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Nolan Ritter

## **Beyond the Average Elasticity – Applying Quantile Panel Regression to German Household Mobility Data**

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Nolan Ritter<sup>1</sup>

## Beyond the Average Elasticity – Applying Quantile Panel Regression to German Household Mobility Data

### Abstract

*This paper employs quantile panel regression to the study of fuel price elasticities. Contrasting with standard panel approaches, this method reveals the impact of explanatory variables across all points in the conditional distribution of the response variable while controlling for unobserved heterogeneity. Applying quantile panel regression to German household data demonstrates that fuel price elasticities are very high in magnitude – below -0.8 – for a small segment of households whose car mileage is low, but that this effect tapers off rapidly among households with higher car mileage. These findings have implications for policy instruments that rely on estimates of fuel price elasticities, for example fuel taxation.*

*JEL Classification: C21, C23, D13, Q41*

*Keywords: Price elasticity; panel data; quantile regression*

*December 2012*

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# 1 Introduction

Over the past three decades, a vast corpus of econometric studies has emerged on the effect of fuel prices on fuel consumption or car mileage demand. Based on a comprehensive overview, Graham and Glaister (2002) find elasticity estimates for the short run between -0.5 and -0.2 and for the long-run between -1.35 and -0.23. These results were derived by a battery of different econometric approaches based on time-series, cross-sectional and panel data encompassing all levels of aggregation, from the household to the country level.

As the reviews by Graham and Glaister (2002) and others indicate (e.g. Basso and Oum, 2007; Dahl, 2012), virtually all of the studies on fuel price elasticities employ some variant of mean regression, thereby effectively assuming that the magnitude of the elasticity is homogeneous across the population. Wadud et al. (2010) is one of the first studies to relax this assumption by including interaction terms in a random effects model to allow for differential elasticities according to the household's income, geographic location, and other socioeconomic attributes.

Similarly, in a study of the rebound effect, Matiaske et al. (2012) capture heterogeneity in the fuel efficiency elasticity via a quadratic specification that allows the magnitude of the elasticity to vary with the level of fuel efficiency. More recently, Frondel et al. (2012) depart from the mean regression approach of these earlier works by employing quantile regression on pooled data to assess the impact of fuel prices for different percentiles of the conditional distribution of car mileage demand. Although their study moves the literature forward by demonstrating that fuel price elasticities vary markedly according to driving intensity, it does not account for unobserved heterogeneity, which is indispensable for ascribing a causative interpretation to the coefficients (Abrevaya and Dahl, 2008).

This article introduces quantile panel regression to evaluate fuel price elasticities for different percentiles of the conditional distribution of car mileage demand while controlling for unobserved heterogeneity. I begin by replicating the results of Frondel et al. (2012), who estimate a median fuel

price elasticity of -0.62 using a pooled quantile approach with data from the German Mobility Panel (see MOP, 2011).

Subsequently, I show that the estimation of a panel quantile model yields a substantially lower median estimate of about -0.2. Moreover, quantile panel regression reveals a very high elasticity in the lower percentiles of the conditional distribution of car mileage, but one that tapers off substantially with increasing levels of car mileage. The robustness of the results is explored by estimating the model on a subsample excluding multi-car households to rule out substitution across cars. The robustness check confirms that households with high mileage are less sensitive to the fuel price.

Given the large discrepancies in the estimates of the pooled- and panel quantile methods, the results show that controlling for unobserved effects in quantile regression is just as important as in mean regression. Moreover, quantile methods enable assessment of the impact of price changes at various percentiles, so that it becomes possible to better understand the impact of fuel tax increases on total fuel tax revenues or their impact on total mobility. While the inelasticity of demand found over most of the conditional distribution promises high tax revenue gains from fuel tax increases, it also gives rise to the question of whether the fuel price is an effective instrument to bring down emissions from private vehicles.

In the further outline of the article, I first introduce the dataset compiled from the German Mobility Panel (see MOP, 2011). Section 3 describes the methodologies employed in this paper, while section 4 turns to interpreting the results. Section 5 discusses policy implications while the last section summarizes and concludes.

## 2 Data

The analysis in this paper is based on survey data taken from the German Mobility Panel, which is collected annually between 1997 and 2009 from a total of 2,165 private households. Of these, 962 are observed once, 474 twice and 729 for three times before ultimately dropping out of the panel. While participating, the households keep a travel diary and disclose their socio-

economic characteristics including their income and the zip code of their residence. This makes it possible to control for the influence of population density at the county level, which is available from the German Federal Statistical Office (2011).

