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# Driver's response to fuel price variation

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## Table of Content

## Table of Tables



## Table of Tables

## 1. Introduction

Fuel demand decreased in 2020 mainly because of the corona pandemic. This triggered the decrease of the fuel price. In 2021, the economy started to recover and thus the fuel demand as well as the fuel price recovered likewise. On top of this, the Ukraine Conflict led to fuel scarcity, forcing the fuel price to further grow (TCS, 2022). Indeed, the fuel price has increased to the degree that it is discussed in papers broadly all over Switzerland and many consumers moan about the high prices (Hosp & Seliger, 2022).

This paper will analyze the compelling question if this fuel price increase encourages drivers to react short term and ultimately reduce their time spend on the road. This paper will provide new evidence on fuel price elasticities in Switzerland. Moreover, it will also investigate the question if there is heterogeneity in short-term response across consumers. The focus is on examining the fuel price elasticity across different regions, income groups, household sizes, and individuals with distinctive personal values. Additionally, this paper will touch upon differences between rural versus urban areas and individuals holding a half fare pass or general travel card (GA). To achieve those objectives, it will work with the MobisCovid panel dataset which combines exceptionally rich survey data with tracking data.

The rich survey data allows to investigate segments which were not particularly investigated before. Especially, household size and indiviudals with distincitve values are consumer segments which are largely dismissed in previous literature. Traditionally, the fuel price elasticity has been investigated using a double-log regression which is estimated using Ordinary Least Squares (OLS) (Goetzke and Vance 2021, p. 5). This paper will use the "Pseudo Poisson Maximum Likelihood Estimation Method" (PPML) to appropriately deal with the large amount of zero values in the data set. All models in this paper engage vehicle kilometers traveled (VKT) as the dependent variable and the fuel price as the key explanatory variable. The PPML regressions are performed using daily and average weekly data points because if the findings are coherent, it will provide profound credibility. I gauge the robustness of the results by employing period dummies that are interreacted with the relevant fuel price. This shows whether there is aberrance in results when looking at different period overtime which would essentially weaken the results.

Previous literature on fuel price elasticities highlight that the results have direct policy implications for the debate on mitigating transportation-related externalities that immediately impact welfare. These externalities incorporate congestion, noise, as well as air pollutants. The results show whether an increase in the greenhouse taxes motivates the drivers to reduce their driving. This boils down to wheatear taxes are a good instrument for this cause (Gillingham &

Munk-Nielsem 2019, p. 28). When consumers do not reduce their driving, taxation is obsolete. This paper will provide further insight into this discussion. Indeed, Switzerland is an especially interesting case. The Swiss transport network is characterized by an exceptionally high density and quality and thus offers a good substitute for driving one's car (Weber 2021, p. 19). So, in comparison to other countries like for example the US, consumers are less forced to drive and therefore one could expect a higher reaction to a price increase. Yet is this really the case?

Supplementary, Borenstein (2017) points out that policies are frequently confronted with concerns about distributional effects. Common concerns are according to Gillingham & Munk-Nielsem (2019, p. 27) that a fuel tax increase to further price exernalities could dispoportionatly affect certain population groups like for example low-income households or urban households since it is supposed that they are less price elastic. Indeed, the investigation of heterogenous segments of households can shed light on whether these concerns are justified. This paper has implications for the above described debate but moreover also has implications for the oposing current debate in Switzerland to reduce gasoline taxes to relieve households of the pricing burden. This analysis unveils which population groups faces an excessive burden from the price increase and will ultimatly profit the most from a reduction in gasoline taxes. Conclusively, Mattioli et al. (2018, p. 239) sums the benefit of this analysis up and states that the investigation of heterogenous segments of households is significant to fully comprehend the distributional and ethical consequences of price interventions. Additionally, it affects the acceptability of the price intervention by the people.

This Master paper is organized as follows. Section two will give a short overview on the large literature body on fuel price elasticities. Section three will elaborate on the background of the Mobis and the MobisCovid panels data used in this paper. Section four will describe the data basis used for the analysis in more detail. Section five will present the empirical framework. Section six and seven will present the results of the analysis and discuss the findings. Lastly, section eight concludes.

## 2. Literature Review

### 2.1. Literature Review: Fuel Price Elasticity

This paper relates to the vast amount of literature on price elasticities in transportation. The large body of literature concerning fuel price elasticities can be divided into papers which investigate the long-run and the short-run elasticity. There are significantly more studies investigating short-run rather than long-run elasticity. Additionally, elasticity studies can be classified into two broad classes. One group runs a regression of fuel demand on fuel price while the other group regresses VKTs travelled on the road on fue4el price (Goetzke and Vance 2021, p. 2f). This literature review will focus on the second strang of literature since this paper also belongs to the second class. Moreover, it will focus on the newer papers covering the short-run to medium response to fuel price changes.

A big amount of the previous literature uses survey data, more specifically travel dairies or self-reported odometer readings (Goetzke and Vance 2021; Santos Catchesides 2005; Weber 2021; Alberini et al. 2021). Contrary, there are lots of papers which do not work with survey data but rather with odometer readings records (Gillingham et al. 2015; Gillingham 2014; Gillingham and Munk-Nielsen 2019; Kaechele and Slusky 2017). This paper is a novelty because it considers GPS tracking data as well as survey data from the same individuals. This analysis essentially combines survey data with non-survey data. An advantage of GPS tracking in comparison to travel diaries for mobility research purposes is that the risk of under-reporting the number of trips for example due to response burden and memory recall is mitigated (Molloy, Castro and Götschi et al. 2022, p. 1f).

As table 1 below illustrates, there is no clear consensus in the research on the range of fuel price elasticity. The blue-pigmented papers in table 1 are based on survey papers whereas the yellow-pigmented papers are based on non-survey data. Fuel price elasticities vary from -0.1 up to -1.068. This discrepancy in results is due to many factors among which there is the above-mentioned division into survey data and non-survey data. Additionally, the level of aggregation, the definition of the dependent variable and the focus on short-run versus medium-run elasticities are crucial (Goetzke and Vance 2021, p. 1).

Table 1: Fuel/Diesel/Gasoline Price Elasticities estimated on VMT across Literature

| **Paper** | **Findings** | **Country** | **Year** | **Short versus medium run** | **Dependent variable aggregation** |
|---|---|---|---|---|---|
| Goetzke and Vance 2021 | Fuel price elasticity 2009: close to zero<br>Fuel price elasticity 2009-2017: - 0.3 | USA | 2009 - 2017 | Short run | Vehicle mileage is measured on the survey day |
| Santos Catchesides 2005 | Gasoline price elasticity: for the poorest household: - 0.93<br>Gasoline price elasticity: for the middle-income household: - 0.75 | UK | 1999-2000 | Short run | Not mentioned in the paper |

| | | | | | |
|---|---|---|---|---|---|
| Weber 2021 | Gasoline price elasticity of VKT: -1.068 | Switzerland | 2018 - 2020 | Short run | Vehicle milage is measured per year |
| Alberini et al. 2022 | Gasoline price elasticity: -0.37<br>Diesel cars are insensitive to a diesel price increase | Germany | 2004 - 2019 | Short run | Vehicle mileage is measured monthly |
| Gillingham 2014 | Gasoline price elasticity: - 0.22 | USA | 2001-2009 | Medium run | Vehicle mileage is measured monthly |
| Gillingham and Munk-Nielsen 2019 | Fuel price elasticity (with ample access to public transport): -0.13<br>Mean fuel price elasticity: -0.30 | Denmark | 1998-2011 | Short run | Vehicle mileage is measured per day |
| Gillingham et al. 2015 | Gasoline price elasticity: - 0.1 | USA | 2000 - 2010 | Short run | Vehicle mileage is measured per year |
| Kaechele and Slusky 2017 | Gasoline price elasticity: - 0.391 | USA | 1995 - 2002 | Short run | Vehicle mileage is measured per day |

### 2.2. Literature Review: Heterogeneity in Income

Previous papers have analyzed the heterogeneity in fuel price elasticities for groups of drivers defined on observed socio-demographic benchmarks such as income, location and multiple car ownership or household lifecycles (Weber 2021, p. 3). Indeed, a substantial number of papers look not only at the fuel price response but also at the heterogeneity in responses. Most often earlier research describes classes of drivers based on income levels and location (Weber 2021, p. 6).

There seems to be no consensus among survey-based papers. The findings are conflicting. Santos Catchesides (2005) and Goetzke and Vance (2021) suggest that poorer households are more responsive. Whereas Weber's (2021, p. 20) results show no statistically different price elasticity for different income groups. Indeed, Santos Catchesides (2005, p. 107) found that when considering the car-owning households in the UK, the poorest households have the greatest price sensitivity. In addition, poor households living in rural areas have a smaller price response compared to poor households living in urban areas. Compatible, Goetzke and Vance (2021, p. 5) found that households in the highest income group tend to have 18% higher time spent on the road in comparison to middle-income households. Households in the lowest-income group have 27% lower time spent on the road than middle-income households.

Further, the odometer readings records-based paper by Gillingham (2014) opens an even bigger divide in results. Gillingham (2014, p. 20) looked at newly purchased vehicle data and uncovers a subsample of observations where R. L Polk states the household income of the vehicle purchaser. Overall, Gillingham (2014) found that price elasticity tends to increase as income increases but there is a level-off at the highest income groups. However, he warns that his analysis has shortcomings because wealthier households tend to own more vehicles. Since the analysis only looks at the vehicle and not households, there could be within-household switching cost of vehicles which are more fuel efficient. This may account for the greater responsiveness at higher income levels. Indeed, de Borger et al. (2016, p. 151f.) and Knittel and Sandler (2013, p. 22) find some evidence of within-household switching. However, both authors offer little insight into the impact of income on substitution possibilities. De Borger et al. (2016, p. 151f.) conclude that the effect can in principle go both ways. Alternatively, it might be possible that the wealthy are more prone to substitute flying for driving a car. Lastly, Gillingham (2014, p. 20) also emphasizes that the wealthy have more discretionary driving. Finally, it is also mentioned that it is more difficult to decrease driving for poor individuals since they are most likely already at a minimal driving demand related to essential travel. It might be easier for the rich to cut back on leisure-related trips (Gillingham 2014, p. 20).

### 2.3. Literature Review: Rural versus City

Besides there being a substantial amount of interest in heterogenous responses across income groups, there is also a big body of literature looking at responses across groups living in urban versus rural areas. Indeed, there are papers working with survey data as well as papers working with non-survey data investigating this topic. Across papers based on survey data, there is a general agreement in results concerning fuel price elasticities in a rural area in comparison to urban areas. Santos Catchesides (2005) and Weber (2012, p. 26) both find that city dwellers have significantly higher price elasticities than individuals living on the outskirts of the city. Those results are intuitive since rural households tend to have less flexibility in choosing their mileage compared to urban households. Urban households are more likely to substitute private driving for public transport, walking, or cycling since their commutes allow it (Santos Catchesides 2005, p. 111).

Conversely, there is no clear agreement in results across papers using non-survey data to look at differences in price response across rural and urban areas. Gillingham (2014) using registered data for his analysis found that rural households are slightly less price reactive than city dwellers which well-matches the results of Santos Catchesides (2005) and Weber (2012).

Yet, Gillingham and Munk-Nielsen (2019) who also look at consumer groups living in different locations find deviating results. The paper concludes that individuals who live in outer city areas with long commutes and city-dwellers who have shorter commutes are more responsive to fuel price increases. The results are measured in comparison to people with intermediate travel distances. The authors reason that this is due to the urban population having a strong incentive to consider substitutes because small increases in fuel price affect driving expenses substantially. City dwellers on the other hand have a higher explosion of alternatives for commuting (Gillingham and Munk-Nielsen 2019, p. 39f).

Kaechele and Slusky's (2017) results are somewhat conflicting. They looked at whether people with rail access have a more elastic response to a gasoline price increase in comparison to individuals with no rail access. Rail access was measured according to where the individual's household is located. Indeed, rail access shows that there is a substitute opportunity for riding a car, whereas when there is no rail substitute, opportunity is limited. The authors conclude that individuals with rail access are not more elastic (Kaechele and Slusky 2017, p. 1114ff.). The authors' reason that this result could potentially be accredited to the fact that possible rail ticket prices rose simultaneously to the fuel price. Alternatively, Kaechele and Slusky (2017, p. 1116) refer to the first/last mile problem which entails that it might be hard for some individuals to reach the train station or get home from it.

### 2.4. Literature Review: Household Size and Family Size

If and how household size has an impact on fuel price elasticity is a less studied topic. To my knowledge, no paper looks at how VMT changes across household size when there is a fuel price change. Alberini et al. (2022, p. 8) regresses the logarithm of fuel price on the logarithm of monthly VKT and include family size as a control variable. However, they do not include an interaction term between fuel price and family size. Indeed, even though the family size is mentioned in the paper there is no clear analysis made on how the fuel price elasticity varies across family size. Papers are looking at the household size and fuel demand (Lui 2015; Bento et al. 2009). The first study that looked a family size and fuel demand is Bento et al. (2009). Bento et al. (2009) effectively studies the impact of gasoline tax increases and considers jointly the supply and demand side. He thereby found that families with children are more responsive to changes in the gasoline price in the long run (Bento et al. 2009, p. 683). At this point, it is important to mention that this paper's analysis differs from Bento et al. (2009) substantially. Besides Bento et al. (2009) not looking at the VKT, he also does not look at the short-run elasticity as this analysis does.

### 2.5. Literature Review: GA and Personal Values

If an individual holds a GA or a half fare pass it indicates the extent of substitutability between public and private transportation (Weber 2021, p. 14). To my knowledge no paper looks at GA or half fare passes as an interaction term investigating wheatear individuals with a pass have a higher fuel price elasticity. Weber (2021, p. 14) includes the number of GA cards held by the household members as a socio-demographic attribute in the model specification but does not discuss it as an interaction term like in this paper. Lastly, there is also no paper looking at how VMT changes across people with distinctive personal values when there is a fuel price change. This is probably because it is difficult to find such rich data and the variable distinctive of personal values are hard to quantify.

## 3. The Mobis and MobisCovid Panels

Mobis was a randomized nationwide trial of Swiss transport pricing data. It was created exploiting online surveys, a combination of postal recruitment and GPS tracking. The Mobis randomized control trial lasted 8 weeks and was divided into two 4-week phases. There were two invitation letters sent off in two different waves. The first wave took place in July 2019 and included 60’409 persons. The second wave was in October 2019 and included 30’500 persons. Invitation letters were only sent to individuals living in an agglomeration area of Switzerland excluding the canton of Ticino. Individuals who received an invitation were requested to fill in a screening survey. If they met the inclusion criteria, they were then asked to participate in a smartphone-based mobility experiment for 8 weeks and in return, they received 100 Swiss Francs. Individuals were restricted to the age of 18 until 65 and needed to be able to walk without assistance. Also, individuals were prohibited to drive for their profession and had to use a car at least two days a week (Molloy, Castro and Götschi et al. 2022, p. 5f.).

Overall, 90’909 persons got an invitation to fill in the introduction survey. 21’571 (23.7%) individuals completed the screening survey, and 6’895 persons were qualified. Finally, 3’519 persons (3.9%) completed the experiment including the final survey (Molloy, Castro and Götschi et al. 2022, p. 5). The Catch-My-Day GPS tracking app was developed by motion tag. This app registers all outdoor movements and groups GPS points into activities, trips and stages as well as attributes travel mode (Hintermann et al. 2021, p.7). For more insight on the tracking app or the response rates see Molly et al. (2020).

When the study ended some participants kept the tracking app active. Indeed, by mid-March 2020 roughly 400 participants were still tracking. The remaining participants were encouraged to re-install the tracking app and 1’200 individuals restarted tracking. The MobisCovid panel is essentially made up of the individuals which never deactivated the tracking and those who resumed tracking. The original MobisCovid panel eventually underwent a participant decline which however was lessened by additional participants from LINK in the fall of 2020. Up until the 30th of May 2021, the MobisCovid panel registered over 2’400 participants and has over 4’500 person-day observations (Hintermann et al., 2021, p. 7f.).

