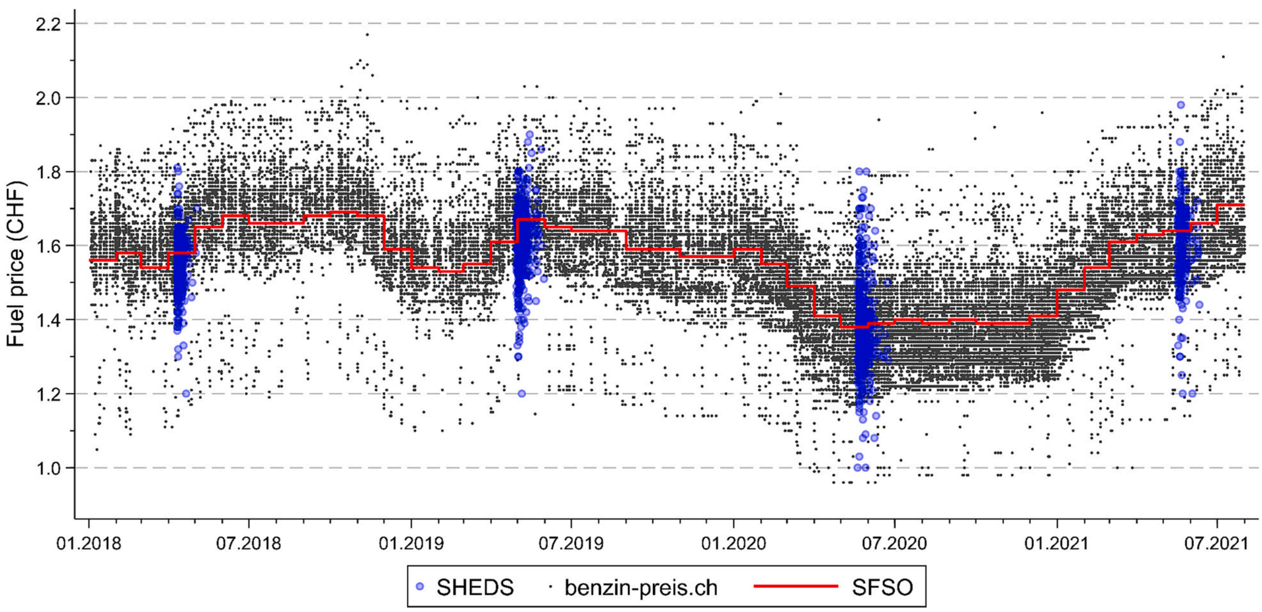

Fig. 2. Gasoline prices in Switzerland, from different sources.

higher travel distance it implies (TCS, 2022). In practice, when they stop at a gas station, most drivers do not entirely fill the tank. For instance, in the 2016–2017 German Mobility Panel (Eisenmann et al., 2017) German drivers report that only about 20% of the time they entirely fill the tank. Thus, we believe that while endogenous search could be problematic in models relying on between variation, such as RE or OLS, self-selection should not affect the estimates of gasoline price elasticities in longitudinal datasets with short panels.

Local or regional demand shocks are another spatial factor which might affect the exogeneity of gasoline price in models of car travel or fuel demand. Those shocks could be related to specific features of oil refineries in a given region, such as their capacity constraints and their decisions on fuel mix. This could in turn have important impacts on regional gasoline prices, as suggested by the gasoline prices differences observed between the West Coast and the rest of the United States (see Taylor and Fischer, 2003; EIA, 2021). In Switzerland, a large proportion (about 75%) of the imports of fuel consumed for transport purposes, i.e. petrol and diesel, are transported via the Rhine route to Basel (Avenergy Suisse, 2021). The rest is produced by the only Swiss refinery in Cressier, also situated in the north of the country. It appears that lower gasoline prices are indeed observed in this region (ABE, 2019). In order to control for regional differences, we therefore estimate various regression models with cantonal fixed effects.

Temporal aspects of refueling behavior may also play an important role in the estimation of gasoline price elasticity. Forward-looking drivers may indeed anticipate future gasoline price variations in order to choose the optimal time for refueling. In the context of gasoline tax changes – a case where gasoline price variations are easy to predict – Coglianese et al. (2017) indeed observe that distributors, retailers and final consumers adopt an anticipatory behavior and "*this intertemporal substitution by buyers creates an endogeneity problem*" (p. 3). The reason for this is that gasoline demand may adjust ahead of changes in gasoline prices, even before the price changes occur, thereby resulting in a spurious relationship between gasoline demand and gasoline prices. While this could indeed be problematic for models of car fuel demand, we believe that this is less likely to lead to a spurious relationship in the estimation of travel demand (VKT), or at least to a much lesser extent. Also, in contrast to tax-induced variations in gasoline prices, our dataset covers a period from 2018 to 2021, when the tax rates on gasoline were left unaltered in Switzerland. The evolution of car fuel prices was therefore not easily predictable for consumers.