**Table 1:** *Descriptive statistics*

Variable	Description	<i>Mean</i>	<i>Std.Dev.</i>
mileage	Monthly kilometers driven	1,546.3	1,145.9
price	Real fuel price per liter	1.01	0.15
income	Monthly real income	2,351	754
licenses	Number of driving licenses	1.76	0.75
children	1 if hh. has children	0.18	–
job change	1 in case of job change	0.13	–
multicar	1 if hh. owns 2+ cars	0.35	–
carvacation	1 if hh took car on holiday	0.20	–
employed	Number of employed in hh.	1.17	0.89
density	1000 people per km <sup>2</sup>	0.84	1.00

Variable	Percentiles				
	10th	25th	Median	75th	90th
mileage	458.9	764.2	1,263.9	2,007.0	2,945.09
price	0.82	0.88	1.03	1.09	1.22
income	1,287	1,750	2,296	2,832	3,330
licenses	1	1	2	2	3
children	0	0	0	0	1
job change	0	0	0	0	1
multicar	0	0	0	1	1
carvacation	0	0	0	0	1
employed	0	0	1	2	2
density	0.10	0.14	0.29	1.24	2.39

hh stands for households.

Table 1 gives the descriptive statistics of the dataset underlying the analysis. Turning to the first row, one can see that the monthly kilometers driven by the households vary considerably. In the 10th (90th) percentile, car travel is about 460 (2,945) kilometers, with a median of 1,264 kilometers. In comparison to the median, the mean travel distance of 1,546 kilometers

is about 22.3% higher. Considering the 10th to 90th percentile, the range of the fuel price over the total observation period is between 0.82 and 1.22 Euros per liter, with a median of 1.03 Euros. The mean price is 1.01 Euro per liter, which is very close to the median, with a standard deviation of 0.15 Euros.

The average household in the dataset has 1.76 driving licenses. Some 18% of the households have children below the age of 18, 35% own more than one car and in roughly 13% of the households at least one household member changed jobs during the time they participated in the travel survey. The penultimate row of Table 1 gives the population density of the county in which the households are located. While the average population density is 836 people per square kilometer, it is 100.2 (2,389.1) in the 10th (90th) percentile, with a median of 1,240.4.

### 3 Methodology

As this study is, to the author’s knowledge, the first application of quantile panel regression to the estimation of fuel elasticities, a brief overview of the method is provided here. Quantile regression was first introduced by Koenker and Bassett (1978). The method generates insights beyond that of mean regression by making it possible to evaluate the impact of regressors at any point in the conditional distribution of the dependent variable (Koenker and Hallock, 2001, p. 143). Abrevaya and Dahl (2008) introduce Chamberlain’s correlated-random effects approach (1982; 1984) to quantile regression to account for unobserved heterogeneity when panel data is available. For simplicity, the intuition is explained for the case where all units are observed over two time points. The description closely follows that of Abrevaya and Dahl (2008, pp. 380-382). The model under consideration is

$$y_{it} = \mathbf{x}_{it}^T \cdot \boldsymbol{\beta} + a_i + u_{it} , \tag{1}$$

where  $y$  is the dependent variable for household  $i$  in time  $t$ . The variable  $u_{it}$  denotes an error term varying across individuals and observations and  $a_i$  is

the unobservable individual fixed effect.  $\mathbf{x}$  is a vector of explanatory variables with a corresponding vector of parameters  $\beta$ . In the conventional fixed effects mean regression framework, the unobservable effect could either be eliminated by demeaning or differencing. In the context of quantile regression, however, these options are precluded because quantiles are non-linear operators (Abrevaya and Dahl, 2008, p. 381). Specifically, the differenced variables no longer hold information about the conditional quantiles in which the undifferenced variables are located (Ponomareva, 2010, p. 3).

To address this difficulty, Chamberlain's correlated random-effects approach (1982; 1984) opens up a possibility to account for unobserved heterogeneity. Just as in the case of fixed effects regression it assumes strict exogeneity of the explanatory variables conditional on the fixed effect  $a_i$  (Wooldridge, 2002, p. 266):

$$E(u_{ij} \mid \mathbf{x}_i, a_i) = 0, \quad (2)$$

while allowing for any correlation between the unobservable effect  $a_i$  and the explanatory variables  $\mathbf{x}_i$  (Wooldridge, 2002, p. 323).

In fact, Chamberlain (1982, 1984) deals with the unobserved effect  $a_i$  by explaining it by

$$a_i = \phi + \mathbf{x}_{i1}^T \cdot \boldsymbol{\lambda}_1 + \mathbf{x}_{i2}^T \cdot \boldsymbol{\lambda}_2 + \omega_i, \quad (3)$$

where  $\mathbf{x}_{i1}$  ( $\mathbf{x}_{i2}$ ) is the first (second) set of observations for the explanatory variables with corresponding parameter vectors  $\boldsymbol{\lambda}_1$  and  $\boldsymbol{\lambda}_2$ .  $\phi$  is a constant and  $\omega_i$  represents a disturbance term uncorrelated with the explanatory variables. As in fixed effects panel regression, no assumption about the conditional distribution of the unobserved effect given the explanatory variables is made (Wooldridge, 2002, pp. 323-324).