## 4. Data

This paper uses the MobisCovid panel. The dataset includes 1’131 participants. For the following analysis, I included only individuals who own at least one car. The assumption behind this is that if individuals own at least one car they can be characterized as a regular driver. In the dataset, 462 participants met this criterium. Overall, this paper looks at 86’569 observations of those participants. The period which is analyzed goes from 2021-06-01 until 2022-05-31. The MobisCovid panel data provides the daily meter spend on the road driving a car.

The MobisCovid panel dataset include several zero values for the daily meters spent on the road driving a car. For this analysis however, the daily meters are converted into daily kilometers to better fit the model. Overall, 22.47% of all observations are zeros. This is plausible since there might be days when the participants do not use the car. Thus, they spend zero kilometers on the road for that specific day. One alternative explanation for the zeros might be that they are a result of rounding errors (Santos Silva and Tenreyro 2006, p. 643). It is possible that some participants did not reach a minimum value and thus the time spent on the road is registered as zero kilometers. However, rounding might exist, but it does not play a major role since it is most likely partly compensated by rounded-up ones. Thus, the whole effect of these errors should be reasonably minor. Since the price of fuel is essential for the investigation of fuel price elasticity, the average daily price of diesel and gasoline was added from the Swiss Federal Statistic Office website. In table 4 and 5 in the appendix one can find the progression of the fuel price over the analyzed period.

Further, the MobisCovid panel data through the surveys taken by the participants gives insight into socio-demographic, personal values as well as transport-related characteristics. Indeed, participants were asked whether they own a half fare pass or a GA. Those questions were essentially answered with yes or no. Moreover, they were also asked how many individuals live in their household and what their monthly gross income for the household amounts to.  For the income question, they were asked to reveal their income group.

Furthermore, the participants were also questioned to what degree they consider 16 value items as guiding principles in their lives. Following up the responses were documented on a Likert scale and lastly aggregated to 4 meta-values. The four meta-values are named egoistic, altruistic, hedonic and biospheric. Egoism is based on the want of social power, the want of wealth meaning material possessions, the want of authority, the influence on people as well as events and being hard-working as well as aspiring. Altruism is based on the want of equal opportunity for everybody, the fear of war and conflict, the commitment to social justice and the desire to be helpful to others. Further, hedonic represents enjoying life and being self-indulgent. Finally, biospheric is founded on the deep desire to respect the earth, harmony with nature, guarding the environment and preventing pollution (Hintermann et al., 2021, p. 15).

Since this paper is also interested in examining the heterogeneity between rural and urban areas as well as across different geographical regions, the original MobisCovid panel data was extended by suitable data from the Swiss Federal Statistic Office. Essentially the participant's living location was categorized into rural, urban, and intermediate. Furthermore, the participant's living location was assigned to the matching labor market area. The definition of the labor market areas given by the BFS are regions where most employed persons live and work (Swiss Federal Statistic Office 2022). Indeed, the labor market areas provide a good measurement of geographical differences across Switzerland.

For vehicle VKT weather information and covid information are significant predictors. Thus, the MobisCovid panel dataset is complementing the tracking data with temperature, rainfall, and sunshine data points (Hintermann et al. 2021, p. 11). A period of heat and cold is measured in degree days and defined for a trip $j$ on day $t$. The formula goes as follows:

$$Heat_{jt} \equiv \max\left(tmaxd_{jt} - 25, 0\right)$$
$$Cold_{jt} \equiv \max\left(10 - tmind_{jt}, 0\right)$$

The variables $tmind_{jt}$ and $tmaxd_{jt}$ signify the minimum daily temperature and the maximum daily temperature. Those variables are measured on a $1 \times 1km$ grid. For the $tmind_{jt}$ and $tmaxd_{jt}$, the temperature at the departure location is taken for trips $j$. Precipitation and the number of sunshine hours are also part of the analysis and are measured on the same $1 \times 1km$ grid. The average sunshine and precipitation across all trips $j$ on a given day $t$ is the basis on which the variables are computed. Moreover, because covid infections are a significant predictor of VKT, there is a need to complement the tracking data with weekly covid infection data. This data was added from the Swiss Federal Statistic Office website. The infections are scaled per 1'000'000'000 to better fit the model.

The composition of the MobisCovid panel used for this analysis is found in table 1 in the appendix. Comparing the MobisCovid panel to the newest representative Swiss Transport Micro Census, which is conducted every 5 years, there are several differences (Hintermann et al., 2021, p. 9). Table 1 in the appendix shows that the MobisCovid panel participants are on average older than individuals part-taking in the Swiss Transport Micro Census. Since the Swiss Transport Micro Census is representative, it is reasonable to say the MobisCovid panel participants are on average older than the Swiss population. Additionally, the survey participants are more educated, have a higher number of employments, have higher income and live in larger households compared to the overall Swiss population. Hintermann et al. (2021, p. 9) explains those differences by self-selection and the focus of the Mobis study. The Mobis study focuses on working people who drive a minimum of two days a week and live in urban agglomerations in the German and French speaking regions.

## 5. Empirical Framework

Traditionally the fuel price elasticity has been investigated using a double-log regression which is estimated using Ordinary Least Squares (OLS) (Goetzke and Vance 2021, p. 5). The main issue is that the log-linearization is not reasonable if the dependent variable contains zero values since the log of zero is negative infinity (Motta et al. 2019, p. 2). A huge majority of empirical studies approach this problem by simply dropping the zeros (Santos Silva and Tenreyro 2006, p. 643).

This paper will use the "Pseudo Poisson Maximum Likelihood Estimation Method" (PPML) to not have to throw away the dependent variable observations which are zero (Santos Silva and Tenreyro 2006, p. 643). A potential alternative to address this issue is to add a small constant to the zero value before taking the logarithm to prevent the omission of the observation from the model. This is amicable for zeros values since log (0+1) = 0. However, this method is ad hoc and there is no guarantee that this reflects the underlying expected value (Xu 2022).

The requirements for the PPML estimator are simply that the conditional mean of the dependent variable is properly specified. There is no additional assumption required about the distribution of the error term (Correia et al., 2020, p. 95). To better interpret the results of the PPML regression, the coefficients reported in this paper are exponentiated (incidence-rate ratios = $e^{\hat{\beta}}$). The model of this paper like most models in preview analyses implies that consumers respond symmetrically to increases as well as decreases in fuel prices. Thus, the results of the analysis should be viewed as estimating an average response.

To find the fuel price elasticity, this analysis starts with the following equation:

$$Y_{it} = c + a * FP_t + b * CI_t \times \left[1 \ \ CI_t \ \ {CI_t}^2 \ {CI_t}^3\right] + c * W_{it} \times [1 \ \ WE_t] + \mu_i + u_{it} \qquad (1)$$

This paper estimates the proportional change of outcome $Y_{it}$ for person $i$ on day $t$ as a function. The vector $Y_{it}$ is the dependent variable in this analysis and contains the kilometers spend on the road by a person on a specific day. Depending on which fuel type is investigated only individuals driving a car with the respective fuel type are considered. The vector $FP_t$ displays the average fuel prices on a given day t. The fuel price is measured per liter and in Swiss Francs. The estimated vector of coefficients $\hat{a}$ measures the relative daily change in $Y_{it}$ to the fuel price change bearing in mind person-specific and day-of-the-week-specific effects and is corrected for daily weather conditions as well as covid infections. The vector $CI_t$ accounts for the weekly average covid infections by the 1'000'000'000. The effect of covid infections is controlled with a polynomial. This analysis enters the information by itself in the form of the unit vector and then interacts the information with itself. The vector $W_{it}$ contains the daily weather information. To account for a potentially different effect of weather on mobility between workdays and leisure days, the weather information is entered by itself in form of the unit vector and interacted with the weekend dummy $WE_t$. The vector $WE_t$ represents leisure trips since it is reasonable to assume that individuals do not have work obligations on weekends and obligatory national holidays. This regression includes person and day-of the week fixed effects $\mu_i$ to captivate unobserved heterogeneity that is constant across time. The error term $u_{it}$ has an expectation of zero. Finally, all inferences in this estimation are based on the Eicker-White robust covariance matrix estimator.

To investigate the heterogeneity in the fuel price elasticity on leisure days in comparison to non-leisure days, an interaction variable of fuel price with the weekend dummy is added to equation (1). The equation looks as followed:

$$Y_{it} = c + a * FP_t \times [1 \ \ WE_t] + b * CI_t \times \left[1 \ \ CI_t \ \ {CI_t}^2 \ {CI_t}^3\right] + c * W_{it} \times [1 \ \ WE_t] + \mu_i + u_{it} \ \ (2)$$

This interaction between the vector $FP_t$ and the vector $WE_t$ is used to investigate heterogenous responses to a change in the fuel price. Essentially the coefficient of the interaction term will display the leisure trip's aberrance from the non-leisure trips. Thus, the estimated relative daily change in $Y_{it}$ to the fuel price $FP_t$ for leisure trips is calculated by multiplying the coefficient of the vector $FP_t$ and the interaction term of $FP_t$ with $WE_t$.

Further, this paper goes beyond investigating whether consumers' reactions differ for leisure-related trips. To investigate the heterogeneity in the fuel price elasticity for several subgroups in the population, there is an interaction term of fuel price with the group of interest dummy added to equation (1). The equation looks as followed:

$$Y_{it} = c + a * FP_t \times [1 \;\; D_{it}] + b * CI_t \times \left[1 \;\; CI_t \;\; {CI_t}^2 \; {CI_t}^3\right] + c * W_{it} \times [1 \;\; WE_t] + \mu_i + u_{it} \quad (3)$$

The vector $D_i$ displays a dummy that splits the total population into a subgroup according to a shared characteristic. This interaction between the vector $FP_t$ and the vector $D_i$ is used to investigate heterogenous responses to a change in the fuel price. For example, the vector $D_i$ can symbolize an income dummy variable that is used to split the population into a different subgroup according to income. Subsequently, the coefficient of the interaction term will display the specific income group's aberrance from the reference group. The estimated relative daily change in $Y_{it}$ to the fuel price $FP_t$ for this income group is calculated by multiplying the coefficient of the vector $FP_t$ and the interaction term of $FP_t$ with $D_i$.

To further support the main results based on daily data, the PPML regressions based on equations (1) and (3) are also performed using average weekly data points. If the results are the same this will strengthen the overall findings of this paper.

Lastly, to investigate the heterogeneity in the fuel price elasticity for leisure-based trips for several subgroups in the population, the original equation must be further modified. Indeed, an interaction term of fuel price with the weekend dummy with the group of interest dummy must be added to equation (2). The equation looks as followed:

$$Y_{it} = c + a * FP_t \times [1 \;\; WE_t \;\; (D_{it} * WE_t)] + b * CI_t \times \left[1 \;\; CI_t \;\; {CI_t}^2 \; {CI_t}^3\right] + c * W_{it} \times [1 \;\; WE_t] + \mu_i + u_{it} \quad (4)$$

This interaction term between the vector $FP_t$, $D_{it}$ and $WE_t$ is used to investigate heterogenous responses to a change in the fuel price for a subgroup of interest for leisure-based trips. The coefficient of the interaction term will display the aberrance from the interaction term of fuel price with weekend which will display the aberrance from the reference group. Thus, the estimated relative daily change in $Y_{it}$ to the fuel price $FP_t$ for leisure trips is calculated by multiplying the coefficient of the vector $FP_t$ , the interaction term of $FP_t$ with $WE_t$ and the interaction term of $FP_t$ with $WE_t$ and $D_{it}$.

## 6. Results

### 6.1. Gasoline Price Elasticity

This section and table 2 present the results of the average gasoline price elasticity analysis. Beginning with column 1 in table 2 the results show a positive gasoline price elasticity of VKT of 0.009. Yet the gasoline price elasticity is not significant since the p-value is above 0.10. However, it is reasonable to assume that consumers need a certain period to adjust their behavior since driving habits developed over time are most likely hard to instantly change. To allow for a certain adjustment period there is a need to have a first look at the lag gasoline price elasticity. The lag gasoline price variable is four days belayed in comparison to the current and original gasoline price variable. Essentially column 2 in table 2 includes the lag gasoline price as well as the gasoline price as an independent variable in the PPML regression. The results in column 2 show that the lag gasoline price indicates a negative response whereas the gasoline price elasticity is still positive. Thus, this is an indication that consumers need a certain adjustment period. Column 3 in table 2 further examines the lag gasoline price elasticity. The PPML regression shows a negative elasticity of -0.001 which yet is not significant.

It is reasonable to assume that VKT is not just influenced by the fuel price but rather also by covid and weather conditions. Column 4 in table 2 adds covid control variables to the PPML regression in column 3 to control for influences on travel behavior caused by the ongoing covid pandemic situation. But the included covid infection does not change the pseudo-$R^2$. The pseudo-$R^2$ indicates the goodness of the fit. A higher value of the pseudo-$R^2$ indicates a better model fit. Thus, simply including the covid control variables does not affect the model fit according to the pseudo-$R^2$. Column 5 in table 2 adds weather control variables to the PPML regression in column 3. The PPML regression shows that when adding weather controls to the lag gasoline price the pseudo-$R^2$ increases by 0.001 in comparison to the previous column 3 in table 2. Thus, according to the pseudo-$R^2$ the weather control variable is needed to increase the goodness of the model fit.

Finally, column 6 in table 2 adds the covid as well as the weather control variables jointly to the PPML regression. The result shows that when adding both control variables to the lag gasoline price, the pseudo-$R^2$ increases by 0.002 in comparison to the previous column 3 in table 2. This is an additional increase of 0.001 in comparison to column 5 in table 2. Also, while the covid infection variables do not affect the model fit according to the pseudo-$R^2$ in column 4 in table 2, the results in column 6 in table 2 show that the covid control variables in combination with the weather variables offer the best model fit out of all 6 PPML regressions in table 2. Thus, this shows that the control variables as well as the weather variables are needed for this analysis and explain changes in the VKT. Moreover, we can see that that the lag gasoline price elasticity without any control variable is -0.001 whereas it changes to -0.018 when we include the control variables. Nevertheless, both gasoline price elasticities are not significant.

Table 2: PPML Regression Gasoline Price and VMT

| | **VKT_1** | **VKT_2** | **VKT_3** | **VKT_4** | **VKT_5** | **VKT_6** |
|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 38.681*** | 38.997*** | 39.413*** | 36.933*** | 40.536*** | 38.474*** |
| | -3.344 | -3.444 | -3.372 | -3.144 | -3.518 | -3.356 |
| **gasoline** | 1.009 | 1.066 | | | | |
| | -0.048 | -0.113 | | | | |
| **lag*gasoline** | | 0.942 | 0.999 | 1.049 | 0.952 | 0.982 |
| | | -0.099 | -0.047 | -0.050 | -0.046 | -0.048 |
| **infections_weekly_1000000k** | | | | 0.998 | | 1.146 |
| | | | | -0.820 | | -1.047 |
| **infections_weekly_1000000k2** | | | | 0.000 | | 0.000' |
| | | | | 0.000 | | 0.000 |
| **infections_weekly_1000000k3** | | | | 1.252e+48* | | 3.722e+59* |
| | | | | -7.005E+49 | | -2.112E+61 |
| **infections_weekly_1000000k4** | | | | 0.000* | | 0.000** |
| | | | | 0.000 | | 0.000 |
| **heat** | | | | | 0.997 | 1.005* |
| | | | | | -0.002 | -0.002 |
| **sunshine** | | | | | 1.010*** | 1.010*** |
| | | | | | -0.002 | -0.002 |
| **rain** | | | | | 1.001 | 1.001 |
| | | | | | -0.001 | -0.001 |
| **cold** | | | | | 0.971*** | 0.972*** |
| | | | | | -0.007 | -0.007 |
| **heat*weekend** | | | | | 1.004 | 1.004 |
| | | | | | -0.003 | -0.003 |
| **sunshine*weekend** | | | | | 1.002 | 1.003 |
| | | | | | -0.003 | -0.003 |
| **rain*weekend** | | | | | 1.007* | 1.007* |
| | | | | | -0.003 | -0.003 |
| **cold*weekend** | | | | | 0.998 | 0.997 |
| | | | | | -0.014 | -0.014 |
| **N** | 51653.000 | 51649.000 | 51649.000 | 51649.000 | 51649.000 | 51649.000 |
| **r2_p** | 0.187 | 0.187 | 0.187 | 0.187 | 0.188 | 0.189 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | | |

### 6.2. Diesel Price Elasticity

This section and table 3 present the results of the average diesel price elasticity analysis. Column 1 in table 3 shows that the diesel price elasticity amounts to -0.081 and is significant at the 10% level. Analog to the gasoline price elasticity analysis, it is necessary to investigate whether consumers potentially need an adjustment period to modify their behavior after seeing the change in the diesel price. Column 2 in table 3 includes the lag diesel price elasticity as well as the diesel price elasticity. The lag diesel price variable which this analysis looks at is four days belayed to the current and original diesel price variable. The coefficients show that the lag diesel variable indicates a negative response to a diesel price increase whereas the variable diesel suggests the opposite reaction. Overall, the lag diesel variable reflects a sounder consumer response. Matching the conclusion of the gasoline elasticity analysis, the diesel consumers need some time to adjust their behavior after having seen a diesel price change and thus show a delayed reaction. Column 3 in table 3 examines the lag diesel price elasticity as the sole explanatory variable. The results show a negative lag diesel price elasticity of -0.089 which is significant at the 10% level.