Another temporal aspect is the seasonality in gasoline demand observed throughout the northern hemisphere: people drive more during the summer months than in winter. This phenomenon, related to weather conditions and holidays (see EIA, 2022; Chakravorty et al., 2008), leads to higher car fuel prices in summer. An analysis of national fuel prices from the Swiss Federal Statistical Office (SFSO, 2022) reveals that a seasonal pattern with higher gasoline prices in the summer months is indeed observed in Switzerland. We therefore follow previous studies (e.g., Allcott and Wozny, 2014; Goetzke and Vance, 2021), where seasonality is controlled for by adding month dummies in the regression models. In our case, the survey takes place each year between April and June, so we add fixed effects for May and June (using April as the base category) in our econometric models.

In order to address endogeneity, previous research has predominantly used instrumental variables (IV) to analyze causal relationships between gasoline prices and distance traveled/gasoline demand. Gasoline taxes are commonly used as an instrument for fuel prices because they strongly correlate with the endogenous variable (gasoline prices) but are unlikely to be related to unobserved shocks to car fuel or VMT demand (that is with the error term). Studies relying on such an instrument have found higher price elasticities.[20] However, Liu (2017) argues that this IV approach might still lead to biased results since tax changes are more salient for consumers and more persistent over time than natural fuel price changes. As discussed before, Coglianese et al. (2017) notice that the anticipatory behavior of drivers renders taxes endogenous. In addition, Hammar et al. (2004) point out that gasoline taxes are likely affected by the level of national gasoline demand, thereby providing another argument for the endogeneity of taxes.[21]

In order to address endogeneity stemming from local demand shocks, an oft-used approach (e.g., Gillingham and Munk-Nielsen, 2019; Gillingham et al., 2015; Gillingham, 2014; Levin et al., 2017) is to

[20] For instance, using US data, Davis and Kilian (2011) observe a price elasticity of gasoline demand of − 1.14, while Li et al. (2014) find an elasticity of − 0.77. Dieler et al. (2015) estimate an elasticity of −0.82 in their analysis of gasoline demand for several European countries.

[21] These authors use one lead and one lag of the change in gasoline prices, as well as one lead and one lag of the tax instrument in their models of gasoline demand. Using this IV approach, they observe a drop in the estimated price elasticity of gasoline demand from −1.14 to − 0.37, although the latter coefficient is not statistically significant.

instrument aggregate-level gasoline prices by global oil prices. However, these studies do not find evidence for endogeneity bias in the IV-estimated gasoline price elasticities. Gillingham and Munk-Nielsen (2019) explain this result by stating that small countries like Denmark buy *"…both gasoline and diesel on the larger European market, so it is not likely that* [country]*-specific demand shocks lead to an endogeneity issue."* (p. 37). In this context, Levin et al. (2017) point out that controlling for local demand shocks is important mainly in studies using aggregate car-fuel price data.[22]

Finally, some earlier studies (e.g., Santos and Catchesides, 2005; Blow & Crowford, 1997) use car fuel price reported by neighboring drivers (i.e., from the same region) as an instrument the own gasoline price.[23] This approach relies on the assumption that it is unlikely that the average gasoline price of other drivers in the same region affect the own demand for gasoline, which makes this variable a potential candidate for instrumenting the own price of gasoline. Neighbors' behavior has been used as an instrument for one's own consumption by researchers in the field of residential energy demand (e.g., Miller and Alberini, 2016; Volland, 2017). In the present article, we instrument the own gasoline price with the average gasoline price reported for each year by SHEDS participants living in the same canton.[24]

5. Results and discussion

Our empirical findings are presented as follows. First, we discuss the results concerning average elasticities of VKT, which constitute a useful starting point for the later analysis of heterogeneous elasticities. These results also allow us to discuss the role of various determinants of VKT. Second, and most importantly, we present and discuss our investigation of price elasticity heterogeneity.

Table 2 displays the estimations of eq. (1) obtained with random effects (RE), fixed effects (FE) and correlated random effects (CRE). For each model, we present one baseline specification and our preferred specification that encompasses a larger set of determinants.[25] All estimated price elasticities are significant and of non-negligible magnitude. RE models yield estimates close to those from FE and CRE models, suggesting that the self-selection issue discussed at the end of Section 4 is not a major concern in our estimations. A cluster-robust Hausman test (Arellano, 1993) shows that FE estimations are preferable to RE estimations (Sargan-Hansen statistic: 18.54; $\chi^2 = 11$; p-value = 0.0698).