Substituting (3) into (1) yields the following two equations, one for each of the two times an individual is observed indicated by the subscript:

$$y_{i1} = \phi_1 + \mathbf{x}_{i1}^T \cdot (\boldsymbol{\beta} + \boldsymbol{\lambda}_1) + \mathbf{x}_{i2}^T \cdot \boldsymbol{\lambda}_2 + \omega_i + u_{i1} \quad (4)$$

$$y_{i2} = \phi_2 + \mathbf{x}_{i1}^T \cdot \boldsymbol{\lambda}_1 + \mathbf{x}_{i2}^T \cdot (\boldsymbol{\beta} + \boldsymbol{\lambda}_2) + \omega_i + u_{i2}. \quad (5)$$

The first time an individual is observed,  $\mathbf{x}_{i1}$  affects the dependent variable  $y_{i1}$  through two channels: the direct effect given by  $\mathbf{x}_{i1}^T \cdot \boldsymbol{\beta}$  and the indirect effect given by  $\mathbf{x}_{i1}^T \cdot \boldsymbol{\lambda}_1$ . The second time an individual is observed,  $\mathbf{x}_{i1}$  affects the dependent variable  $y_{i2}$  only indirectly by the unobserved effect  $a_i$  (Abrevaya and Dahl, 2008, p. 382).

Transferred to the realm of quantile regression, employing Chamberlain's approach (1982, 1984) gives us the impact of the observables on the response for any conditional quantile  $\tau$ . In case that the error terms  $u_{i1}$ ,  $u_{i2}$  and  $\omega_i$  are independent of the control variables, the conditional quantile functions for the  $\tau$ th quantile  $Q_\tau(y_{i1} | \mathbf{x}_i) = f_\tau^1$  and  $Q_\tau(y_{i2} | \mathbf{x}_i) = f_\tau^2$  that correspond to (4) and (5) are (Abrevaya and Dahl, 2008, p. 381):

$$Q_\tau(y_{i1} | \mathbf{x}_i) = \phi_\tau^1 + \mathbf{x}_{i1}^T \cdot (\boldsymbol{\beta} + \boldsymbol{\lambda}_1) + \mathbf{x}_{i2}^T \cdot \boldsymbol{\lambda}_2 \quad (6)$$

$$Q_\tau(y_{i2} | \mathbf{x}_i) = \phi_\tau^2 + \mathbf{x}_{i1}^T \cdot \boldsymbol{\lambda}_1 + \mathbf{x}_{i2}^T \cdot (\boldsymbol{\beta} + \boldsymbol{\lambda}_2) . \quad (7)$$

In this case, the slopes of the control variables would be identical across all conditional quantiles.

Without the independence assumption, besides the intercepts the slope parameters vary as well, indicated by the subscript  $\tau$ . Reduced-form linear approximations of the true conditional quantile functions  $Q_\tau(y_{i1} | \mathbf{x}_i) = f_\tau^1$  and  $Q_\tau(y_{i2} | \mathbf{x}_i) = f_\tau^2$  can be consistently estimated with linear quantile regression following Koenker and Bassett (1978):

$$Q_\tau(y_{i1} | \mathbf{x}_i) = \pi_\tau^1 + \mathbf{x}_{i1}^T \cdot \boldsymbol{\theta}_\tau^1 + \mathbf{x}_{i2}^T \cdot \boldsymbol{\lambda}_\tau^2 \quad (8)$$

$$Q_\tau(y_{i2} | \mathbf{x}_i) = \pi_\tau^2 + \mathbf{x}_{i1}^T \cdot \boldsymbol{\lambda}_\tau^1 + \mathbf{x}_{i2}^T \cdot \boldsymbol{\theta}_\tau^2 , \quad (9)$$

where  $\pi_\tau^1$  and  $\pi_\tau^2$  are intercepts and  $\beta_\tau^1 = \boldsymbol{\theta}_\tau^1 - \boldsymbol{\lambda}_\tau^1$  measures the influence of the observables for the first and  $\beta_\tau^2 = \boldsymbol{\theta}_\tau^2 - \boldsymbol{\lambda}_\tau^2$  for the second observation for a given percentile  $\tau$ .

Under the assumption of parameter stability across time, that is  $\beta_\tau^1 =$

$\beta_\tau^2 = \beta_\tau$ , the slope estimates are

$$\beta_\tau = \theta_\tau^1 - \lambda_\tau^1 = \theta_\tau^2 - \lambda_\tau^2 \quad (10)$$

and the conditional quantile functions are

$$Q_\tau(y_{i1} | \mathbf{x}_i) = \pi_\tau^1 + \mathbf{x}_{i1}^T \cdot (\beta_\tau + \lambda_\tau^1) + \mathbf{x}_{i2}^T \cdot \lambda_\tau^2 \quad (11)$$

$$Q_\tau(y_{i2} | \mathbf{x}_i) = \pi_\tau^2 + \mathbf{x}_{i1}^T \cdot \lambda_\tau^1 + \mathbf{x}_{i2}^T \cdot (\beta_\tau + \lambda_\tau^2) . \quad (12)$$