Analog to the gasoline price elasticity analysis, it is reasonable to assume that VKT is not solely influenced by the diesel price but rather also by covid and weather conditions. Column 4 in table 3 adds covid control variables to the PPML regression. The regression shows a higher pseudo-$R^2$ compared to column 3 in table 3. The increase in pseudo-$R^2$ amounts to 0.001. The higher value of the pseudo-$R^2$ indicates a better model fit. Thus, simply including the covid control variables betters the model fit according to the pseudo-$R^2$. Column 5 in table 3 adds solely weather control variables to the PPML regression in column 3. The regression in column 5 does not display a higher pseudo-$R^2$ compared to column 3 in table 3. Thus, according to the pseudo-$R^2$ including solely the weather control variable does not increase the goodness of the model fit.

Lastly, column 6 in table 3 adds the covid as well as the weather control variables to the PPML regression in column 3. This PPML regression shows that when adding both control variables to the lag gasoline price variable the pseudo-$R^2$ increases by 0.002 in comparison to column 3 in table 3. According to the pseudo-$R^2$, the regression in column 6 in table 3 offers the best model fit out of all 6 PPML regressions in table 3. Moreover, we can see that that the lag diesel price elasticity without any control variable is -0.081 and significant at the 10% level whereas it changes to -0.113 and is significant at the 5% level when we include the control variables.

Table 3: PPML Regression Diesel Price and VKT

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 | VKT_6 |
|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 52.247*** | 52.991*** | 53.162*** | 51.737*** | 52.653*** | 51.517*** |
| | -4.958 | -5.107 | -4.958 | -4.810 | -4.936 | -4.870 |
| **diesel** | 0.919' | 1.020 | | | | |
| | -0.046 | -0.122 | | | | |
| **lag*diesel** | | 0.895 | 0.911' | 0.920' | 0.902* | 0.887* |
| | | -0.105 | -0.045 | -0.045 | -0.045 | -0.045 |
| **infections_weekly_1000000k** | | | | 10.400* | | 65.506*** |
| | | | | -11.497 | | -79.416 |
| **infections_weekly_1000000k2** | | | | 0.000* | | 0.000** |
| | | | | 0.000 | | 0.000 |
| **infections_weekly_1000000k3** | | | | 1.478e+64* | | 2.150e+82* |
| | | | | -1.101E+66 | | -1.632E+84 |
| **infections_weekly_1000000k4** | | | | 0.000' | | 0.000* |
| | | | | 0.000 | | 0.000 |
| **heat** | | | | | 0.996* | 0.995' |
| | | | | | -0.002 | -0.003 |
| **sunshine** | | | | | 1.006** | 1.008*** |
| | | | | | -0.002 | -0.002 |
| **rain** | | | | | 1.001 | 1.002 |
| | | | | | -0.001 | -0.001 |
| **cold** | | | | | 0.985' | 0.985' |
| | | | | | -0.009 | -0.009 |
| **heat*weekend** | | | | | 1.002 | 1.002 |
| | | | | | -0.004 | -0.004 |
| **sunshine*weekend** | | | | | 1.002 | 1.002 |
| | | | | | -0.004 | -0.004 |
| **rain*weekend** | | | | | 1.003 | 1.003 |
| | | | | | -0.003 | -0.003 |
| **cold*weekend** | | | | | 1.038' | 1.036' |
| | | | | | -0.021 | -0.021 |
| **N** | 27558.000 | 27554.000 | 27554.000 | 27554.000 | 27554.000 | 27554.000 |
| **r2_p** | 0.180 | 0.180 | 0.180 | 0.181 | 0.181 | 0.182 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | | |

## 6.3. Heterogeneity in the Gasoline Price Elasticity with Daily Data

This section and fundamentally table 4 present the results of the heterogeneity analysis in the lag gasoline price elasticity. Column 1 in table 4 examines the difference in gasoline price elasticity considering weekend and holiday trips only. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the weekend dummy shows a p-value of

0.34. Thus, the results show that the lag gasoline price elasticity on leisure trips does not have a significantly different reaction to non-leisure trips.

Column 2 and column 3 in table 4 look at the difference in lag gasoline price elasticity across different labor market areas in Switzerland. The reference group is for both regressions Zürich. Zürich is the reference area because most participants are assigned to this labor market area. The labor market area Lausanne only recorded 9 observations. Since it would be misleading to conclude this amount of observation, I decided to drop the area variable for Lausanne and exclude those 9 observations from the regression in columns 2 and 3 in table 4.

The analysis in column 2 looks particularly at the difference in lag gasoline price elasticity across different labor market areas focusing on all trips. The reference group shows a lag gasoline price elasticity of 0.032 which however is not significant since the p-value is above 0.1. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Aareland dummy shows a p-value of 0.382. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Zentralschweiz dummy shows a p-value of 0.145. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Biel and Jura dummy shows a p-value of 0.716. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Bern dummy shows a p-value of 0.583. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Basel dummy shows a p-value of 0.14. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Genf dummy shows a p-value of 0.339. The results show no significantly different lag in gasoline price elasticity from Zürich across all different labor market areas in Switzerland. Essentially, there is no significant lag in gasoline price elasticity found for any area.

The analysis in column 3 looks at the difference in lag gasoline price elasticity across different labor market areas focusing on leisure trips. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the weekend dummy shows a p-value of 0.435. This shows that the reference group has a lag gasoline price elasticity of -0.0486 which however is not statistically different. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with the Zentralschweiz dummy variable shows a p-value of 0.529. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of weekend with Biel and Jura dummy variable shows a p-value of 0.529. A F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with Basel dummy variable show a p-value of 0.573. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with Genf dummy variable show a p-value of 0.731. This shows that there is no significant different in leisure of the lag gasoline price elasticity from the reference group found for the labor market areas in Zentralschweiz, Biel and Jura, Basel as well as Genf. A F-test of the lag gasoline price, the interaction term of the lag gasoline price with the weekend dummy and the interaction term of the weekend with the Aareland dummy shows a p-value of 0.008. This shows that the leisure lag gasoline price elasticity for Aareland is -0.198 which is significant at the 1% level. Those findings however need to be cautiously interpreted since they are based on only 154 observations. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with Bern dummy variable shows a p-value of 0.072. Thus, we see that the weekend lag gasoline elasticity for the labor market area Bern is essentially -0.105 and significant at the 5% level. Those findings are based on 2’664 observations in Bern. The results indicate that individuals living in Bern and Aareland tend to decrease their leisure driving when there is an increase in the lag gasoline price.

Column 4 and column 5 in table 4 look at the difference in lag gasoline price elasticity across different income groups in Switzerland. 6’257 observations needed to be dropped for those two regressions since participants preferred to not display their income. The reference group for both regressions are households with a gross monthly income of 8’000 – 12’000 Swiss Francs. The decision to choose this reference group is because most participants fit into this category.

The analysis in column 4 looks especially at the difference in the lag gasoline price elasticity across different income groups focusing on all trips. The reference group shows a lag gasoline price elasticity of -0.198 which is significant at the 5% level. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy variable for households earning 12’000-16’000 shows a p-value of 0.542. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy variable for households with a gross monthly income of 4’000-8’000 shows a p-value of 0.369. These two F-tests show that the price elasticity for households earning 12’000-16’000 and 4’000-8’000 do not significantly differ from the reference group. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy variable for households having a gross monthly income of more than 16’000 shows a p-value of 0.080. The lag gasoline price elasticity of households earning more than 16’000 is 0.290 and significant at the 10 % level. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy variable for households having a gross monthly income less than 4’000 shows a p-value of 0. The lag gasoline price elasticity of households having a gross monthly income less than 4’000 is 1.856 and significant at the 1% level. In sum, the households earning less than 4’000 and more than 16’000 show that they will increase their driving when there is a price increase. This is counterintuitive. However, those two income groups are also having the lowest percentage of participants fitting into this category. Indeed, only 3.34% of all observations fall into the income category of less than 4’000 Swiss Francs and only 9.24 % of all observations fall into the income category of more than 16’000 Swiss Francs. 17% of all observations fall into the income category 12’000-16’000, 30.8% fall into the income category 4’000-8’000 and lastly 38.6% fall into the income category 8’000-12’000 Swiss Francs per month.

The analysis in column 5 looks contrary to column 4 at the difference in lag gasoline price elasticity across different income groups focusing on leisure trips. The F-test of the lag gasoline price and the interaction term of the lag in gasoline price with weekend shows a p-value of 0.204. This shows that there is no significant leisure lag gasoline price elasticity for the reference income group. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with the weekend and the interaction term of the weekend with households earning more than 16’000 Swiss Francs show a p-value of 0.988. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with households earning 12’000 -16’000 Swiss Francs shows a p-value of 0.437. A F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of weekend with households earning 4’000 -8’000 Swiss Francs shows a p-value of 0.264. These results show that the households earning 4’000-8’000, 12’000-16’000 and the households earning more than 16’000 display no significantly different reaction to the reference group. Further, an F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend with households earning a gross monthly income less than 4’000 Swiss Francs shows a p-value of 0.033. The weekend price elasticity of this income group is -0.143 and significant at the 5% level. Consequently, this shows that only the poorest households reduce their driving significantly for leisure trips when there is a price increase.

Column 6 and column 7 in table 4 look at heterogeneity in the lag gasoline price elasticity across the different household sizes. The analysis in column 6 focuses on all trips. The reference group are households with less than 3 individuals. The reference group shows a lag gasoline price elasticity of -0.039 which is not significant. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy for households with 3 persons shows a p-value of 0.162. An F-test of the lag gasoline price and the interaction term with the lag gasoline price and the dummy for households with more than 5 persons shows a p-value of 0.701. This shows that there is no significantly different reaction to the reference group. An F-test of the lag gasoline price and the interaction term with the lag gasoline price and the dummy for households with 4 persons shows a p-value of 0.036. The lag gasoline price elasticity for households with 4 people is 0.243 and significant at the 5% level. This shows that only this household size has a significant lag in gasoline price elasticity. This group will increase their driving when there is a price increase.

The analysis in column 7 contrary to column 6 focuses on leisure-based trips. The reference group shows a leisure lag gasoline price elasticity of the reference group is -0.093 which is not significant. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend dummy for households with 3 persons show a p-value of 0.451. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend dummy for households with 4 persons show a p-value of 0.229. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend dummy for households with more than 5 persons show a p-value of 0.268. Subsequently, there is no leisure lag gasoline price elasticity found and essentially there is also no heterogeneity.

Column 8 and column 9 in table 4 investigate the heterogeneity in lag gasoline price elasticity across individuals with distinctive personal values. Since some of the participants were not ranked according to their personal values, this regression had to ignore 1’340 observations. Column 8 focuses on all trips. An F-test of the lag gasoline price and the interaction term of the lag gasoline with a distinctive egoistic character trait shows a p-value of 0.318. An F-test of the lag gasoline price and the interaction term of the lag gasoline with a distinctive hedonic character trait shows a p-value of 0.318. An F-test of the lag gasoline price and the interaction term of the lag gasoline with a distinctive biospheric character trait shows a p-value of 0.657. An F-test of the lag gasoline price and the interaction term of the lag gasoline with a distinctive altruistic character trait shows a p-value of 0.131. In sum, these results show no difference between individuals having distinctive egoistic, biospheric, altruistic or hedonic personal values in comparison to individuals who don’t.

The analysis in column 9 contrary to column 8 focuses on leisure-based trips. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend for individuals with a distinctive hedonic character trait show a p-value of 0.006. The lag gasoline price elasticity on leisure-based trips of individuals with a distinctive hedonic character trait is -0.200 and significant at the 1% level. This shows that individuals with a distinctive hedonic character reduce their leisure driving when there is a price increase. The reference group of individuals with no distinctive personal values show no response since their lag gasoline price elasticity is not significant. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend for individuals with a distinctive egoistic character trait show a p-value of 0.530. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend for individuals with a distinctive biospheric character trait show a p-value of 0.255. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with weekend and the interaction term of the weekend for individuals with a distinctive altruistic character trait show a p-value of 0.954. This show that there is no difference between an individual having distinctive egoistic, biospheric or altruistic personal value in comparison to individuals who don't. None of them display a significant response.

Besides the investigation of heterogeneity of the different population groups presented in table 3, I further investigated the heterogenicity in living location and whether individuals own a half-fare pass or a GA. The results are in table 2 in the appendix. There is no heterogeneity in lag gasoline price elasticity for individuals who own a half-fare in comparison to individuals who own no half-fare pass. This result of no heterogeneity holds across all trips as well as leisure-based trips. Looking at all trips and investigating the heterogeneity in whether individuals own a GA, there is heterogeneity. An F-test of the lag gasoline price and the interaction term with the lag gasoline price and the dummy for individuals owning a GA shows a p-value of 0.05. The results also show a lag gasoline price elasticity of individuals owning a GA of -0.333. This suggests that individuals with a GA are more likely to reduce their driving in comparison to individuals not owning a GA. This result is intuitive since individuals owning a GA can switch from driving a car to taking the train without the extra cost of having to buy a train ticket. This effect is however not found when looking at leisure-based trips. An F-test of the lag gasoline price, the interaction term of the lag gasoline price with the weekend and the interaction term of weekend with individuals owning a GA show a p-value of 0.097. The lag gasoline price elasticity for leisure trips of individuals owning a GA is 0.120 and significant at the 1% level. This result is counterintuitive, displaying that individuals with a GA tend to increase their driving when there is a price increase. Finally, results on heterogeneity in the lag gasoline price elasticity across more urban or more rural areas show no significant difference.