FE and CRE models yield price elasticities between 0.7 and 0.8 in absolute value, implying that a 1% change in fuel price would lead to a 0.7%–0.8% decrease in VKT. Considering that VKT is generally less responsive than fuel consumption (Frondel et al., 2012; Graham and Glaister, 2004), the magnitude of our estimates appears particularly strong. This finding suggests that price-based policies might have a much more important impact on energy consumption and GHG emissions than previously thought. Former studies on car fuel demand for Switzerland indeed estimate much lower price elasticity in the interval from −0.25 to −0.4 (see Baranzini and Weber, 2013; Carlevaro et al., 1992; Filippini and Heimsch, 2016; Peter et al., 2002; Schleiniger, 1995; Wasserfallen and 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).[26] De Borger et al. (2016a), Frondel et al. (2012) and Santos and 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.

There are several reasons why relatively strong price elasticities of VKT can be expected in Switzerland. 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 prices, where gasoline price is about half that in Switzerland[27]) 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.[28] However, our estimated point price elasticities should be interpreted carefully, for the related standard errors are also relatively large: in model RE2, the estimated coefficient's 95%-confidence interval spans from −1.31 to − 0.157.

Results in Table 2 also show that the income elasticity of VKT is about 0.10, but this result is statistically significant only in RE1. This finding is in line with previous estimations by Frondel et al. (2012) for Germany and Weber and 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 such a low estimated income elasticity 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 across households. Nevertheless, income elasticities in Switzerland can be expected to be low because of the high standards of living which make fuel costs largely 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 *Swiss household budget survey* (SFSO, 2020c) reveals monthly gasoline expenditures of about 100 CHF per month, which represents <2% of households' monthly disposable income.

Another remarkable result obtained in Table 2 is that distance traveled in 2020 is about 20% lower than in the reference year 2018. The strict national lockdown related to the Covid-19 pandemic between mid-March and June 2020 is of course the principal reason for such a decrease. While the FE and CRE show that the impact of socio-demographic and vehicle characteristics on driving distance is

[22] In order to account for price endogeneity, Levin et al. (2017) try different model specifications with city-level and/or day-of sample fixed effects, but do not find evidence for endogeneity bias either. An IV estimation using wholesale spot gasoline prices as an instrument for local retail prices also confirms OLS results.

[23] It is not clear whether and how the IV-estimations in those studies are different from those obtained in basic models which do not instrument the cost of driving/the price of car fuel.

[24] We also tried to calculate the average *annual* gasoline price of neighbor households (living in the same canton) using data from *www.benzin-preis.ch*. However, for some cantons, data are insufficient or simply lacking, which does not allow us to use this data source.

[25] We also tried specifications including further covariates, e.g., psychological determinants, months or canton fixed effects. This does not affect the estimated price elasticities but yields higher information criteria (AIC, BIC), which implies less preferred models.

[26] 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), gasoline price elasticity estimates might *"differ by magnitudes large enough to substantially impact subsequent policy evaluation or market analysis."*

[27] See for instance Bloomberg (2021). More generally, in Europe, motorized transportation is organized very differently from that in North America. Detailed comparisons are provided by Buehler (2011), Giuliano and Dargay (2006), and Sprei et al. (2019).

[28] See MTMC for Switzerland (SFSO, 2017), NHTS (2017) for the US, NTS (2018) in the UK, and MOP (2018) for Germany.

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

	RE1	RE2	FE1	FE2	CRE1	CRE2
Gasoline price (ln)	−0.866***	−0.734**	−0.688*	−0.686*	−0.785**	−0.822**
	(0.302)	(0.294)	(0.383)	(0.381)	(0.359)	(0.356)
HH gross income (ln)	0.141***	0.054	0.098	0.089	0.091	0.088
	(0.045)	(0.046)	(0.076)	(0.077)	(0.076)	(0.077)
Fuel efficiency (ln)	0.249**	0.140			0.251**	0.131
	(0.113)	(0.108)			(0.112)	(0.108)
Year 2019	0.058	0.064	0.046	0.043	0.054	0.058
	(0.046)	(0.046)	(0.048)	(0.048)	(0.047)	(0.047)
Year 2020	−0.177***	−0.157***	−0.157**	−0.158**	−0.170***	−0.173***
	(0.060)	(0.059)	(0.069)	(0.069)	(0.062)	(0.061)
Year 2021	−0.101	−0.105	−0.107	−0.104	−0.106	−0.108
	(0.066)	(0.066)	(0.074)	(0.075)	(0.069)	(0.069)
HH with a single car	−0.183***	−0.095	−0.091	−0.084	−0.107	−0.092
	(0.058)	(0.059)	(0.139)	(0.143)	(0.139)	(0.143)
Age of car (years)		−0.002				−0.002
		(0.005)				(0.005)
# HH members		0.082***		−0.154		−0.142
		(0.023)		(0.290)		(0.293)
Age of reference person (years)		−0.012***				−0.012***
		(0.002)				(0.002)
# GA travel cards per HH member		−0.209***		0.203		0.200
		(0.075)		(0.150)		(0.154)
Living location: agglomeration		0.025		−0.155		−0.158
		(0.059)		(0.144)		(0.145)
Living location: countryside		0.142**		−0.025		−0.050
		(0.061)		(0.170)		(0.175)
Av. gasoline price (by HH)	No	No	No	No	Yes	Yes
Av. HH gross income (by HH)	No	No	No	No	Yes	Yes
Av. # HH members (by HH)	No	No	No	No	No	Yes
Av. # GA cards per HH member (by HH)	No	No	No	No	No	Yes
Av. single car (by HH)	No	No	No	No	Yes	Yes
Av. living location: agglomeration (by HH)	No	No	No	No	No	Yes
Av. living location: countryside (by HH)	No	No	No	No	No	Yes
Observations	1560	1560	1560	1560	1560	1560
Households	646	646	646	646	646	646
R^2 within	0.014	0.009	0.014	0.017	0.014	0.018
AIC	3561	3495	2006	2008	3565	3496