Abrevaya and Dahl (2008, p. 382) suggest estimating Equations (11) and (12) by running a pooled linear quantile regression introduced by Koenker and Bassett (1978), ordering the observations by observation unit and number of observation in the following form:

$$y = \begin{bmatrix} y_{11} \\ y_{12} \\ y_{21} \\ y_{22} \\ \dots \\ \vdots \\ \dots \\ y_{n1} \\ y_{n2} \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} 1 & 0 & \mathbf{x}_{11}^T & \mathbf{x}_{11}^T & \mathbf{x}_{12}^T \\ 1 & 1 & \mathbf{x}_{12}^T & \mathbf{x}_{11}^T & \mathbf{x}_{12}^T \\ 1 & 0 & \mathbf{x}_{21}^T & \mathbf{x}_{21}^T & \mathbf{x}_{22}^T \\ 1 & 1 & \mathbf{x}_{22}^T & \mathbf{x}_{21}^T & \mathbf{x}_{22}^T \\ \dots & \dots & \dots & \dots & \dots \\ & & \vdots & & \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & \mathbf{x}_{n1}^T & \mathbf{x}_{n1}^T & \mathbf{x}_{n2}^T \\ 1 & 1 & \mathbf{x}_{n2}^T & \mathbf{x}_{n1}^T & \mathbf{x}_{n2}^T \end{bmatrix}, \quad (13)$$

where the columns of  $\mathbf{X}$  indicate  $\pi_\tau^1$ ,  $\pi_\tau^2 - \pi_\tau^1$ ,  $\beta_\tau$ ,  $\lambda_\tau^1$ , and  $\lambda_\tau^2$ .

The correlated random-effects approach outlined here by Abrevaya and Dahl (2008) accommodates balanced panels. The present analysis, however, employs an unbalanced panel consisting of either 2 or 3 observations for each household. Therefore, I use the estimator suggested by Bache et al. (2011) which advances the one suggested by Abrevaya and Dahl (2008) to accommodate unbalanced panels.

## 4 The model

As one aim of this study is to illustrate the insights that can be gained from the application of quantile panel regression as compared with more conventional approaches of estimating fuel price elasticities, the empirical point of departure draws on a recently published study by Frondel et al. (2012) that uses pooled quantile regression to estimate elasticities from a panel of German households.

This analysis provides an especially useful basis for comparison, because it itself builds on several studies (Frondel et al., 2008; Frondel and Vance, 2010) that explore fuel price elasticities using an array of techniques with the same data, including sample selection models and various panel estimators. One of the more notable outcomes emerging from this work is that the fuel price elasticities estimated from the German sample are relatively high and significant, ranging between -0.6 and -0.4.

This conclusion is confirmed in their most recent study using pooled quantile regression Frondel et al. (2012), which uncovers elasticity estimates as high as -0.9 for the lowest 10% quantile. These findings lead the authors to advocate fuel taxes as a climate protection measure.

### 4.1 The mean regression approach

The natural starting point for the analysis is the replication of the results obtained by Frondel et al. (2012) from a random effects regression, which are presented in Table 2. The key result is that a 1% increase in the fuel price leads on average to a 0.57% decrease in car mileage. Further, an increase in income by 1% increases mileage about 0.08%.

Moreover, multiple car households drive on average 45.6% more than single car households, while households that use their car to go on vacation exhibit an average increase in mileage of about 25.2%. All variables are significant at the 5% level with the exception of the impact of job change on car mileage.

Departing from Frondel et al. (2012), who proceed with the estimation of a pooled quantile regression, I contrast these findings with results from

a fixed effects regression presented in column two. Here, only the impact of fuel price, ownership of multiple cars and taking the car on vacation has a significant impact. Moreover, the magnitude of the fuel price elasticity decreases substantially, by nearly half.

**Table 2:** *Regression results*

Observations	Random Effects N=4,097	Fixed Effects N=3,136
ln(realprice)	-0.574** (0.063)	-0.297** (0.090)
kids	0.065* (0.027)	-0.009 (0.063)
ln(income)	0.077* (0.032)	-0.007 (0.044)
licenses	0.079** (0.019)	0.015 (0.032)
employed	0.128** (0.016)	-0.015 (0.031)
newjob	0.051 (0.029)	0.050 (0.035)
carvacation	0.252** (0.020)	0.219** (0.026)
density	-0.000** (0.000)	0.000 (0.000)
multicar	0.456** (0.028)	0.340** (0.054)
intercept	6.059** (0.235)	6.866** (0.350)

\*\* (\*) indicates significance at the 1% (5%) level. Standard errors in parentheses.

It is thus not surprising that a model-specification test by Schaffer and Stillman (2010), which is more general than Hausman (1978) in that it allows for clustering, rejects that random effects and fixed effects are identical. A prudent approach with this data would consequently dictate using fixed effects to avoid biases from unobserved heterogeneity. This, in turn, raises the question of the extent to which unobserved heterogeneity may also bias the pooled variant of the quantile regression. Moreover, a random effects approach would have to control for a host of additional time-invariant variables including household size, education, road density, public transportation, and

congestion in order to separate the influences of these controls from the price elasticity estimates.