Table 4: Heterogeneity in the Gasoline Price Elasticity with Daily Data

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 | VKT_6 | VKT_7 | VKT_8 | VKT_9 |
|---|---|---|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 38.036*** | 37.591*** | 37.758*** | 39.082*** | 38.798*** | 38.316*** | 38.002*** | 38.109*** | 38.005*** |
| | -3.301 | -3.257 | -3.270 | -3.555 | -3.533 | -3.323 | -3.295 | -3.334 | -3.329 |
| **laggasoline** | 1.007 | 1.032 | 1.011 | 0.802* | 1.007 | 0.961 | 1.007 | 0.996 | 1.003 |
| | -0.051 | -0.117 | -0.052 | -0.073 | -0.054 | -0.061 | -0.051 | -0.077 | -0.052 |
| **laggasoline*weekend** | 0.937 | 0.935 | 0.941 | 0.928 | 0.913 | 0.936 | 0.901* | 0.939 | 0.953 |
| | -0.048 | -0.048 | -0.052 | -0.052 | -0.052 | -0.048 | -0.047 | -0.049 | -0.051 |
| **Aareland*laggasoline** | | 0.717 | | | | | | | |
| | | -0.260 | | | | | | | |
| **Zentralschweiz*laggasoline** | | 1.078 | | | | | | | |
| | | -0.144 | | | | | | | |
| **BielJura*laggasoline** | | 0.922 | | | | | | | |
| | | -0.164 | | | | | | | |
| **Bern*laggasoline** | | 0.911 | | | | | | | |
| | | -0.145 | | | | | | | |
| **Basel*laggasoline** | | 0.545 | | | | | | | |
| | | -0.221 | | | | | | | |
| **Genf*laggasoline** | | 0.814 | | | | | | | |
| | | -0.174 | | | | | | | |
| **Aareland*Weekend*laggasoline** | | | 0.843** | | | | | | |
| | | | -0.051 | | | | | | |
| **Zentralschweiz*Weekend*laggasoline** | | | 1.011 | | | | | | |
| | | | -0.023 | | | | | | |
| **BielJura*Weekend*laggasoline** | | | 0.953 | | | | | | |
| | | | -0.029 | | | | | | |
| **Bern*Weekend*laggasoline** | | | 0.941* | | | | | | |
| | | | -0.027 | | | | | | |
| **Basel*Weekend*laggasoline** | | | 1.106 | | | | | | |
| | | | -0.076 | | | | | | |
| **Genf*Weekend*laggasoline** | | | 1.075* | | | | | | |
| | | | -0.037 | | | | | | |
| **more16000*laggasoline** | | | | 1.608** | | | | | |
| | | | | -0.270 | | | | | |
| **12000-16000*laggasoline** | | | | 1.157 | | | | | |
| | | | | -0.172 | | | | | |
| **4000-8000*laggasoline** | | | | 1.320* | | | | | |
| | | | | -0.155 | | | | | |
| **less4000*laggasoline** | | | | 3.561*** | | | | | |
| | | | | -0.922 | | | | | |
| **more16000*Weekend*laggasoline** | | | | | 1.087** | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | -0.030 | | | | |
| **12000-16000*Weekend*laggasoline** | | | | | 1.031 | | | | |
| | | | | | -0.026 | | | | |
| **4000-8000*Weekend*laggasoline** | | | | | 1.011 | | | | |
| | | | | | -0.020 | | | | |
| **less4000*Weekend*laggasoline** | | | | | 0.932' | | | | |
| | | | | | -0.038 | | | | |
| **House_3_Person*laggasoline** | | | | | | 0.864 | | | |
| | | | | | | -0.124 | | | |
| **House_4_Person*laggasoline** | | | | | | 1.293* | | | |
| | | | | | | -0.152 | | | |
| **House_m5_Person*laggasoline** | | | | | | 1.113 | | | |
| | | | | | | -0.206 | | | |
| **House_3_Person*Weekend*laggasoline** | | | | | | | 1.157*** | | |
| | | | | | | | -0.026 | | |
| **House_4_Person*Weekend*laggasoline** | | | | | | | 1.021 | | |
| | | | | | | | -0.020 | | |
| **House_m5_Person*Weekend*laggasoline** | | | | | | | 1.186*** | | |
| | | | | | | | -0.035 | | |
| **egoistic*laggasoline** | | | | | | | | 0.918 | |
| | | | | | | | | -0.088 | |
| **hedonic*laggasoline** | | | | | | | | 1.577 | |
| | | | | | | | | -0.454 | |
| **biospheric*laggasoline** | | | | | | | | 1.042 | |
| | | | | | | | | -0.098 | |
| **altruistic*laggasoline** | | | | | | | | 2.318 | |
| | | | | | | | | -1.283 | |
| **egoistic*Weekend*laggasoline** | | | | | | | | | 1.006 |
| | | | | | | | | | -0.016 |
| **hedonic*Weekend*laggasoline** | | | | | | | | | 0.837*** |
| | | | | | | | | | -0.042 |
| **biospheric*Weekend*laggasoline** | | | | | | | | | 0.974' |
| | | | | | | | | | -0.015 |
| **altruistic*Weekend*laggasoline** | | | | | | | | | 1.038 |
| | | | | | | | | | -0.130 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **cold** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heatweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshineweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rainweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **coldweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **N** | 51649.000 | 51640.000 | 51640.000 | 45392.000 | 45392.000 | 51649.000 | 51649.000 | 50309.000 | 50309.000 |
| **r2_p** | 0.189 | 0.189 | 0.190 | 0.194 | 0.193 | 0.189 | 0.191 | 0.187 | 0.187 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | | | | | |

## 6.4. Heterogeneity in the Diesel Price Elasticity with Daily Data

This section presents the results of the heterogeneity analysis of the lag diesel price elasticity. Column 1 in table 5 examines the difference in lag diesel price elasticity focusing on all trips in comparison to just leisure-based trips. An F-test of the lag diesel price and the interaction term of the lag diesel price with the weekend dummy shows a p-value of 0.006. The results display that the weekend lag diesel price elasticity is -0.201 and significant at the 1% level. Compared to non-leisure trips, individuals show a higher willingness to reduce their driving for leisure trips.

Column 2 and column 3 in table 5 look at the heterogeneity in the lag diesel price elasticity across different labor market areas in Switzerland. As in the heterogeneity analysis of the lag gasoline price elasticity across different labor market areas in Switzerland, the reference labor market area for column 2 and column 3 in table 5 is Zürich. Other than in the heterogeneity analysis of the lag gasoline price elasticity, there are 1'441 observations for the labor market area Lausanne. Thus, it is possible to include Lausanne as a variable in the regressions.

The analysis in column 2 focuses on all trips. The lag diesel coefficient shows a p-value of 0.063. This means that the reference group has a lag diesel price elasticity of -0.128 which is significant at the 5% level. Besides Lausanne, no other area has a significant lag diesel price elasticity which is different from the reference area because the p-value is above 0.1 when conducting an F-test. An F-test of the lag diesel price and the interaction term of the lag diesel price with Lausanne shows a p-value of 0.017. This shows that the diesel price elasticity of Lausanne is essentially 0.857 and significant at the 5% level.

The analysis in column 3 contrary to column 2 looks at the heterogeneity in the lag diesel price elasticity across different labor market areas focusing on leisure-based trips. The leisure lag diesel price elasticity for the area of Zürich is -0.225 which is not significant. An F-test of the lag diesel price, the interaction term of the lag diesel price with the weekend and the interaction term of weekend with the Bern dummy show a p-value of 0.002. This shows that the leisure trip price elasticity for the labor market area Bern is essentially -0.227 and significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the Basel dummy show a p-value of 0.068. This result shows that the leisure trip price elasticity for the area Basel is -0.175 and significant at the 10% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the Genf dummy show a p-value of 0.004. This shows that the leisure trip price elasticity is -0.228. An F-test of the lag diesel price, the interaction term of the lag diesel price with the weekend dummy and the interaction term of the weekend with the Aareland dummy show a p-value of 0.264. The results show no significant difference from the reference group. Further, an F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with Zentralschweiz dummy show a p-value of 0.11. There is no significant difference from the reference group shown for the area Zentralschweiz. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the Lausanne dummy show a p-value of 0.078. Thus, we see that the weekend price elasticity for the labor market area Lausanne is essentially 0.185 and significant at the 10% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the Jura and Biel dummy shows a p-value of 0.032. Thus, we see that the weekend price elasticity for the labor market area of Jura and Biel is essentially -0.162 and significant at the 5% level.

Column 4 and column 5 in table 5 look at the difference in the lag diesel price elasticity across different income groups in Switzerland. 1’968 observations needed to be dropped for those two regressions since participants preferred to not display their income. The reference group for both regressions are households with a gross monthly income of 8’000–12’000 Swiss Francs.

The analysis in column 4 focuses on all trips. The reference group are households with a gross monthly income between 8’000 and 12’000 Swiss Francs. This reference income group shows a lag diesel price elasticity of 0.021 which however is not statistically significant since the p-value is above 0.1. An F-test of the lag diesel price and the interaction term of the lag diesel price with the households having a gross monthly income of more than 16’000 dummy shows a p-value of 0.29. An F-test of the lag diesel price and the interaction term of the lag diesel price with the households earning 12’000-16’000 dummy shows a p-value of 0.852. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households earning less than 4’000 shows a p-value of 0.646. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households having a gross monthly income of 4’000-8’000 shows a p-value of 0.003. The lag diesel price elasticity of households having a gross monthly income of 4’000-8’000 is -0.229 and significant at the 1% level. This shows that the heterogeneity in the average lag diesel price elasticity is purely driven by the households earning 4’000-8’000 Swiss France.

The analysis in column 5 contrary to column 4 focuses on leisure trips. An F-test of the lag diesel price and the interaction term of the lag diesel price with weekend shows a p-value of 0.001. This indicates that the reference group has a leisure lag diesel price elasticity of -0.241 which is significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the income group dummy more than 16’000 show a p-value of 0.001. This indicates a leisure lag diesel price elasticity of -0.249 which is significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the income group 12’000-16’000 dummy show a p-value of 0.001. This shows a leisure trip lag diesel price elasticity of -0.239 which is significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the income group 4’000-8’000 dummy shows a p-value of 0.210. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with the income group with a gross monthly income less than 4’000 dummy shows a p-value of 0.672. This shows that the poorer households have no significantly different reaction from the reference group. Whereas the higher income households do. The income group 12’000-16’000 is less responsive than the reference group whereas the income group more than 16’000 is more responsive than the reference group. The highest earning households reduce their driving the most when there is a price increase.

Column 6 and column 7 in table 5 examine the heterogeneity in the lag diesel price elasticity across the household size. The reference group are individuals living in households with less than 3 individuals. The analysis in column 6 focuses on all trips. The lag diesel price elasticity for the reference group is -0.08 but not significant since the p-value is above 0.1. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals living in a 3-person household show a p-value of 0.001. This shows a lag in diesel price elasticity for a household with 3 individuals of -0.217 which is significant at the 1% level. A F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of weekend for individuals living in a 4-person household show a p-value of 0.652. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals living in a more than 5-person household show a p-value of 0.367. This shows that the heterogeneity in the average lag diesel price elasticity is purely driven by 3-person households.

The analysis in column 7 contrary to column 6 focuses on leisure trips. An F-test of the lag diesel price and the interaction term of the lag diesel price with weekend shows a p-value of 0.002. This shows a leisure lag diesel price elasticity for the reference group of -0.222 which is significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of weekend for individuals living in a 3-person household show a p-value of 0.005. This indicates a leisure lag diesel price elasticity of -0.207 which is significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals living in a 4-person household show a p-value of 0.039. Thus, we see that the lag diesel price elasticity of households with 4 individuals is -0.157 and significant at the 5% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals living in a 5-person or more household shows a p-value of 0.122. Overall, these results show that the responsiveness for leisure trips decreases with the number of individuals living in the household. Yet, individuals living in a 5-person household show no significantly different reaction to the reference group.

Column 8 and column 9 in table 5 look at the heterogeneity in diesel price elasticity across different individuals with different distinctive personal values. The analysis in column 8 focuses on all trips. This analysis could not include the term altruistic because there were no observations of individuals with distinctive altruistic personal values. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of weekend with a distinctive egoistic character trait shows a p-value of 0.266. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with a distinctive hedonic character trait show a p-value of 0.944. Thus, there is no difference between individuals having a distinctive egoistic or hedonic personal values in comparison to individuals who don't. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend with a distinctive biospheric character trait show a p-value of 0.005. The lag diesel price elasticity of individuals with a distinctive biospheric character trait is -0.225 and significant at the 1% level. This finding is interesting because it shows that the heterogeneity in average diesel price elasticity is driven by individuals with distinctive biospheric values. Indeed, the results show that individuals with distinctive biospheric values are more likely to reduce their driving when there is a price increase in comparison to people who don't have these distinctive specific personal values.

The analysis in column 9 contrary to column 8 focuses on leisure-based trips. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals with a distinctive biospheric character trait show a p-value of 0.071. There is a lag diesel price elasticity of -0.141, which is significant at the 5% level, for individuals with a distinctive biospheric value. Moreover, an F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals with distinctive egoistic values show a p-value of 0.002. There is a lag in diesel price elasticity of individuals with distinctive egoistic values is -0.238 and significant at the 1% level. An F-test of the lag diesel price, the interaction term of the lag diesel price with weekend and the interaction term of the weekend for individuals with a distinctive hedonic character trait shows a p-value of 0.069. There is a lag in diesel price elasticity of individuals with a hedonic egoistic character trait is -0.160 and significant at the 1 % level.

Besides the different population groups presented in table 5, I further investigated the heterogenicity in living locations, and whether individuals own a half-fare pass or a GA. The results are in table 3 in the appendix. There is no heterogeneity with individuals owning a half-fare pass focusing on all trips. However, there is heterogeneity with individuals owning a half fare pass focusing only on leisure trips. The diesel price elasticity is -0.217 and significant with a p-value of 0.003. This result is intuitive since individuals owning a half-fare pass can switch from driving a car to taking the train with the half price of the extra cost of having to buy a train ticket in comparison to individuals not owning a half-fare pass. Focusing on all trips, the examination of the heterogeneity in the lag diesel price elasticity for individuals who own a GA in comparison to individuals who do not shows a lag diesel price elasticity of -0.423. This result is significant at the 1% level. Indeed, this result is intuitive since individuals owning a GA can switch from driving a diesel car to taking the train without the extra cost of having to buy a train ticket. Focusing on the leisure trip there is no significantly different lag diesel price elasticity found for individuals with a GA. Finally, the results show that there is no heterogeneity across more urban or more rural areas.

Table 5: Heterogeneity in the Diesel Price Elasticity with Daily Data

| | **VKT_1** | **VKT_2** | **VKT_3** | **VKT_4** | **VKT_5** | **VKT_6** | **VKT_7** | **VKT_8** | **VKT_9** |
|---|---|---|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 50.623*** | 51.232*** | 50.678*** | 55.237*** | 54.530*** | 50.574*** | 50.632*** | 49.194*** | 48.875*** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | -4.747 | -4.763 | -4.732 | -5.335 | -5.302 | -4.750 | -4.747 | -4.718 | -4.713 |
| **lagdiesel** | 0.934 | 0.872' | 0.929 | 1.021 | 0.911' | 0.920 | 0.934 | 0.962 | 0.943 |
| | -0.050 | -0.064 | -0.050 | -0.091 | -0.051 | -0.065 | -0.050 | -0.081 | -0.052 |
| **lagdiesel*weekend** | 0.855' | 0.856' | 0.834* | 0.846' | 0.833* | 0.853' | 0.833* | 0.856' | 0.862' |
| | -0.072 | -0.072 | -0.069 | -0.074 | -0.074 | -0.071 | -0.070 | -0.073 | -0.074 |
| **Aareland*lagdiesel** | | 1.187 | | | | | | | |
| | | -0.719 | | | | | | | |
| **Zentralschweiz*lagdiesel** | | 0.528 | | | | | | | |
| | | -0.340 | | | | | | | |
| **Lausanne*lagdiesel** | | 2.130** | | | | | | | |
| | | -0.574 | | | | | | | |
| **BielJura*lagdiesel** | | 0.997 | | | | | | | |
| | | -0.133 | | | | | | | |
| **Bern*lagdiesel** | | 1.124 | | | | | | | |
| | | -0.152 | | | | | | | |
| **Basel*lagdiesel** | | 1.379 | | | | | | | |
| | | -0.461 | | | | | | | |
| **Genf*lagdiesel** | | 1.011 | | | | | | | |
| | | -0.193 | | | | | | | |
| **Aareland*Weekend*lagdiesel** | | | 1.556** | | | | | | |
| | | | -0.234 | | | | | | |
| **Zentralschweiz*Weekend*lagdiesel** | | | 1.644*** | | | | | | |
| | | | -0.209 | | | | | | |
| **Lausanne*Weekend*lagdiesel** | | | 1.530*** | | | | | | |
| | | | -0.077 | | | | | | |
| **BielJura*Weekend*lagdiesel** | | | 1.081** | | | | | | |
| | | | -0.029 | | | | | | |
| **Bern*Weekend*lagdiesel** | | | 0.998 | | | | | | |
| | | | -0.030 | | | | | | |
| **Basel*Weekend*lagdiesel** | | | 1.065 | | | | | | |
| | | | -0.072 | | | | | | |
| **Genf*Weekend*lagdiesel** | | | 0.996 | | | | | | |
| | | | -0.041 | | | | | | |
| **more16000*lagdiesel** | | | | 0.858 | | | | | |
| | | | | -0.131 | | | | | |
| **12000-16000*lagdiesel** | | | | 0.957 | | | | | |
| | | | | -0.147 | | | | | |
| **4000-8000*lagdiesel** | | | | 0.755* | | | | | |
| | | | | -0.092 | | | | | |
| **less4000*lagdiesel** | | | | 0.825 | | | | | |
| | | | | -0.322 | | | | | |
| **more16000*Weekend*lagdiesel** | | | | | 0.989 | | | | |
| | | | | | -0.032 | | | | |
| **12000-16000*Weekend*lagdiesel** | | | | | 1.003 | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | -0.035 | | | | |
| **4000-8000*Weekend*lagdiesel** | | | | | 1.041 | | | | |
| | | | | | -0.027 | | | | |
| **less4000*Weekend*lagdiesel** | | | | | 1.224** | | | | |
| | | | | | -0.092 | | | | |
| **House_3_Person*lagdiesel** | | | | | | 0.851 | | | |
| | | | | | | -0.107 | | | |
| **House_4_Person*lagdiesel** | | | | | | 1.207 | | | |
| | | | | | | -0.145 | | | |
| **House_m5_Person*lagdiesel** | | | | | | 0.990 | | | |
| | | | | | | -0.270 | | | |
| **House_3_Person*Weekend*lagdiesel** | | | | | | | 1.019 | | |
| | | | | | | | -0.029 | | |
| **House_4_Person*Weekend*lagdiesel** | | | | | | | 1.083** | | |
| | | | | | | | -0.027 | | |
| **House_m5_Person*Weekend*lagdiesel** | | | | | | | 1.101' | | |
| | | | | | | | -0.057 | | |
| **egoistic*lagdiesel** | | | | | | | | 1.146 | |
| | | | | | | | | -0.119 | |
| **hedonic*lagdiesel** | | | | | | | | 1.059 | |
| | | | | | | | | -0.269 | |
| **biospheric*lagdiesel** | | | | | | | | 0.806* | |
| | | | | | | | | -0.084 | |
| **egoistic*Weekend*lagdiesel** | | | | | | | | | 0.937** |
| | | | | | | | | | -0.021 |
| **hedonic*Weekend*lagdiesel** | | | | | | | | | 1.033 |
| | | | | | | | | | -0.054 |
| **biospheric*Weekend*lagdiesel** | | | | | | | | | 1.057** |
| | | | | | | | | | -0.023 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **cold** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heatweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshineweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rainweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **coldweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **N** | 27554.00 | 27554.00 | 27554.00 | 25566.00 | 25566.00 | 27554.00 | 27554.00 | 26698.00 | 26698.00 |
| **r2_p** | 0.182 | 0.183 | 0.187 | 0.179 | 0.179 | 0.182 | 0.183 | 0.176 | 0.177 |