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

statistically insignificant (as should be expected in the short run),[29] we obtain the expected coefficients for most covariates in RE1 and RE2.

As a robustness check, we estimate an FE model using an instrumental variable approach in order to address any potential price endogeneity. For this purpose, we use the average gasoline consumption of households living in the same canton. These results are displayed in Table 3, where we compare the fixed effect model FE2 already presented to a similar model specification estimated via fixed effects with an instrumental variable approach.

The IV estimation in column (2) of Table 3 shows a somewhat lower point price elasticity (about − 0.6) in comparison to our findings in Table 2. The IV estimator still yields higher estimation than earlier findings in the relevant literature. The Cragg-Donald Wald F-statistic (24.40) presented at the bottom of Table 3 is above the critical value of 16.38 suggested by Stock and Yogo (2005), which means that the performance of our instrument could be considered as good. However, the standard errors that we observe are extremely high and the estimated coefficient is statistically insignificant. We remain cautious about our IV results because for some cantons the number of observations is low. In addition, while neighbor prices are used as IV in the field of residential electricity demand because similar households who live in the same region have the same electricity provider and thus face similar electricity prices, there is more flexibility in the field of private mobility and each driver has more freedom with respect to driving and refueling behavior. Yet, our attempt could be considered as indicative of potential endogeneity leading to an overestimation of the magnitude of the price coefficient.

As another robustness check, we construct an alternative price measure using data from the online platform www.benzin-preis.ch allows consumers to self-report fuel prices observed in specific locations. For each respondent of our survey, we compute the observed average gasoline price between two interview dates in the respondent's canton. For cantons where no data is available in the relevant period, we compute a national average. We finally use this individual-specific gasoline-price measure as a substitute for the individual gasoline prices self-reported in our survey.

This strategy yields a point gasoline price elasticity of about −0.16 (column FE3 in Table 3), which is much lower than the coefficients obtained in estimations FE2 and FE IV. Yet, it should be noted the average cantonal prices computed from www.benzin-preis.ch are

[29] 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 fixed effects.

Table 3
Determinants of VKT: fixed effects (FE) and instrumental variable (IV) models.

	FE2	FE IV	FE3
Gasoline price SHEDS (ln)	−0.686*	−0.591	
	(0.381)	(3.420)	
Gasoline price benzin-preis.ch (ln)			−0.155
			(0.571)
HH gross income (ln)	0.089	0.088	0.089
	(0.077)	(0.078)	(0.079)
Year 2018	0.043	0.039	0.031
	(0.048)	(0.140)	(0.066)
Year 2019	−0.158**	−0.146	−0.068
	(0.069)	(0.410)	(0.057)
Year 2020	−0.104	−0.107	−0.128*
	(0.075)	(0.140)	(0.075)
HH with a single car	−0.084	−0.083	−0.073
	(0.143)	(0.145)	(0.143)
# HH members	−0.154	−0.158	−0.187
	(0.290)	(0.339)	(0.293)
# GA travel cards per HH member	0.203	0.201	0.187
	(0.150)	(0.172)	(0.148)
Living location: agglomeration	−0.155	−0.156	−0.163
	(0.144)	(0.147)	(0.141)
Living location: countryside	−0.025	−0.023	−0.016
	(0.170)	(0.173)	(0.167)
Observations	1560	1560	1560
Households	646	646	646
R^2 within	0.017	0.017	0.018
Cragg-Donald Wald F-statistic	.	24.40	.

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

relatively noisy and it is therefore likely that price elasticity estimates based on such measures are downward biased.[30]

The picture of the “average” (or “typical”) reactions discussed so far could conceal important differences across households. To examine the possibility of heterogeneous price elasticities, we interact socio-demographic and car characteristics with gasoline price. The coefficients of these interactions are displayed in Table 4, where each pair of lines comes from a separate model estimated through FE. The bottom line of the Table shows the *p*-values related to Wald tests of the difference between the gasoline price coefficients.