## 4.2 The quantile approach

To pursue this question, I first estimate the quantile regressions based on treating the panel data as pooled cross-sections similar to Frondel et al. (2012). However, I restrict the sample to those households that were observed multiple times. I then contrast these findings with those obtained from a panel quantile regression having the same set of observations and explanatory variables. Finally, I explore the robustness of the panel quantile results to both changes in the model specification and in the estimation sample.

Turning to Figure 1, the upper panel highlighting the results from treating the panel data as pooled cross-sectional as in Frondel et al. (2012) indicates a high and moderately increasing elasticity that is statistically significant at any conventional level for the entire conditional distribution of car mileage demand with the exception of the first percentile. From this result we would conclude that while the fuel price elasticity declines with increasing driving intensity, it remains substantial over most of the range. Even households above the 90th quantile have an elasticity well below -0.5. This is essentially the same pattern obtained from Frondel et al. (2012), which is not surprising given that the only feature distinguishing the models is their larger sample size.

The lower panel of Figure 1, generated from a quantile panel regression controlling for unobserved heterogeneity, conveys a markedly different picture of the impact of fuel prices on car mileage. As in the pooled quantile regression, households that drive little display relatively high fuel price elasticities: between the 1st and 14th percentiles these elasticities vary between -1.6 and -0.6 and are statistically significant at the 1% level.

Thereafter, however, the elasticities remain below -0.5 in magnitude over most of the remaining quantiles. From the 39th percentile onward, the estimate is about -0.2. Moreover, the estimated confidence interval straddles

zero over most of the range. Based on these results that control for unobserved heterogeneity, we would ascribe only households with a low driving intensity a statistically and economically significant fuel price elasticity.

**Table 3:** *Quantile panel regression results for the full sample (N=3,136)*

ln(mileage)	Percentiles						
	5th	10th	25th	50th	75th	90th	95th
ln(price)	-1.021** (0.311)	-0.973** (0.261)	-0.303 (0.187)	-0.210 (0.150)	-0.246 (0.144)	-0.005 (0.131)	-0.088 (0.201)
ln(income)	-0.231 (0.157)	-0.114 (0.109)	0.051 (0.080)	-0.048 (0.069)	0.074 (0.068)	-0.071 (0.075)	-0.031 (0.089)
licences	0.061 (0.068)	0.040 (0.077)	0.008 (0.056)	0.001 (0.046)	0.004 (0.037)	0.071* (0.036)	0.158* (0.067)
kids	0.052 (0.170)	-0.070 (0.165)	-0.131 (0.120)	-0.003 (0.084)	0.031 (0.113)	0.046 (0.087)	-0.011 (0.115)
jobchange	-0.080 (0.114)	-0.079 (0.102)	0.063 (0.059)	0.101** (0.038)	0.066 (0.049)	0.128* (0.051)	0.105 (0.060)
multicar	0.522** (0.120)	0.356** (0.128)	0.257** (0.097)	0.352** (0.067)	0.342** (0.068)	0.378** (0.082)	0.318** (0.111)
density	0.003 (0.005)	-0.002 (0.003)	0.001 (0.001)	0.002 (0.001)	0.003 (0.001)	0.000 (0.002)	0.000 (0.002)
employed	-0.126 (0.089)	-0.015 (0.071)	-0.011 (0.044)	-0.007 (0.047)	0.039 (0.037)	0.077 (0.052)	-0.005 (0.071)
carvacation	0.418** (0.089)	0.289** (0.056)	0.257** (0.043)	0.266** (0.034)	0.140** (0.034)	0.053 (0.041)	-0.012 (0.062)
intercept	4.550** (0.912)	4.380** (0.881)	4.072** (0.638)	4.432** (0.519)	5.407** (0.490)	5.669** (0.486)	6.061** (0.556)

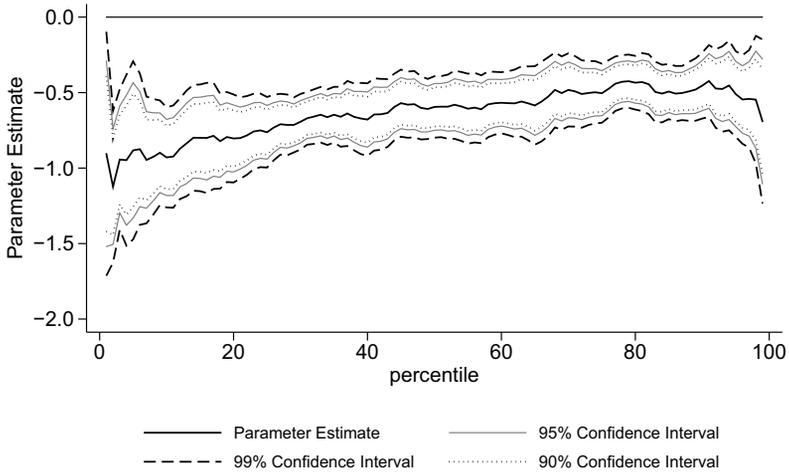
\*\* (\*) indicates significance at the 1% (5%) level. Standard errors in parentheses.