| ' p<0.10 | * p<0.05 | ** p<0.01 | *** p<0.001 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|

### 6.5. Heterogeneity in the Gasoline Price Elasticity with Weekly Average Datapoints

This section and fundamentally table 6 present the results of the average lag gasoline price elasticity and the heterogeneity analysis in the lag gasoline price elasticity with weekly data. Contrary to the previous analyses based on daily data, there is no focus on leisure trips. Column 1 in table 6 particularly examines the overall lag gasoline price elasticity without any group specification. The results in column 1 in table 6 shows a lag gasoline price elasticity of 0.025 which however is not significant.

Column 2 in table 6 looks at the heterogeneity in the lag gasoline price elasticity across different labor market areas in Switzerland. The reference labor market area is Zürich. Because there are only a few observations for the labor market area Lausanne, it is excluded from the regression. This exclusion matches the procedure of the lag gasoline and the heterogeneity of lag gasoline analysis based on daily data. The lag gasoline price elasticity of the reference group is -0.021 which is not significant. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Aareland dummy shows a p-value of 0.419. A F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Zentralschweiz dummy shows a p-value of 0.195. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Biel and Jura dummy shows a p-value of 0.736. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Bern dummy shows a p-value of 0.428. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Basel dummy shows a p-value of 0.394. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the Genf dummy shows a p-value of 0.387. The results of column 2 in table 6 show no heterogeneity across the labor market area.

Colum 3 in table 6 examines the heterogeneity in the lag gasoline price elasticity across different income groups. The reference group are households with a gross monthly income of 8’000-12’000 Swiss Francs. 1’023 observations were dropped for this regression since participants preferred to not display their income. The lag gasoline price elasticity of the reference group is -0.175 which is not significant. An F-test of the lag gasoline price and the interaction term of the lag gasoline price and the dummy for households earning more than 16’000 shows a p-value of 0.937. An F-test of the lag gasoline price and the interaction term of the lag gasoline price and the dummy for households earning more than 12’000-16’000 shows a p-value of 0.658. An F-test of the lag gasoline price and the interaction term of the lag gasoline price and the dummy for households earning more than 4’000-8’000 shows a p-value of 0.306.

This shows that households earning more than 16'000, 12'000-16'000 and 4'000-8'000 Swiss Francs have no significantly different reaction to the reference group. An F-test of the lag gasoline price and the interaction term of the lag gasoline price and the dummy for households having a gross monthly income less of 4'000 Swiss Francs shows a p-value of 0.004. This income group has a lag gasoline price elasticity of 1.866 which is significant at the 1% level. Thus, the income group with less than 4'000 Swiss Francs drive more when there is a price increase. This result is counterintuitive. However as mentioned in the daily data analysis, this category is based on rather few observations and thus needs to be interpreted cautiously.

Colum 4 in table 6 assesses the heterogeneity in the lag gasoline price elasticity across different household sizes. The reference group are households with less than 3 people and shows a lag gasoline price elasticity of -0.019 which however is not significant. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy for households with 3 individuals shows a p-value of 0.245. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy for households with more than 5 individuals shows a p-value of 0.499. This shows that there is no significant lag in gasoline price elasticity for households with 3 or 5 individuals and no significant difference to the reference group. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the dummy for households with 4 individuals shows a p-value of 0.033. This income group has a lag gasoline price elasticity of 0.378 which is significant at the 5% level. This shows that this group drives more when there is a price increase. This result is counterintuitive.

Column 5 in table 6 looks at the heterogeneity in the lag gasoline price elasticity for individuals with distinctive personal values. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the egoistic dummy shows a p-value of 0.499. An F-test of the lag diesel price and the interaction term of the lag gasoline price with the hedonic dummy shows a p-value of 0.575. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the altruistic dummy shows a p-value of 0.131. An F-test of the lag gasoline price and the interaction term of the lag gasoline price with the biospheric dummy shows a p-value of 0.493. The results show no heterogeneity in groups with distinctive personal values.

Table 6: Heterogeneity in the Gasoline Price Elasticity with Data of the Weekly Average

| | **VKT_1** | **VKT_2** | **VKT_3** | **VKT_4** | **VKT_5** |
|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 35.581*** | 35.666*** | 37.780*** | 35.829*** | 35.698*** |
| | -4.411 | -4.381 | -4.865 | -4.418 | -4.421 |

| | | | | | |
|---|---|---|---|---|---|
| **laggasoline** | 1.025 | 0.979 | 0.825 | 0.981 | 0.982 |
| | -0.073 | -0.150 | -0.102 | -0.085 | -0.099 |
| **Aareland*laggasoline** | | 0.708 | | | |
| | | -0.340 | | | |
| **Zentralschweiz*laggasoline** | | 1.163 | | | |
| | | -0.214 | | | |
| **BielJura*laggasoline** | | 1.101 | | | |
| | | -0.291 | | | |
| **Bern*laggasoline** | | 0.909 | | | |
| | | -0.195 | | | |
| **Basel*laggasoline** | | 0.748 | | | |
| | | -0.296 | | | |
| **Genf*laggasoline** | | 0.853 | | | |
| | | -0.219 | | | |
| **more16000*laggasoline** | | | 1.201 | | |
| | | | -0.269 | | |
| **12000-16000*laggasoline** | | | 1.107 | | |
| | | | -0.209 | | |
| **4000-8000*laggasoline** | | | 1.329' | | |
| | | | -0.214 | | |
| **less4000*laggasoline** | | | 3.474** | | |
| | | | -1.364 | | |
| **House_3 *laggasoline** | | | | 0.838 | |
| | | | | -0.152 | |
| **House_4*laggasoline** | | | | 1.405* | |
| | | | | -0.236 | |
| **House_m5*laggasoline** | | | | 0.875 | |
| | | | | -0.207 | |
| **egoistic*laggasoline** | | | | | 0.944 |
| | | | | | -0.117 |
| **hedonic*laggasoline** | | | | | 1.325 |
| | | | | | -0.608 |
| **biospheric*laggasoline** | | | | | 1.107 |
| | | | | | -0.137 |
| **altruistic*laggasoline** | | | | | 2.853 |
| | | | | | -1.932 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes |
| **cold** | Yes | Yes | Yes | Yes | Yes |

| | | | | | |
|---|---|---|---|---|---|
| **N** | 8754.000 | 8752.000 | 7732.000 | 8754.000 | 8754.000 |
| **r2_p** | 0.353 | 0.354 | 0.364 | 0.354 | 0.354 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | |

### 6.6. Heterogeneity in the Diesel Price Elasticity with Weekly Average Datapoints

This section and fundamentally table 7 present the results of the overall lag diesel price elasticity and the heterogeneity analysis in the lag diesel price elasticity with weekly data. Column 1 in table 7 particularly examines the overall lag gasoline price elasticity without any group specification. The results in column 1 in table 7 shows a lag diesel price elasticity of -0.114 which is significant at the 10% level.

Colum 2 in table 7, looks at the heterogeneity in the lag in diesel price elasticity across different labor market areas in Switzerland. The reference labor market area is Zürich. There are 258 observations for the labor market area of Lausanne. Thus, it is possible to include Lausanne as a variable in the regressions. The reference group shows a lag diesel price elasticity of -0.223 which is significant at the 5% level. A F-test of the lag diesel price, the interaction term of the lag diesel price with the Aareland dummy shows a p-value of 0.79. An F-test of the lag diesel price, the interaction term of the lag diesel price with the Bern dummy shows a p-value of 0.978. An F-test of the lag diesel price, the interaction term of the lag diesel price with the Basel dummy shows a p-value of 0.418. An F-test of the lag diesel price, the interaction term of the lag diesel price with the Genf dummy shows a p-value of 0.946. This shows that the labor market areas of Aareland, Biel and Jura, Bern, Genf as well as Basel show no significant different reaction to the reference group. An F-test of the lag diesel price, the interaction term of the lag diesel price with the Biel and Jura dummy shows a p-value of 0.103. An F-test of the lag diesel price, the interaction term of the lag diesel price with the Lausanne dummy shows a p-value of 0.066. Thus, we see that the lag diesel price elasticity for the labor market area Lausanne is essentially 0.706 and significant at the 10% level. Thus, there is indeed heterogeneity.

Colum 3 in table 7 examines the heterogeneity in the lag diesel price elasticity across different income groups. The reference group are households with a gross monthly income of 8000-12000 Swiss Francs. 350 observations were dropped since participants preferred to not display their income. The reference group show a lag diesel price elasticity of 0.020 which is not significant. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households earning more than 16’000 shows a p-value of 0.139. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households earning 12’000-16’000 shows a p-value of 0.385. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households earning less than 4’000 shows a p-value of 0.254. Thus, the income groups earning less than 4’000, more than 16’000 and 12’000-16’000 Swiss Francs show no different reaction to the reference group. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households having a gross monthly income between 4’000-8’000 shows a p-value of 0.018. This income group has a lag diesel price elasticity of -0.244 which is significant at the 5% level. This shows that the heterogeneity in the average lag diesel price elasticity is purely driven by the households earning 4’000-8’000 Swiss France.

Colum 4 in table 7 assesses the heterogeneity in the lag diesel price elasticity across different household sizes. The reference group are households with less than 3 people. The reference group shows a lag diesel price elasticity of -0.111 which is not significant. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households with 4 individuals shows a p-value of 0.815. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households with 5 or more individuals shows a p-value of 0.527. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for households with 3 individuals shows a p-value of 0.076. The lag diesel price elasticity for households with 3 individuals is -0.211 which is significant at the 10% level. This shows that the heterogeneity in the average lag diesel price elasticity is purely driven by 3-person households.

Column 5 in table 7 examines the heterogeneity in the lag diesel price elasticity for individuals with distinctive personal values. This analysis could not include the term altruistic because there were no observations of individuals with distinctive altruistic personal values. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for individuals with a distinctive egoistic character trait shows a p-value of 0.550. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for individuals with a distinctive hedonic character trait shows a p-value of 0.870. This show that there is no difference between an individual having a distinctive egoistic or hedonic personal value in comparison to individuals who don’t. An F-test of the lag diesel price and the interaction term of the lag diesel price with the dummy for individuals with a distinctive biospheric character trait shows a p-value of 0.001. This group has a lag diesel price elasticity of -0.302 which is significant at the 1% level.

Table 7: Heterogeneity in the Diesel Price Elasticity with Data of the Weekly Average

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 |
|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se |
| _cons | 48.581*** | 48.646*** | 51.709*** | 48.575*** | 49.051*** |
| | -5.923 | -5.866 | -6.528 | -5.917 | -5.905 |
| (mean) lagdiesel | 0.886' | 0.777* | 1.020 | 0.889 | 0.920 |
| | -0.060 | -0.077 | -0.117 | -0.086 | -0.092 |
| Aareland*lagdiesel | | 1.068 | | | |
| | | -0.755 | | | |
| Zentralschweiz*lagdiesel | | 0.952 | | | |
| | | -0.860 | | | |
| Lausanne*lagdiesel | | 2.195* | | | |
| | | -0.680 | | | |
| BielJura*lagdiesel | | 1.023 | | | |
| | | -0.176 | | | |
| Bern*lagdiesel | | 1.292 | | | |
| | | -0.220 | | | |
| Basel*lagdiesel | | 1.674 | | | |
| | | -0.563 | | | |
| Genf*lagdiesel | | 1.304 | | | |
| | | -0.274 | | | |
| more16000*lagdiesel | | | 0.754 | | |
| | | | -0.157 | | |
| 12000-16000*lagdiesel | | | 0.861 | | |
| | | | -0.165 | | |
| 4000-8000*lagdiesel | | | 0.741' | | |
| | | | -0.115 | | |
| less4000*lagdiesel | | | 0.651 | | |
| | | | -0.245 | | |
| House_3 *lagdiesel | | | | 0.888 | |
| | | | | -0.144 | |
| House_4*lagdiesel | | | | 1.096 | |
| | | | | -0.157 | |
| House_m5*lagdiesel | | | | 0.937 | |
| | | | | -0.284 | |
| egoistic*lagdiesel | | | | | 1.162 |
| | | | | | -0.150 |
| hedonic*lagdiesel | | | | | 1.027 |
| | | | | | -0.337 |
| biospheric*lagdiesel | | | | | 0.759* |
| | | | | | -0.098 |
| infections_weekly_1000000k | Yes | Yes | Yes | Yes | Yes |
| infections_weekly_1000000k2 | Yes | Yes | Yes | Yes | Yes |
| infections_weekly_1000000k3 | Yes | Yes | Yes | Yes | Yes |

| | | | | | |
|---|---|---|---|---|---|
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes |
| **cold** | Yes | Yes | Yes | Yes | Yes |
| **N** | 4610.000 | 4610.000 | 4260.000 | 4610.000 | 4610.000 |
| **r2_p** | 0.355 | 0.356 | 0.356 | 0.355 | 0.356 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | |

## 6.7. Robustness Check

I perform a robustness check to inspect the sensitivity of the gasoline price elasticity and the diesel price elasticity result. Overall, the dataset is divided into 4 observation periods with 91 observation dates. Period 1 ranges from the first of June 2021 until the 30th of August 2021. Period 2 ranges from the 31st of August 2021 until the 29th of November 2021. Period 3 ranges from the 30th of November 2021 until the 28th of February 2022. Period 4 ranges from the first of March 2022 until the 31st of May 2022. The period dummy is then interreacted with the lag of the relevant fuel price. The resulting coefficients of the interaction terms show the aberrance from the reference group which is period 1. In the appendix figure 1 and appendix figure 2, the interaction terms are displayed.