We find evidence of statistically different price elasticities only for households of different size. Single-member households are characterized by a significantly higher price elasticity compared to multiple-member households, probably because the latter group consists mostly of families with children. These households are certainly more dependent on private car transportation, while single-member households can more easily adapt to higher gasoline prices by switching to public transportation or carpooling. This result is important with respect to the expected increase of the number of single-member households by 30% in the next 30 years in Switzerland (SFSO, 2020d). It is likely that this demographic evolution will be accompanied by an increase of the private vehicle stock. On the other hand, the demand for VKT should also become more price-responsive because of the higher price-reactivity of single-member households, other things being equal. From a policy perspective, the increase of gasoline price could lead to important decreases in the demand for car travel stemming from single-member households. However, such a policy would affect households who rely on their vehicles because of family-related constraints, such as the presence of children at young age. To alleviate the tax burden, these households could be offered special conditions or financial incentives for using car-sharing schemes or public transportation.

Even though our test of differences between living locations is not conclusive (p-value is 0.34), our point estimates indicate a much stronger price elasticity in cities than in rural regions. This result is in line with previous findings in the existing literature (e.g., Blow and Crawford, 1997; Gillingham et al., 2015; West, 2004) and is usually explained by the less developed public transportation system in rural 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 therefore be used as complementary policy instruments in order to limit the impacts of fuel taxation on non-urban residents.

We further examine heterogeneity in gasoline price elasticity of VKT in Table 5 using a quantile regression approach adapted for panel data (CRE QR). This strategy allows us to focus on segments of households defined on unobserved factors, which we interpret as translating driving intensity.

Our estimations show 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 travel-intensive households do not exhibit statistically significant price elasticities. Most likely, households situated at the ninth conditional decile have an important amount of discretionary driving (e.g., driving related to leisure activities), which they can easily adjust 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 households. 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), Gillingham (2014) and Gillingham and Munk-Nielsen (2019), who apply QR to pooled datasets. Probably related to the different types of data used and their temporal interpretation,[31] the difference between our findings and those obtained in these studies could also be explained by the characteristics of the population under study. As mentioned earlier, national car-travel surveys show that Swiss households use their cars mainly for leisure trips, while the main purpose of vehicle usage in Germany and the US – the two countries analyzed by Frondel et al. (2012) and Gillingham (2014) – is related to professional and non-recreational activities. This behavior might be particularly pronounced for households situated at the upper tail of the conditional VKT distribution. By analogy, frugal car users could have different motivations to use their vehicles parsimoniously, which could depend on the national, regional or local contexts. We believe that the differences between those environments could explain why contrasting results with respect to the price elasticities estimated across the VKT spectrum could be observed.

To investigate the sensitivity of our findings, we run a number of robustness checks. First, because the last two waves of SHEDS (2020–2021) took place during the Covid-19 pandemic – a period during which mobility and gasoline prices were subject to important shocks – these two waves might affect our estimations of average price elasticities. In Table A.2 in Annex A, we report the results obtained when

[30] We have also explored gasoline price data from other independent databases. Gasoline price series collected by the Swiss Federal Statistical Office (SFSO) in the context of the Consumer Price Index (CPI) is not representative at the cantonal level and can therefore not be used to compute approximate individual prices for our respondents. Further online platforms (tcs.ch/carburants, www.ton-plein.ch) allow consumers to self-report fuel prices observed in specific locations. These platforms were either launched recently or lack a satisfactory national coverage that would make it possible to compute a representative average price for each canton and each relevant time period. Finally, gasoline companies with national coverage may hold historical databases but – as far as we can judge based on our exchanges with such companies – these are confidential, not always centralized, and often incomplete.

[31] Some authors interpret the results of models using cross-section and pooled data as reflecting the long run (e.g., Dahl, 1986), whereas others (e.g., Santos and Catchesides, 2005) argue that they translate developments taking place in the short run.

Table 4
Price elasticities for various subsamples (FE models).

	Income	Fuel efficiency	Car age	Single car	# HH members	GA travel cards per HH member	Age of ref. person	Living location
Low-income HH	−0.919**							
	(0.441)							
High-income HH	−0.604							
	(0.388)							
HH with fuel-inefficient car		−0.726*						
		(0.384)						
HH with fuel-efficient car		−0.665*						
		(0.396)						
HH with new car			−0.841**					
			(0.413)					
HH with old car			−0.621					
			(0.385)					
HH with a single car				−0.657				
				(0.419)				
HH with multiple cars				−0.703				
				(0.429)				
Single-member HH					−1.301***			
					(0.470)			
Multiple-member HH					−0.532			
					(0.393)			
HH with 0 GA cards HH member						−0.623		
						(0.389)		
HH with >0 GA cards HH member						−0.895*		
						(0.505)		
HH in working age (≤65 y.o)							−0.607	
							(0.381)	
HH in retirement age (>65 y.o)							−1.023**	
							(0.505)	
Living location: city								−0.904**
								(0.449)
Living location: out of city								−0.537
								(0.405)
Observations	1560	1560	1560	1560	1560	1560	1560	1560
Households	646	646	646	646	646	646	646	646
Adjusted R^2	0.012	0.011	0.012	0.010	0.014	0.011	0.012	0.011
R^2 within	0.019	0.018	0.019	0.017	0.021	0.018	0.019	0.018
p-value	0.265	0.752	0.319	0.907	0.048	0.499	0.251	0.336