Table 3 catalogues the quantile panel parameter estimates for all explanatory variables for select percentiles. It can be seen that neither the prevalence of children, nor the population density of the area in which the household resides, nor the number of employed exhibit significant impacts on car mileage. For some percentiles, the dummy controlling for job changes is significant at the 5% level, while the dummies *multicar* and *carvacation* show significant parameters at the 1% level for most percentiles on display.

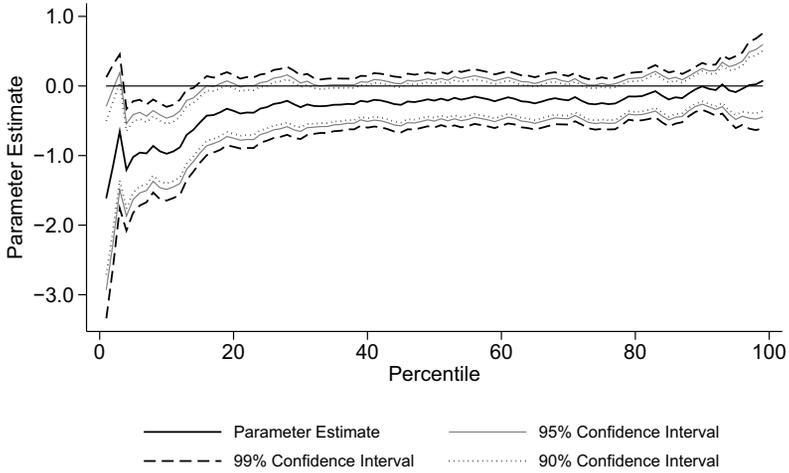
Turning to Figure 2, it is seen that the impact of taking the car on vacation diminishes with a growing household car mileage demand. This is expected, since households with a high mileage would have had a high car

**Figure 1:** *The fuel price elasticity of car mileage in the full sample*

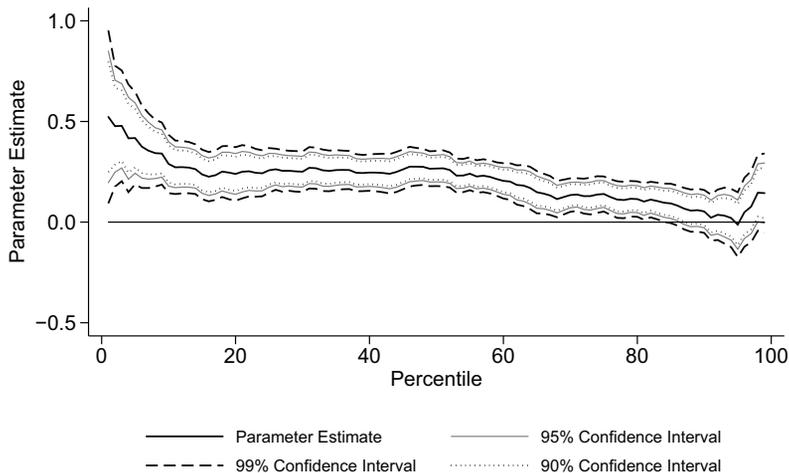
**(a)** *Pooled quantile regression results (N=3,136)*



**(b)** *Panel quantile regression results (N=3,136)*



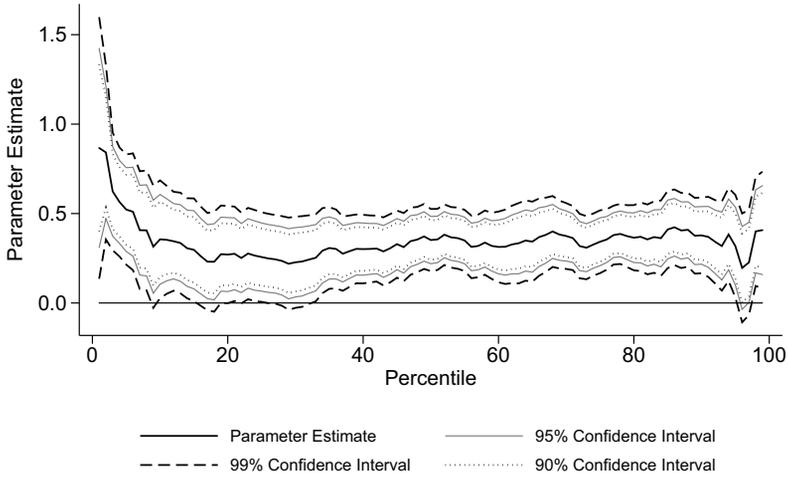
**Figure 2:** *The effect of taking the car on vacation on vehicle mileage (N=3,136)*



use anyway, while households with a low car mileage demand may experience a sharp increase. Comparing Figure 2 to the mean-regression fixed effects results from Table 2, we see that the average estimate fails to accurately describes the influence of taking the car on vacation at both ends of the conditional distribution of vehicle mileage demand. At the lower end of the distribution, taking the car on vacation may account for an increase in the demand for vehicle mileage of more than 50%, while from the 90th percentile onwards no significant effect can be discerned.