Figure 1 shows the lag gasoline price elasticity over those above-described 4 periods. The lag gasoline elasticity is calculated by multiplying the coefficient of the variable lag gasoline and the interaction term of lag gasoline with the period dummy and lastly subtracting 1. The lag gasoline price elasticities range from -0.668 and 2.150. The lag gasoline price elasticity of period 1 shows a p-value of 0.085. An F-test of the lag gasoline variable and the interaction term of lag gasoline with the period 2 dummy shows a p-value of 0.003. An F-test of the lag gasoline variable and the interaction term of lag gasoline with the period 3 dummy shows a p-value of 0.003. An F-test of the lag gasoline variable and the interaction term of lag gasoline with the period 4 dummy shows a p-value of 0. Thus, all elasticities are significant. Because the robustness checks show a change in results over the periods, this weakens the findings of this paper.

Figure 1: Lag Gasoline Price Elasticity over Time

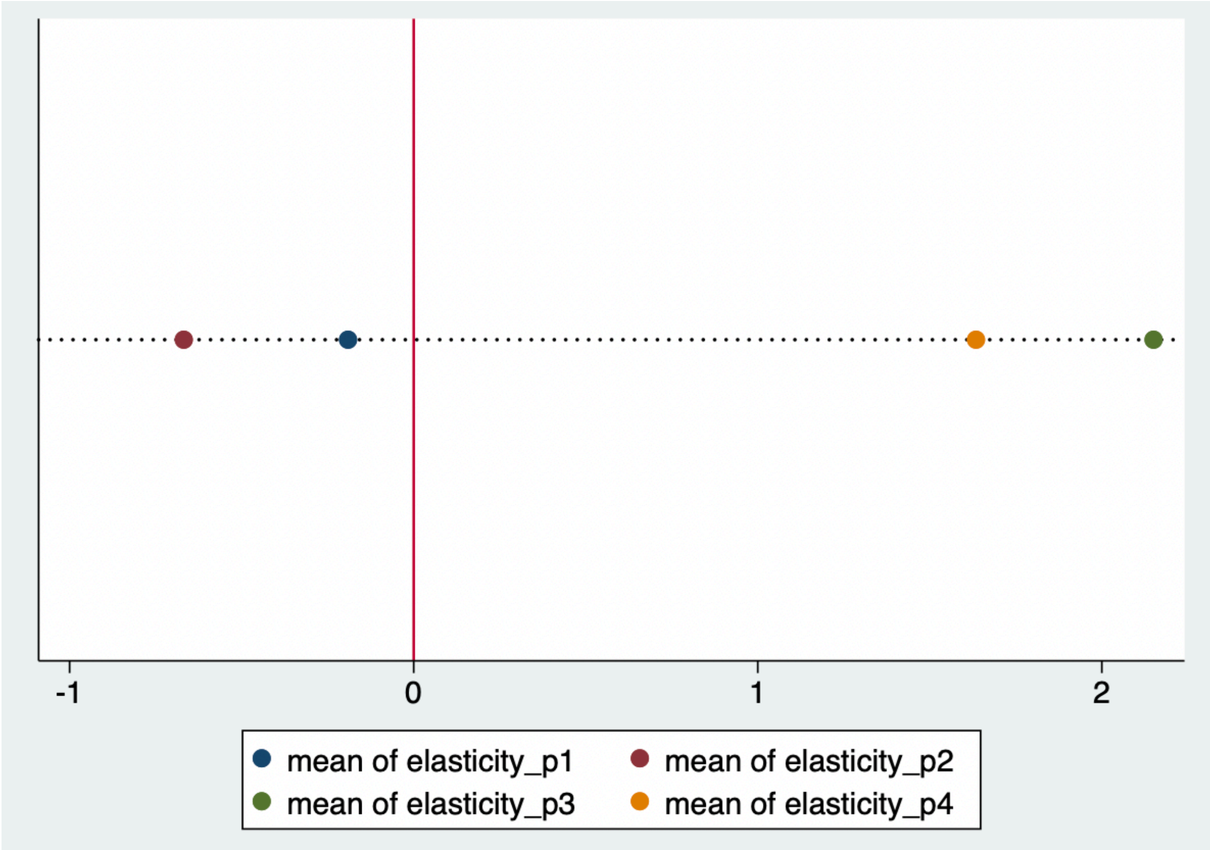
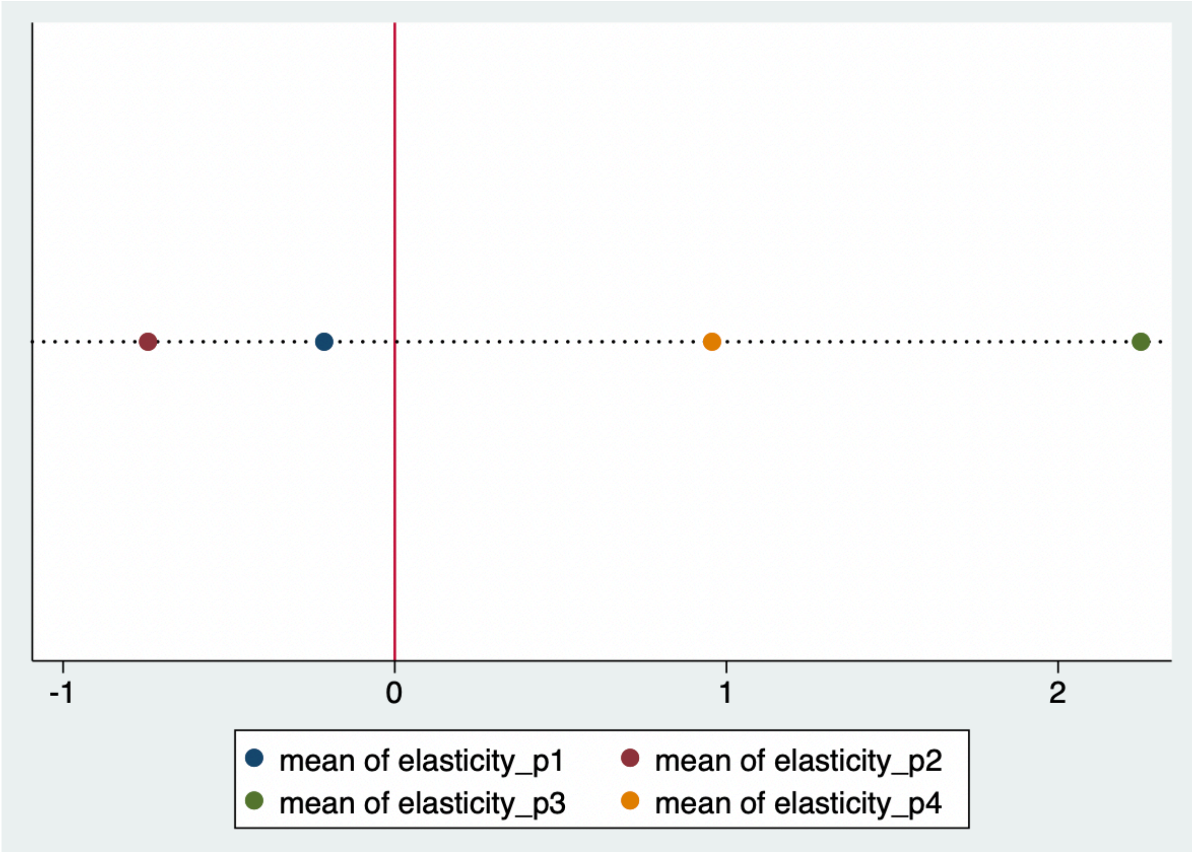



Figure 2 shows the lag diesel price elasticity over the described 4 periods. The lag diesel price elasticity is calculated by multiplying the coefficient of the variable lag diesel and the interaction term of lag diesel with the period dummy and lastly subtracting 1. The lag diesel price elasticities range from -0.744 and 2.250. The lag diesel price elasticity of period 1 shows a p-value of 0.083. An F-test of the lag diesel variable and the interaction term of lag diesel with the period 2 dummy shows a p-value of 0.077. An F-test of the lag diesel variable and the interaction term of lag diesel with the period 3 dummy shows a p-value of 0.003. A F-test of the lag diesel variable and the interaction term of lag diesel with the period 4 dummy shows a p-value of 0. The p-values show that all elasticities are significant. Thus, the robustness checks conclude a change in results over the periods which weakens the findings of this paper.

Figure 2: Lag Diesel Price Elasticity over Time




## 7. Discussion

Overall, the results illustrate that diesel and gasoline car drivers show a different reaction to a change in fuel price. This is demonstrated by the diverse findings of the average lag gasoline price elasticity in comparison to the average lag diesel price elasticity. Whereas the lag diesel price elasticity in the daily data is -0.113 and significant, the lag gasoline price elasticity is negative but not significant. The average lag diesel price elasticity found in the weekly data is -0.114 and significant. The analysis with weekly data showed no significant lag gasoline price elasticity. Thus, this shows that diesel drivers reduce their driving when there is a price increase. The findings in the daily and the weekly data show a difference of 0.001 which is small. The lag diesel price elasticity found in the daily data is within the diesel price elasticity range found in previous literature. Yet when looking at table 1 on page 5 in this paper, it is on the rather lower spectrum. At this point, it is worth to mentioning that the fuel price increased predominantly due to the Ukraine and Russian war. Individuals could also have had an alternative reason to reduce their driving namely to not render support to Russia. This is reasonable since the western media and politics tend to support the impression of Russia being the attacker and Ukraine the defender.

Moreover, the difference in reaction is also demonstrated in the diesel driver's tendency to reduce their driving for leisure-trips when there is a price increase whereas the gasoline drivers do not reduce their driving. This section will begin discussing the gasoline diver's reaction. When discussing the lag gasoline price elasticity there is a need to compare the findings of the daily analysis with the findings of the weekly analysis because if they match, it strengthens the credibility of the overall result.

First, there is agreement in the daily data and the weekly data analysis that there is no heterogeneity in the lag gasoline price elasticity across labor market areas and distinctive personal values held by individuals. This consensus strengthens the overall findings. Further, there is agreement between the daily data and the weekly data analysis for the heterogeneity investigation of different household sizes. The results show that there is a consensus on households with 4 individuals reacting different to gasoline price change than the reference group. Indeed, households with 4 individuals show a counter intuitive positive income price elasticity which indicates that they drive more when there is a price increase. This contrasts with the findings of Bento et al. (2009).

Finally, the heterogeneity results of lag gasoline price elasticity across income groups with daily data are somewhat conflicting with the results of the weekly analysis. The weekly data shows agreement with the daily data in the sense that it shows that the income groups 12'000-16'000, 4'000-8'000 and 8'000-12'000 show no significant different reaction among themselves. Further, the lag gasoline price elasticity with weekly as well as daily data shows that households with less than 4'000 Swiss Francs income are the only group significantly different from the reference group. They have a positive and significant gasoline price elasticity, which indicates that the group tends to increase driving when there is a price increase. There is conflict on the income group earning more than 16'000 Swiss Francs. In the daily data analysis, the result shows a positive lag gasoline price elasticity whereas in the weekly data there is no significant different in reaction from the income group which shows no significant elasticity. This conflicting finding damages the coherency.

Having concentrated on the reaction of the gasoline driver, this section will now examine the diesel driver's reaction. This section will begin with discussing the findings on the labor market area. There is agreement between the daily and the weekly data analysis. Indeed, all labor market regions except Lausanne show no difference to the lag diesel price elasticity of Zürich. In the daily data, the lag diesel price elasticity of Zürich is -0.128 whereas in the weekly data the lag diesel price elasticity of Zürich is -0.223. Essentially there is merely a 0.095

difference in elasticities. Lausanne shows in the weekly and daily data that when there is a price increase, individuals tend to increase their driving.

Moreover, there is agreement in the daily and the weekly data analysis for the heterogeneity across income groups. Indeed, households earning 4’000-8’000 Swiss Francs are the only income group showing a negative significant lag diesel price elasticity. This indicates that the average lag diesel price elasticity found is purely driven by this income group. The lag diesel price elasticity based on daily data for households earning 4’000-8’000 is robust when truncating the data sample at different periods. This renders even more support to the findings and is illustrated in figure 3 in the appendix. Since 66.54% of the household earn more or equal to the amount of the reference household group, it is legitimate to say that the income group of 4’000-8’000 represent the relatively fewer wealthy individuals in the data sample. This result renders support to the findings of Santos Catchesides (2005) and Goetzke and Vance (2021). Yet, the lowest income group shows no different reaction to a change in diesel price which could be attributed to only 1.84% of the Mobis participants belonging to this group. Alternatively, it can also be argued in agreement with Gillingham (2014) that the poorest of the poor might not be able to further decrease their driving since they are already at minimal driving demand.

Further, there is agreement between the daily and the weekly data on heterogeneity in household sizes. The daily and the weekly data show that the heterogeneity in the average lag diesel price elasticity is purely driven by 3-person households. The daily data shows a lag diesel price elasticity of -0.217 and the weekly data show a lag diesel price elasticity of -0.211. Thus, there is merely a small difference in results which amounts to 0.006. This renders support to the credibility of the heterogeneity found.

The paper’s findings show that there is agreement in daily and weekly data of there being no difference between an individual having a distinctive egoistic, hedonic or altruistic personal value in comparison to individuals who don’t. The daily data showed a lag diesel price elasticity of -0.225 and the weekly data showed a lag diesel price elasticity of -0.302. The difference is small and amounts to 0.077 which renders support to the finding that individuals with distinctive biospheric personal values have been more responsive in comparison to individuals who don’t share this distinctiveness. Indeed, biospheric individuals who have distinctive desire to respect the earth and value guarding the environment tend to be the ones reducing their car driving the most. One possible reason for this finding could be that biospheric individuals are already sensitive to protecting the environment and this gave them additional incentive to reduce their driving. However, it could also be that the biospheric individuals are more left-orientated and thus reduce their driving not just because of the fuel price but rather to not support Russia in their war activities.

## 8. Conclusion

This paper examined the gasoline and diesel price elasticity. It looked particularly at heterogeneity in price responsiveness of various segments of consumers. One important strength of this paper is that it relies on a rich dataset. This allows to investigate household segments which were not particularly investigated in previous literature. Indeed, this paper regresses the fuel price on VKT. It relays on the PPML regression other than most previous papers which allows an adequate handling of zero values.  Interaction terms are included for a detailed analysis on heterogeneity between households.

Overall, this paper shows that consumer need some time to adjust their behavior to the fuel price change. Moreover, it shows that diesel and gasoline drivers react differently to fuel price increases. The gasoline drivers due not show an average lag gasoline price elasticity in the daily data which is significant. Contrary the diesel drivers show a lag diesel price elasticity in the daily data of -0.113. This indicates that diesel driver reduces their driving when there is a price increase.  The credibility of this finding is strengthened because weekly data analysis shows a statistically significant average lag diesel price elasticity of -0.114. Yet, the results are not robust across different time periods.

In the lag diesel price elasticity analysis, it was found that salient heterogeneity exists. Indeed, it exists between leisure versus non-leisure trips, household income and size as well as individuals with distinctive biospheric values versus people who don't share this distinctiveness in values. Essentially this was found in the daily as well as weekly data. Indeed, households earning 4'000-8'000 Swiss Francs are the only income group showing a responsive significant lag diesel price elasticity. This income group reduces driving when there is a price increase. Also, households with 3 individuals are the only ones out of all household sizes considered that have a negative lag diesel price elasticity. It ranges from -0.217 in the weekly data to -0.211 in the daily data. Individuals with distinctive biospheric personal values are more responsive in comparison to individuals who don't share this distinctiveness.

Further, the paper also shows that Zürich has a lag diesel price elasticity ranging from -0.128 in the daily data to -0.223 in the weekly data. There is no clear heterogeneity across labor markets except Lausanne which shows a counter intuitive positive lag diesel price elasticity which indicates that individuals increase driving when there is a price increase. Lastly, there was no statistically significant heterogeneity found in individuals with a distinctive egoistic, hedonic, or altruistic personal value or individuals who don't have those values.

In the lag gasoline price elasticity analysis, it was found that heterogeneity exists. Indeed, the results of the daily and weekly data analysis show that households with 4 individuals and income groups earning less than 4'000 Swiss Francs react different to gasoline price changes than the reference group. They show a counterintuitive positive income price elasticity which indicates that they drive more when there is a price increase. Further, there are conflicting results for the income group earning more than 16'000 Swiss Francs in the daily and weekly data. Finally, there is agreement in the daily and weekly data analysis that there is no heterogeneity in the lag gasoline price elasticity across labor market areas and distinctive personal values held by individuals.