Clustered standard errors (by household) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
In each model, we also control for the same set of covariates as in FE2 but omit these results from the output presented here for the sake of space.

years 2020 and 2021 are excluded from the dataset and with an RE model including the same set of determinants as in model RE2 of Table 2. For price elasticity, we find a point estimate of −0.857 (standard-error is 0.528, *p*-value is 0.104), which is close to our baseline finding.

In a second attempt to verify whether there are important differences in the gasoline-price elasticities estimated for each year of the SHEDS questionnaire, we interact the gasoline price variable in our preferred RE model with year fixed effects. These results are presented in Table A.3 and show a non-significant price elasticity for the reference year (2018), with a point estimate that is in fact positive. For 2019, we observe a price elasticity of about − 1.35, which is significant at the 90% confidence level, and the gasoline price elasticities estimated for 2020 and 2021 are close in magnitude to the elasticities obtained in the main analysis, although they are not statistically different from zero. Unsurprisingly, the standard errors become large since the number of observations on which each coefficient relies become small. Yet, considering the wide differences across the coefficients, it seems plausible that the overall price elasticity obtained for the entire observation period masks temporal variations, as also observed by Goetzke and Vance (2021).

We then estimate our models using alternative thresholds for splitting the sample.[32] Instead of taking the median of the distribution of the continuous variables, we use the first and the last quartiles. The results are relatively similar to the ones reported in Table 4. We do not observe any significant differences across segments of households defined by their income levels and the age of their vehicles. However, we find that households with (very) low fuel efficiency (below the 25th percentile of fuel efficiency) are more price-elastic than others. Earlier analyses (e.g., Liu, 2015; Spiller et al., 2017) also observe that owners of (the most) fuel-inefficient cars are more price-sensitive. This result could be expected, since, as argued by Gillingham et al. (2015), drivers of fuel-inefficient vehicles face a higher burden at the pump and should therefore rationally be more price-sensitive. On the other hand, this result also implies that drivers of cars with average or higher fuel efficiency would bear most of the cost of fuel taxation, while an increase in the price of gasoline will have a desired negative effect on the VKT demand of the owners of inefficient vehicles. In order to limit a negative welfare impact on the drivers of "average" cars, alongside the introduction of a gasoline tax, special rebates or subsidies could be offered when vehicles below a certain efficiency level are replaced with more efficient ones.

We finally estimate price elasticities from various model specifications such as FE1 in Table 2, but including only gasoline price, household income and year fixed effects as independent variables, or adding regional fixed effects to capture local fuel demand conditions. We also define alternative limits for excluding extreme observations for VKT and gasoline prices. Our results are robust to these sensitivity checks.

Overall, we consider our findings as relatively robust to different

[32] For the sake of space, the results of the following robustness checks are not displayed. All tables are available on request from the authors.

Table 5
Quantile regression with correlated random effects (QR CRE).