While the parameter measuring the impact of taking the car on vacation declines with increases in car mileage, the effect of owning multiple cars seems relatively stable across the conditional distribution of the response (Figure 3). However, in the lower part of the distribution, the effect is insignificant. This could be the case because in single-car households with low car mileage, the car has a high probability of being available to household members. Increasing the number of cars in these households would, thus,

**Figure 3:** *The effect of owning multiple cars ( $N=3,136$ )*

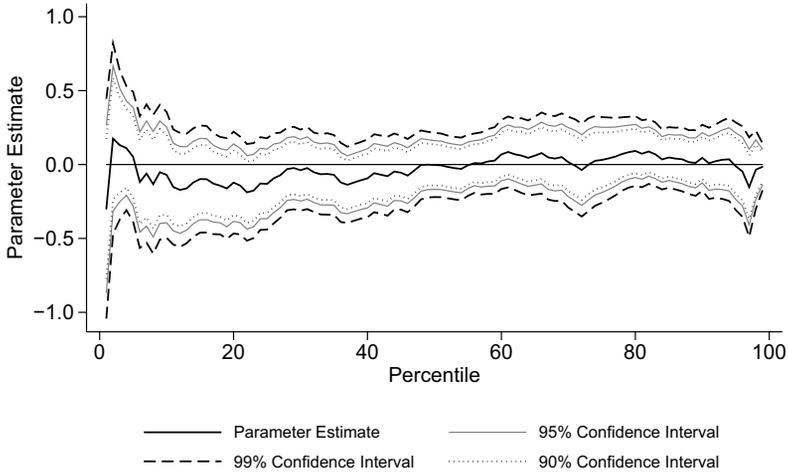


only have a limited effect. In single-car households with a high vehicle mileage demand, however, the probability of the car being available to a household member is smaller. In this case, increasing the number of cars could have a high and positive impact on car mileage demand.

Figure 4 indicates that the impact of children on vehicle mileage demand is insignificant across the distribution of the response. Comparing Figure 4 to the results obtained employing mean regression presented in Table 2, we see that quantile panel regression supports the finding from the fixed effects regression. Although the quantile panel estimates are insignificant over the full range of the conditional distribution of the response, it is still valuable because we now have evidence that the average impact estimated by mean regression is an accurate description of reality. The same applies to the quantile panel estimates for the effect of income on vehicle mileage demand presented in Figure 5, which is insignificant for vehicle mileage demand over the entire conditional distribution of the response.

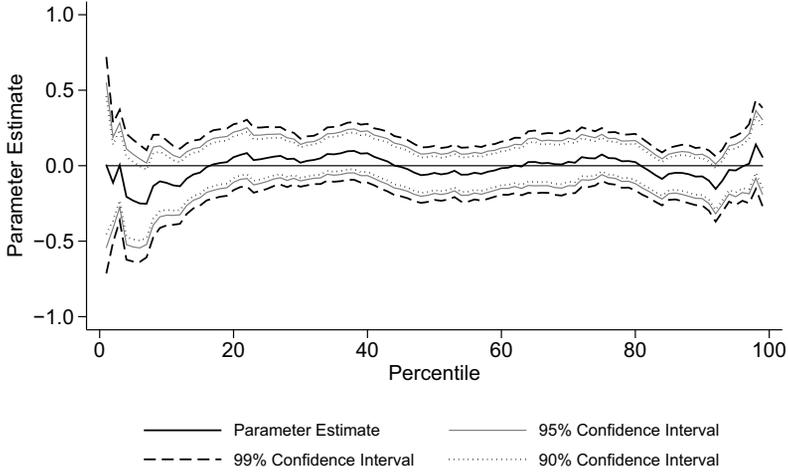
One important factor that may in part account for the results in Table

**Figure 4:** *The effect of the prevalence of children ( $N=3,136$ )*



3 relate to the number of cars from which the household can choose. It is plausible, for example, that households owning multiple cars may exhibit a more muted response to high fuel prices because they have the opportunity to shift car mileage to the more efficient car compared to single-car households. To explore whether this possibility is made use of, I limit the sample to single-car households and accordingly drop the variable accounting for households owning multiple cars. This results in a panel of 2,042 observations. Table 4 presents the results from quantile panel regression for select percentiles for single-car households.