I acknowledge this paper's analysis suffers from some caveats. The paper investigates a rather condensed period ranging from the 2021-06-01 until 2022-05-3. Looking at a longer period would allow the findings to be more well-founded and credible. Additionally, since the peak of the price increase happened at the same times as the covid restrictions were lifted this paper could not control for covid in form of covid wave dummies. These waves would essentially have absorbed the response to the fuel price increase. Conclusively, future research could focus on combination of segmentation criteria such as income groups with rural households or household sizes with rural households. As shown by Gillingham & Munk-Nielsen (2019) this can give deeper insight into the effects of car fuel taxation across the population.

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## 10. Appendix

Table Appendix 1: Composition of the MobisCovid panels

Proportion estimation — Number of obs = 79,260

| | | Proportion | Std. err. | Normal [95% conf. | interval] |
|---|---|---|---|---|---|
| age_below18 | | | | | |
| | 0 | 1 | 0 | 1 | 1 |
| age_18_25 | | | | | |
| | 0 | .9825385 | .0004653 | .9816266 | .9834504 |
| | 1 | .0174615 | .0004653 | .0165496 | .0183734 |
| age_25_35 | | | | | |
| | 0 | .9647489 | .000655 | .9634651 | .9660328 |
| | 1 | .0352511 | .000655 | .0339672 | .0365349 |
| age_35_45 | | | | | |
| | 0 | .8693919 | .0011969 | .8670459 | .8717378 |
| | 1 | .1306081 | .0011969 | .1282622 | .1329541 |
| age_45_55 | | | | | |
| | 0 | .7450795 | .001548 | .7420454 | .7481136 |
| | 1 | .2549205 | .001548 | .2518864 | .2579546 |
| age_55_65 | | | | | |
| | 0 | .6643452 | .0016773 | .6610577 | .6676327 |
| | 1 | .3356548 | .0016773 | .3323673 | .3389423 |
| age_above65 | | | | | |
| | 0 | .7895786 | .0014478 | .7867409 | .7924163 |
| | 1 | .2104214 | .0014478 | .2075837 | .2132591 |
| educ_higher | | | | | |
| | 0 | .5086929 | .0017757 | .5052125 | .5121733 |
| | 1 | .4913071 | .0017757 | .4878267 | .4947875 |
| educ_mandatory | | | | | |
| | 0 | .9458996 | .0008035 | .9443247 | .9474745 |
| | 1 | .0541004 | .0008035 | .0525255 | .0556753 |
| educ_second | | | | | |
| | 0 | .5454075 | .0017687 | .541941 | .5488741 |
| | 1 | .4545925 | .0017687 | .4511259 | .458059 |
| Apprentice | | | | | |
| | 0 | .9995206 | .0000778 | .9993682 | .999673 |
| | 1 | .0004794 | .0000778 | .000327 | .0006318 |
| Employed | | | | | |
| | 0 | .2396291 | .0015162 | .2366573 | .2426008 |
| | 1 | .7603709 | .0015162 | .7573992 | .7633427 |
| Other_Employment | | | | | |
| | 0 | .9245647 | .0009381 | .9227261 | .9264033 |
| | 1 | .0754353 | .0009381 | .0735967 | .0772739 |
| Retired | | | | | |
| | 0 | .9380772 | .0008561 | .9363993 | .9397551 |
| | 1 | .0619228 | .0008561 | .0602449 | .0636007 |
| Self_employed | | | | | |
| | 0 | .9340399 | .0008817 | .9323118 | .9357679 |
| | 1 | .0659601 | .0008817 | .0642321 | .0676882 |
| Student | | | | | |
| | 0 | .9869417 | .0004032 | .9861514 | .9877321 |
| | 1 | .0130583 | .0004032 | .0122679 | .0138486 |
| unemployed | | | | | |
| | 0 | .9772268 | .0005299 | .9761883 | .9782654 |
| | 1 | .0227732 | .0005299 | .0217346 | .0238117 |
| language_German | | | | | |
| | 0 | .2353899 | .0015069 | .2324363 | .2383434 |
| | 1 | .7646101 | .0015069 | .7616566 | .7675637 |
| language_Englisch | | | | | |
| | 0 | .9396291 | .000846 | .9379709 | .9412872 |
| | 1 | .0603709 | .000846 | .0587128 | .0620291 |
| language_French | | | | | |
| | 0 | .8249811 | .0013497 | .8223357 | .8276265 |
| | 1 | .1750189 | .0013497 | .1723735 | .1776643 |
| gender_female | | | | | |
| | 0 | .5558668 | .0017649 | .5524076 | .5593259 |
| | 1 | .4441332 | .0017649 | .4406741 | .4475924 |
| gender_male | | | | | |
| | 0 | .4441332 | .0017649 | .4406741 | .4475924 |
| | 1 | .5558668 | .0017649 | .5524076 | .5593259 |
| I_m16000 | | | | | |
| | 0 | .8971108 | .0010791 | .8949957 | .8992259 |
| | 1 | .1028892 | .0010791 | .1007741 | .1050043 |
| I_l16000 | | | | | |
| | 0 | .8433384 | .0012911 | .8408079 | .8458689 |
| | 1 | .1566616 | .0012911 | .1541311 | .1591921 |
| I_l12000 | | | | | |
| | 0 | .6672975 | .0016736 | .6640172 | .6705778 |
| | 1 | .3327025 | .0016736 | .3294222 | .3359828 |
| I_l8000 | | | | | |
| | 0 | .7214232 | .0015924 | .7183022 | .7245442 |
| | 1 | .2785768 | .0015924 | .2754558 | .2816978 |
| I_l4000 | | | | | |
| | 0 | .974918 | .0005554 | .9738293 | .9760067 |
| | 1 | .025082 | .0005554 | .0239933 | .0261707 |
| I_l16000 | | | | | |
| | 0 | .8433384 | .0012911 | .8408079 | .8458689 |
| | 1 | .1566616 | .0012911 | .1541311 | .1591921 |
| House_1 | | | | | |
| | 0 | .8469215 | .0012789 | .8444148 | .8494282 |
| | 1 | .1530785 | .0012789 | .1505718 | .1555852 |
| House_2 | | | | | |
| | 0 | .6218774 | .0017224 | .6185014 | .6252533 |
| | 1 | .3781226 | .0017224 | .3747467 | .3814986 |
| House_3 | | | | | |
| | 0 | .8251577 | .0013492 | .8225134 | .8278021 |
| | 1 | .1748423 | .0013492 | .1721979 | .1774866 |
| House_4 | | | | | |
| | 0 | .7669569 | .0015017 | .7640136 | .7699001 |
| | 1 | .2330431 | .0015017 | .2300999 | .2359864 |

Table Appendix 2: Additional Heterogeneity in the Gasoline Price Elasticity

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 | VKT_6 | VKT_7 |
|---|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 38.036*** | 38.026*** | 38.026*** | 38.114*** | 37.951*** | 37.753*** | 37.744*** |
| | -3.301 | -3.298 | -3.300 | -3.309 | -3.292 | -3.292 | -3.293 |
| **laggasoline** | 1.007 | 0.901 | 1.008 | 1.035 | 1.008 | 0.996 | 1.012 |
| | -0.051 | -0.066 | -0.051 | -0.054 | -0.051 | -0.077 | -0.052 |
| **laggasoline*weekend** | 0.937 | 0.937 | 0.923 | 0.936 | 0.927 | 0.938 | 0.893* |
| | -0.048 | -0.048 | -0.048 | -0.048 | -0.048 | -0.049 | -0.047 |
| **Halbtax*laggasoline** | | 1.204* | | | | | |
| | | -0.112 | | | | | |
| **Halbtax*Weekend*laggasoline** | | | 1.026 | | | | |
| | | | -0.016 | | | | |
| **GA*laggasoline** | | | | 0.644* | | | |
| | | | | -0.137 | | | |
| **GA*Weekend*laggasoline** | | | | | 1.199*** | | |
| | | | | | -0.038 | | |
| **urban*laggasoline** | | | | | | 1.014 | |
| | | | | | | -0.100 | |
| **rural*laggasoline** | | | | | | 1.107 | |
| | | | | | | -0.188 | |
| **urban*Weekend*laggasoline** | | | | | | | 1.075*** |
| | | | | | | | -0.017 |
| **rural*Weekend*laggasoline** | | | | | | | 1.123*** |
| | | | | | | | -0.032 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **cold** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heatweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshineweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rainweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **coldweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **N** | 51649.000 | 51649.000 | 51649.000 | 51649.000 | 51649.000 | 51189.000 | 51189.000 |
| **r2_p** | 0.189 | 0.189 | 0.189 | 0.189 | 0.190 | 0.190 | 0.191 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | | | |

Table Appendix 3: Additional Heterogeneity in the Diesel Price Elasticity

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 | VKT_6 | VKT_7 |
|---|---|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 50.623*** | 50.764*** | 50.587*** | 50.743*** | 50.639*** | 50.722*** | 51.098*** |
| | -4.747 | -4.768 | -4.743 | -4.748 | -4.749 | -4.795 | -4.825 |
| **lagdiesel** | 0.934 | 0.796** | 0.935 | 0.962 | 0.935 | 0.762** | 0.932 |
| | -0.050 | -0.067 | -0.050 | -0.053 | -0.050 | -0.073 | -0.051 |
| **lagdiesel_weekend** | 0.855' | 0.855' | 0.877 | 0.855' | 0.848' | 0.845' | 0.835* |
| | -0.072 | -0.072 | -0.074 | -0.072 | -0.071 | -0.074 | -0.073 |
| **Halbtax*Weekend*lagdiesel** | | 1.299* | | | | | |
| | | -0.132 | | | | | |
| **HalffareYes_lagdiesel_weekend** | | | 0.955* | | | | |
| | | | -0.020 | | | | |
| **GA*lagdiesel** | | | | 0.600** | | | |
| | | | | -0.110 | | | |
| **GA*Weekend*lagdiesel** | | | | | 1.109** | | |
| | | | | | -0.041 | | |
| **urban*lagdiesel** | | | | | | 1.338** | |
| | | | | | | -0.148 | |
| **rural*lagdiesel** | | | | | | 1.212 | |
| | | | | | | -0.200 | |
| **urban*Weekend*lagdiesel** | | | | | | | 1.028 |
| | | | | | | | -0.025 |
| **rural*Weekend*lagdiesel** | | | | | | | 0.952 |
| | | | | | | | -0.036 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heat** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshine** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rain** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **cold** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **heatweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **sunshineweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **rainweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **coldweekend** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **N** | 27554.000 | 27554.000 | 27554.000 | 27554.000 | 27554.000 | 26716.000 | 26716.000 |
| **r2_p** | 0.182 | 0.182 | 0.182 | 0.182 | 0.182 | 0.185 | 0.185 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | | | |

Table Appendix 4: Heterogeneity in the Gasoline Price Elasticity with the Weekly Weekend Average

| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 |
|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se |
| _cons | 11.988*** | 11.781*** | 14.654*** | 11.995*** | 12.121*** |
| | -2.891 | -2.845 | -3.839 | -2.895 | -2.944 |
| laggasoline | 0.800' | 0.281** | 0.716 | 0.787' | 0.813 |
| | -0.107 | -0.119 | -0.162 | -0.110 | -0.180 |
| Aareland*laggasoline | | 11.255 | | | |
| | | -19.046 | | | |
| Zentralschweiz*laggasoline | | 3.615** | | | |
| | | -1.707 | | | |
| BielJura*laggasoline | | 4.040* | | | |
| | | -2.215 | | | |
| Bern*laggasoline | | 2.457' | | | |
| | | -1.299 | | | |
| Basel*laggasoline | | 5.399' | | | |
| | | -5.367 | | | |
| Genf*laggasoline | | 2.580 | | | |
| | | -1.488 | | | |
| I_m16000*laggasoline | | | 0.702 | | |
| | | | -0.314 | | |
| I_l16000*laggasoline | | | 1.009 | | |
| | | | -0.416 | | |
| I_l8000*laggasoline | | | 1.037 | | |
| | | | -0.341 | | |
| I_l4000*laggasoline | | | 1.303 | | |
| | | | -0.867 | | |
| GA*laggasoline | | | | 1.250 | |
| | | | | -0.535 | |
| egoistic*laggasoline | | | | | 1.041 |
| | | | | | -0.263 |
| hedonic*laggasoline | | | | | 0.387 |
| | | | | | -0.307 |
| biospheric*laggasoline | | | | | 0.938 |
| | | | | | -0.237 |
| altruistic*laggasoline | | | | | 42.274** |
| | | | | | -60.893 |
| infections_weekly_1000000k | Yes | Yes | Yes | Yes | Yes |
| infections_weekly_1000000k2 | Yes | Yes | Yes | Yes | Yes |
| infections_weekly_1000000k3 | Yes | Yes | Yes | Yes | Yes |
| infections_weekly_1000000k4 | Yes | Yes | Yes | Yes | Yes |

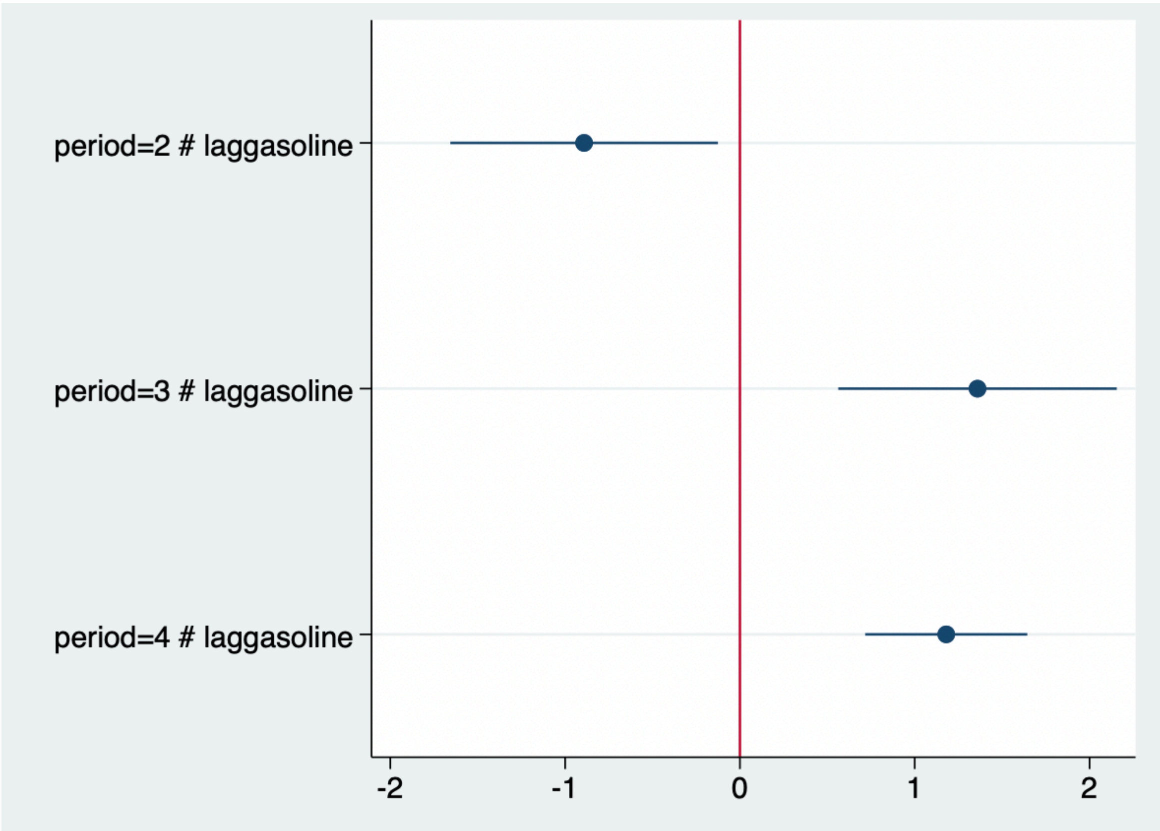
| | | | | | |
|---|---|---|---|---|---|
| **heat_weekend** | Yes | Yes | Yes | Yes | Yes |
| **sunshine_weekend** | Yes | Yes | Yes | Yes | Yes |
| **rain_weekend** | Yes | Yes | Yes | Yes | Yes |
| **cold_weekend** | Yes | Yes | Yes | Yes | Yes |
| **N** | 8736.000 | 8734.000 | 7714.000 | 8736.000 | 8736.000 |
| **r2_p** | 0.267 | 0.267 | 0.256 | 0.267 | 0.267 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | |

Table Appendix 5: Heterogeneity in the Diesel Price Elastic with the Weekly Weekend Average

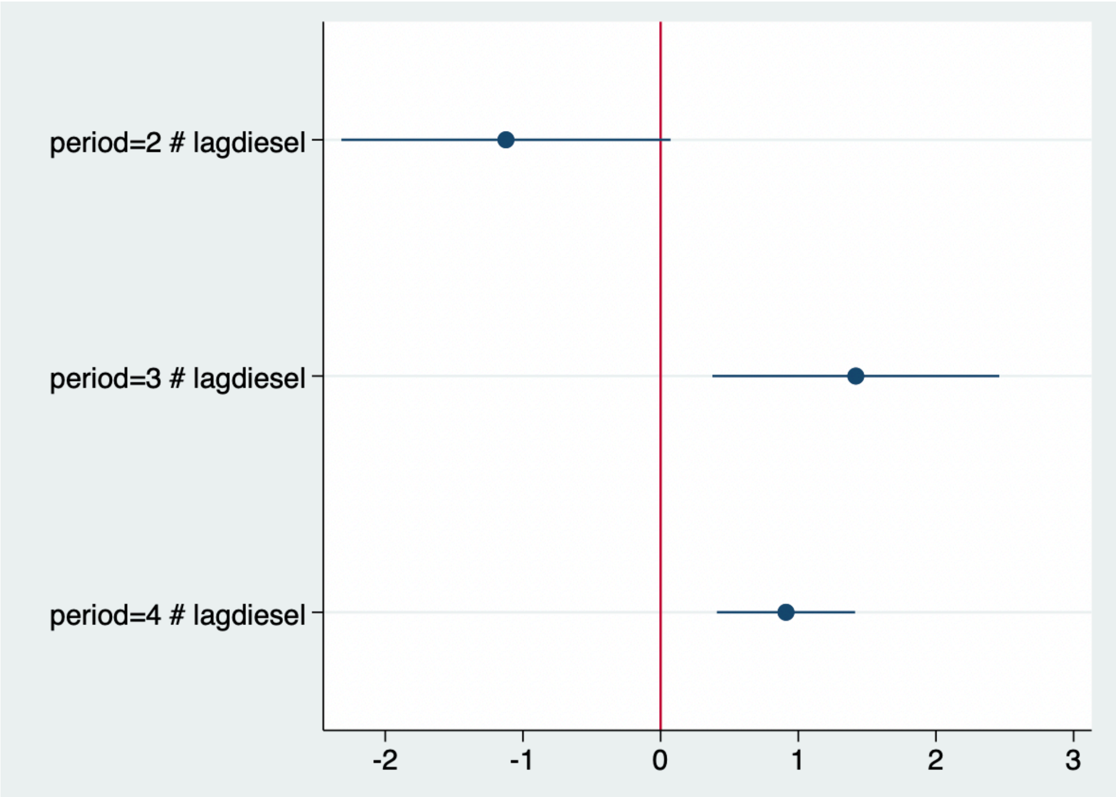
| | VKT_1 | VKT_2 | VKT_3 | VKT_4 | VKT_5 |
|---|---|---|---|---|---|
| | b/se | b/se | b/se | b/se | b/se |
| **_cons** | 15.982*** | 16.587*** | 19.135*** | 16.170*** | 16.155*** |
| | -4.290 | -4.432 | -5.468 | -4.296 | -4.249 |
| **(mean) lagdiesel** | 0.644** | 0.515*** | 0.654' | 0.702* | 0.838 |
| | -0.093 | -0.102 | -0.161 | -0.107 | -0.197 |
| **Aareland*lagdiesel** | | 0.213 | | | |
| | | -0.264 | | | |
| **Zentralschweiz*lagdiesel** | | 0.583 | | | |
| | | -1.165 | | | |
| **Lausanne*lagdiesel** | | 2.957' | | | |
| | | -1.811 | | | |
| **BielJura*lagdiesel** | | 1.374 | | | |
| | | -0.509 | | | |
| **Bern*lagdiesel** | | 1.227 | | | |
| | | -0.487 | | | |
| **Basel*lagdiesel** | | 4.363' | | | |
| | | -3.451 | | | |
| **Genf*lagdiesel** | | 1.075 | | | |
| | | -0.530 | | | |
| **I_m16000*lagdiesel** | | | 0.701 | | |
| | | | -0.347 | | |
| **I_l16000*lagdiesel** | | | 1.005 | | |
| | | | -0.465 | | |
| **I_l8000*lagdiesel** | | | 0.895 | | |
| | | | -0.303 | | |
| **I_l4000*lagdiesel** | | | 0.925 | | |
| | | | -0.678 | | |
| **GA*lagdiesel** | | | | 0.259* | |
| | | | | -0.143 | |
| **egoistic*lagdiesel** | | | | | 1.270 |
| | | | | | -0.368 |
| **hedonic*lagdiesel** | | | | | 0.308' |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | -0.202 |
| **biospheric*lagdiesel** | | | | | 0.487* |
| | | | | | -0.137 |
| **infections_weekly_1000000k** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k2** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k3** | Yes | Yes | Yes | Yes | Yes |
| **infections_weekly_1000000k4** | Yes | Yes | Yes | Yes | Yes |
| **heat_weekend** | Yes | Yes | Yes | Yes | Yes |
| **sunshine_weekend** | Yes | Yes | Yes | Yes | Yes |
| **rain_weekend** | Yes | Yes | Yes | Yes | Yes |
| **cold_weekend** | Yes | Yes | Yes | Yes | Yes |
| **N** | 4608.000 | 4608.000 | 4258.000 | 4608.000 | 4608.000 |
| **r2_p** | 0.268 | 0.270 | 0.263 | 0.269 | 0.270 |
| **' p<0.10** | * p<0.05 | ** p<0.01 | *** p<0.001 | | |

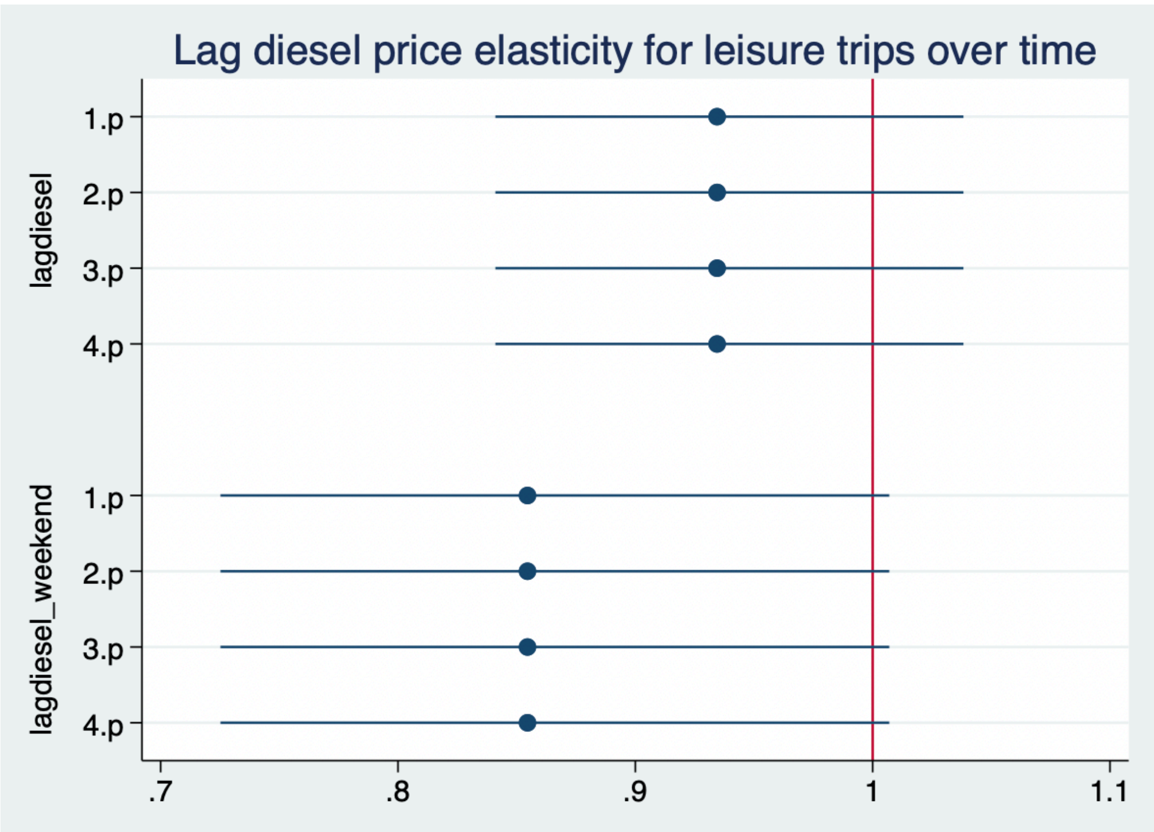
Figures Appendix 1: the Interaction term of Lag Gasoline with the Period Dummy



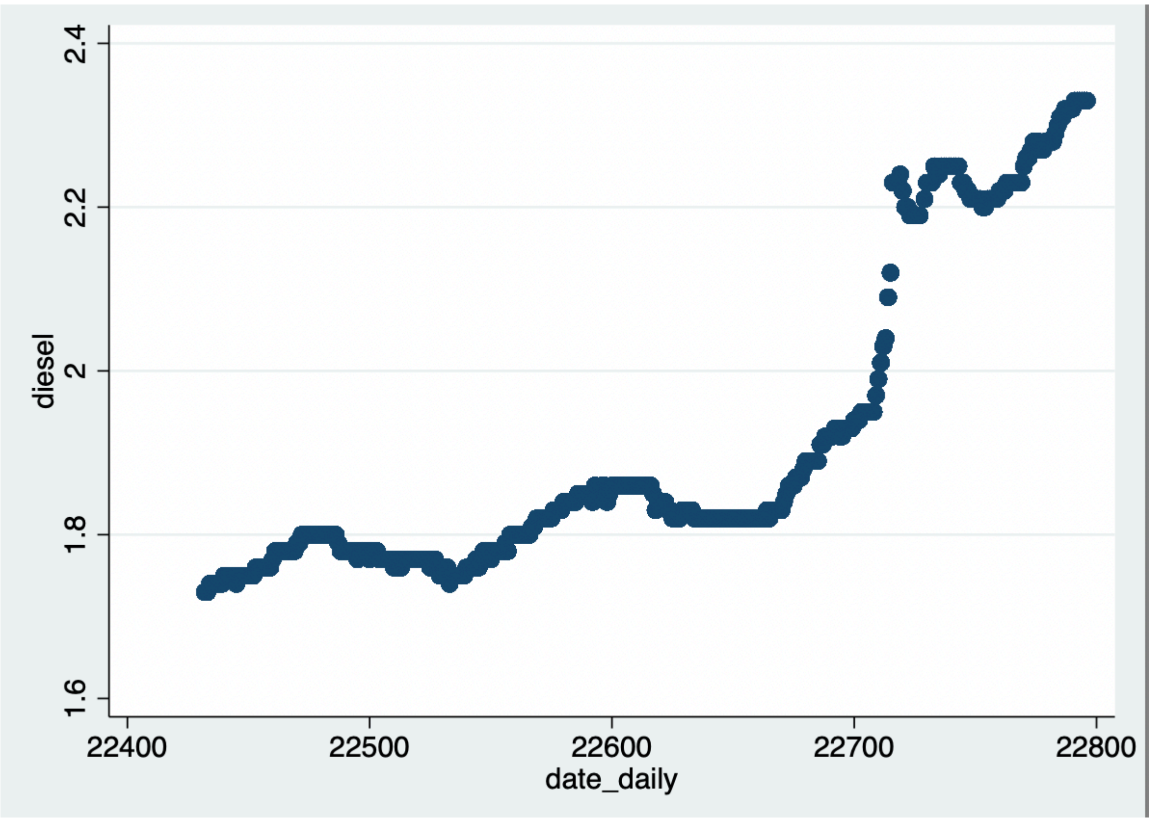
Figures Appendix 2: the Interaction Term of Lag Diesel with the Period Dummy



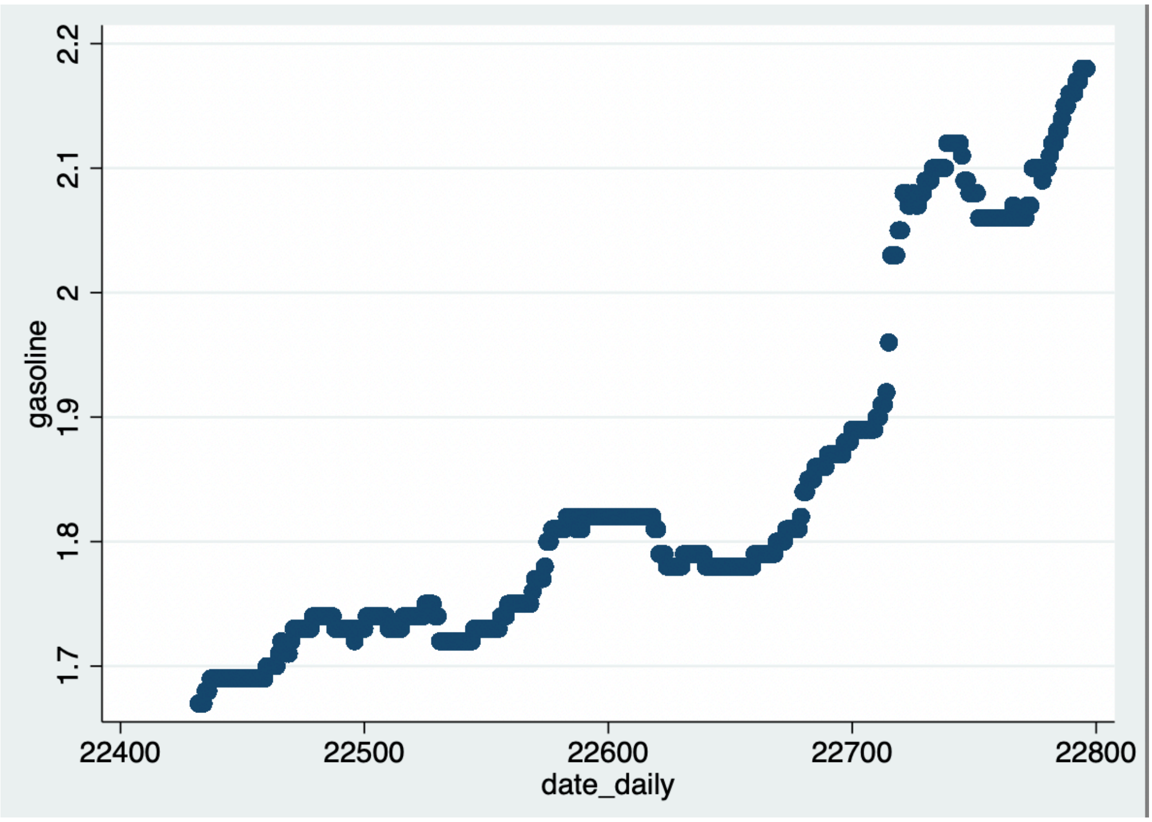

Figures Appendix 3: Lag Diesel Price lasticity for Leisure Trips over Time



Figures Appendix 4: Gasoline Price over time




Figures Appendix 5: Diesel Price over time



„Ich bezeuge mit meiner Unterschrift, dass meine Angaben über die bei der Abfassung meiner Arbeit benützten Hilfsmittel sowie über die mir zuteil gewordene Hilfe in jeder Hinsicht der Wahrheit entsprechen und vollständig sind. Ich habe das Merkblatt zu Plagiat und Betrug vom 22.02.2011 gelesen und bin mir der Konsequenzen eines solchen Handelns bewusst.“

Basel, 4. Januar 2023