	Q10	Q30	Q50	Q70	Q90
Gasoline price (ln)	−0.550	−0.657	−0.644	−0.774	−1.553***
	(0.607)	(0.522)	(0.475)	(0.538)	(0.482)
HH gross income (ln)	0.118	−0.006	0.168	0.119	0.220
	(0.177)	(0.143)	(0.108)	(0.109)	(0.134)
Fuel efficiency (ln)	0.275	0.073	0.096	0.208	0.129
	(0.216)	(0.132)	(0.124)	(0.132)	(0.144)
Year 2019	0.129	−0.024	0.019	0.031	0.017
	(0.094)	(0.065)	(0.055)	(0.062)	(0.073)
Year 2020	−0.106	−0.192**	−0.207**	−0.248***	−0.284***
	(0.106)	(0.090)	(0.084)	(0.088)	(0.084)
Year 2021	−0.128	−0.167**	−0.213***	−0.178**	−0.093
	(0.154)	(0.084)	(0.082)	(0.079)	(0.089)
Age of car (years)	−0.006	−0.006	0.001	0.004	−0.001
	(0.012)	(0.006)	(0.007)	(0.007)	(0.006)
HH with a single car	0.267	0.002	−0.154	−0.181	−0.111
	(0.209)	(0.177)	(0.180)	(0.175)	(0.144)
# HH members	−0.117	−0.662***	−0.565*	−0.051	0.581
	(0.301)	(0.173)	(0.341)	(0.474)	(0.608)
Age of reference person (years)	−0.012***	−0.009***	−0.010***	−0.010***	−0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
# GA travel cards per HH member	−0.287	0.134	0.044	0.096	0.427***
	(0.297)	(0.267)	(0.237)	(0.217)	(0.134)
Living location: agglomeration	0.203	0.081	−0.384	−0.304	−0.289
	(0.425)	(0.145)	(0.252)	(0.256)	(0.191)
Living location: countryside	−0.508	−0.008	−0.226	−0.221	−0.538
	(0.698)	(0.313)	(0.262)	(0.340)	(0.572)
Av. gasoline price (by HH)	Yes	Yes	Yes	Yes	Yes
Av. HH gross income (by HH)	Yes	Yes	Yes	Yes	Yes
Av. single car (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # HH members (by HH)	Yes	Yes	Yes	Yes	Yes
Av. # GA cards per HH member (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: agglomeration (by HH)	Yes	Yes	Yes	Yes	Yes
Av. living location: countryside (by HH)	Yes	Yes	Yes	Yes	Yes
Observations	1560	1560	1560	1560	1560
Households	646	646	646	646	646
Pseudo R^2	0.112	0.111	0.115	0.113	0.109

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

models, specifications and estimation periods. Yet, we acknowledge our research faces several shortcomings, which could affect the results of our analyses but also provide new research opportunities. We discuss these in the final Section 6.

6. Conclusions

This article investigates the fuel price elasticity of Swiss households' vehicle kilometers traveled (VKT). In particular, we focus on the heterogeneity in price responsiveness for various segments of households, defined using both 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 also and 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 1560 observations from waves 2018–2021 of the Swiss Household Energy Demand Survey (SHEDS). Overall, our results point to a price elasticity that is considerably higher than prior estimates for Switzerland (or elsewhere in general), which suggests fuel taxes could have a more important effect on driving than previously assumed.

Several reasons could explain why gasoline price elasticities are higher in Switzerland compared to earlier research mostly focused on the US: distances driven are much shorter and the extremely well-developed public transport system provides a very good substitute for private transportation. Much higher fuel prices could also contribute to stronger reactions. The household-level gasoline price data we use may also partly explain the magnitude of this elasticity. In contrast, most prior analyses in this field use prices averaged at the regional or even national level, which may lead to a downward bias in the estimation of price elasticities (e.g., Levin et al., 2017). Overall, this finding can be seen as a reminder that the low price elasticities obtained in the literature might not necessarily apply to all countries, even those where income levels are high. Policymakers should therefore keep considering the possibility of increasing gasoline prices via taxation in order to reduce GHG emission and household energy consumption.

Furthermore, we show that the average elasticity masks heterogeneity across households. Our findings, obtained from a conditional quantile regression model for panel data, reveal that 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 would have a policy-desirable effect, by reducing discretionary driving of the most travel-intensive groups of households. In addition, we observe that single-member households and (with a lower statistical significance) city-dwellers are characterized by higher price elasticities. From a policy perspective, these results suggest that non-price measures could be considered in combination with gasoline taxes to reduce welfare distortions between different consumer groups. This is especially important in the context of Switzerland's *Energy Strategy 2050*, which clearly states that one of its main goals is to "*… compensate to the extent possible, any negative consequences of the tax on energy*" (SFOE, 2019, p. 6813). For instance, the development of specific financial incentives for using public transport or car-sharing could be considered for multiple-member households and inhabitants of rural regions, who rely more heavily on private transportation. Since an important share of households have moderate to low travel intensity and are price-inelastic, they could be targeted by information campaigns promoting the financial and environmental advantages of fuel-efficient cars, or could be offered special car-swap conditions, rebates, or subsidies for acquiring vehicles consuming less.

We acknowledge that our analysis faces some caveats. First, fuel prices measured at the household level certainly provide an interesting alternative to country-level prices, but the former are of course not exempt from measurement issues. In our dataset, fuel prices are self-reported and valid at a given point in time, and therefore do not reflect what happened over an entire year. Each survey participant reports fuel price for a personally-defined calendar day, so that the previously mentioned point in time is not the same for every household. Observed differences between fuel prices from different years are prone to some distortion, especially if important variability like that observed during the Covid-19 pandemic occurs.

With regard to fuel prices, we acknowledge that our estimations might be affected by endogeneity. We attempt to control for this by using a fixed-effects IV approach, but the performance of the available instrument is questionable. In this context, important future contributions to the literature could be to find stronger and more relevant instruments, to empirically assess who drives more to find cheaper gasoline, and whether such behavior is persistent or limited to specific circumstances. For instance, car owners living close to the border probably have a (more) price-elastic fuel (or VKT) demand, as shown by Banfi et al. (2005), and probably drive additional kilometers to the other side of the border in order to fill the tank, if car fuel is cheaper there.

Another weakness of our analysis is caused by the relatively short time dimension of our panel dataset, which does not allow us to consider changes in vehicle ownership or to capture variation related to socio-demographic variables such as the number of household members and their age. Longer panels would make it possible to investigate the effect of evolving technology, for instance using the continuous-discrete framework suggested by Dubin and McFadden (1984) and Mannering (1986) to correct for endogeneity related to vehicle characteristics such as fuel efficiency or vehicle age.

It is moreover possible that travel price elasticities are asymmetric. For instance, Frondel and 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 whether different segments of households react differently to price increases or decreases. It is conceivable that 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 mostly related to essential travel. In comparison, high-income households could more easily cut off their greater amount of leisure-related driving. Such questions could be addressed through the asymmetric model specifications applied by Batley et al. (2011) and Giuliano and Dargay (2006), but large datasets with more time periods and observations are necessary for this purpose.

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 and Munk-Nielsen (2019) and Mattioli et al. (2018), studying more specific segments of households can enhance our understanding of the effects of car fuel taxation across the whole population, and therefore clearly deserves further attention.

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Credit author statement

Ivan Tilov: Conceptualization, Methodology, Software, Investigation, Data curation, Writing - Original Draft, Writing - Review & Editing.

Sylvain Weber: Methodology, Software, Investigation, Writing - Review & Editing, Visualization, Supervision.

Appendix A

Table A.1
Descriptive statistics, per year.

	2018		2019		2020		2021	
Continuous variables	Average	Std. dev	Average	Std. dev	Average	Std. dev	Average	Std. dev
Vehicle kilometers traveled (km)	14,496.37	12,127.83	14,278.74	11,072.52	12,904.26	10,228.84	13,051.85	12,133.02
Gasoline price (CHF)	1.55	0.07	1.61	0.09	1.38	0.12	1.60	0.10
HH gross income (CHF)	9119.42	4396.40	9141.55	4505.42	9066.57	4555.60	9267.98	4850.37
Fuel efficiency (km/L)	14.31	3.44	14.58	3.76	14.47	3.70	14.67	4.05
Age of car (years)	7.52	4.65	7.99	4.80	8.05	5.02	7.68	4.73
# HH members	2.15	1.04	2.18	1.08	2.28	1.09	2.34	1.16
Age of reference person (years)	52.52	15.30	53.22	15.18	52.79	15.30	51.90	15.11
# GA travel cards per HH member	0.16	0.33	0.14	0.32	0.14	0.31	0.10	0.27
Binary variables	Average		Average		Average		Average	
HH with a single car	0.73		0.74		0.72		0.69	
Living location: city	0.44		0.44		0.43		0.37	
Living location: agglomeration	0.33		0.34		0.32		0.35	
Living location: countryside	0.22		0.22		0.26		0.28	
Observations	362		485		475		238	

Table A.2
Random effects (RE) model, excluding years 2020–2021.

	VKT (ln)
Gasoline price (ln)	−0.857
	(0.528)
HH gross income (ln)	0.005
	(0.061)
Fuel efficiency (ln)	0.211
	(0.136)
Year 2019	0.070
	(0.050)
HH with a single car	−0.119
	(0.075)
Age of car (years)	−0.003
	(0.006)
# HH members	0.088***
	(0.029)
Age of reference person (years)	−0.010***
	(0.002)
# GA travel cards per HH member	−0.279***
	(0.089)
Living location: agglomeration	0.085
	(0.072)
Living location: countryside	0.183**
	(0.077)
Observations	847
Households	526
R^2 within	0.011

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

Table A.3
Random effects (RE) model, with interactions between time fixed effects and gasoline prices.

	VKT (ln)
Gasoline price (ln)	0.348
	(0.870)
Year 2019	0.835*
	(0.431)
Year 2020	0.318
	(0.400)
Year 2021	0.321
	(0.492)
Year 2019 # Gasoline price (ln)	−1.707*
	(0.967)
Year 2020 # Gasoline price (ln)	−1.088
	(0.955)
Year 2021 # Gasoline price (ln)	−0.982
	(1.097)
HH gross income (ln)	0.050
	(0.046)
Fuel efficiency (ln)	0.142
	(0.108)
HH with a single car	−0.092
	(0.059)
Age of car (years)	−0.002
	(0.005)
# HH members	0.083***
	(0.023)
Age of reference person (years)	−0.012***
	(0.002)
# GA travel cards per HH member	−0.209***
	(0.074)
Living location: agglomeration	0.026
	(0.060)
Living location: countryside	0.143**
	(0.062)
Observations	1560
Households	646
R^2 within	0.014

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107078.

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