**Figure 5:** *The effect of the income ( $N=3,136$ )*



**Table 4:** *Quantile panel results for single-car households ( $N=2,042$ )*

ln(mileage)	Percentiles						
	5th	10th	25th	50th	75th	90th	95th
ln(price)	-1.286** (0.365)	-1.075** (0.292)	-0.451 (0.226)	-0.371 (0.201)	-0.278 (0.153)	-0.313 (0.177)	-0.338 (0.330)
ln(income)	-0.211 (0.167)	-0.059 (0.118)	0.107 (0.077)	-0.066 (0.076)	-0.010 (0.072)	-0.158 (0.086)	-0.067 (0.098)
licences	-0.024 (0.111)	-0.076 (0.107)	0.039 (0.095)	0.012 (0.049)	0.045 (0.046)	0.068 (0.073)	0.092 (0.094)
kids	-0.037 (0.200)	-0.186 (0.206)	-0.218 (0.154)	-0.168 (0.161)	0.032 (0.098)	0.138 (0.124)	0.138 (0.120)
jobchange	-0.057 (0.154)	-0.043 (0.122)	0.128 (0.082)	0.116 (0.078)	0.100 (0.067)	0.202* (0.080)	0.252 (0.143)
density	0.002 (0.003)	-0.002 (0.003)	0.002 (0.001)	0.003* (0.001)	0.003 (0.001)	0.001 (0.002)	0.000 (0.003)
employed	-0.323* (0.128)	-0.185 (0.098)	-0.094 (0.064)	-0.104* (0.041)	0.032 (0.043)	0.013 (0.064)	0.028 (0.096)
carvacation	0.528** (0.122)	0.396** (0.081)	0.387** (0.053)	0.325** (0.042)	0.187** (0.050)	0.111 (0.059)	-0.001 (0.074)
intercept	4.287** (0.957)	4.165** (0.883)	4.849** (0.773)	5.108** (0.630)	5.937** (0.535)	6.467** (0.556)	6.811** (0.161)

\*\* (\*) indicates significance at the 1% (5%) level. Standard errors in parentheses.

In the following, the parameter estimates are scrutinized in detail. Figure 6 highlights the findings of the impact of fuel prices on car mileage. Most notably, the comparison between Figure 1b for the full sample and Figure 6 for the subsample reveals that the fuel price elasticity rapidly declines with increases in car mileage. Although the number of observations is significantly smaller, the confidence band is also nearly the same. Therefore, I conclude that the exclusion of multi-car households has no fundamental bearing on the estimation of the fuel price elasticity.

**Figure 6:** *Fuel price elasticity for single-car households ( $N=2,042$ )*

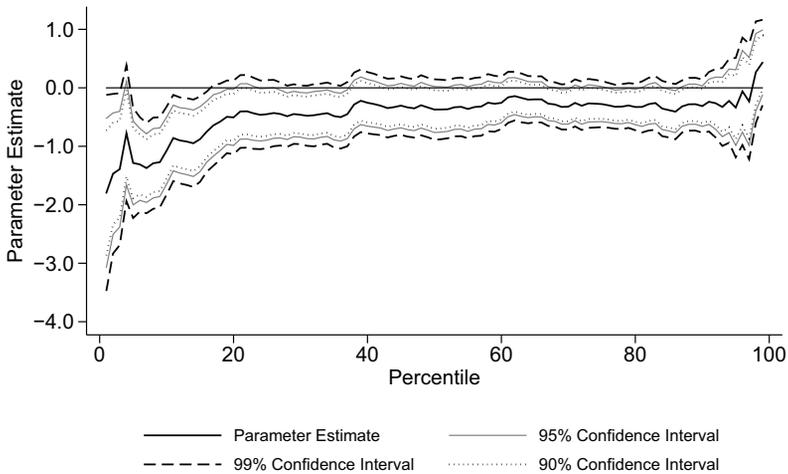
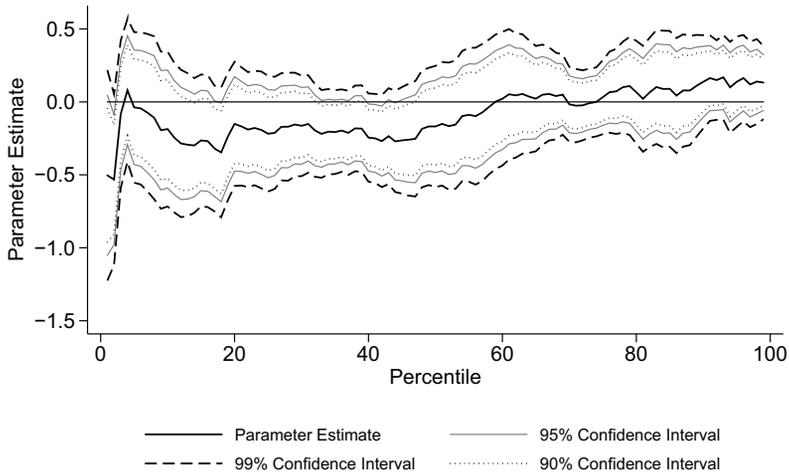


Figure 7 presents the impact of the prevalence of children on car mileage demand. Compared to Figure 4, there are a few percentiles at which significant parameter estimates emerge. However, for the majority of the conditional distribution of the response, children have no significant impact on car mileage demand. The robustness check therefore confirms the findings with respect to the impact of children from the estimates on the full sample.

With respect to the number of employed household members, Figure 8 also confirms the findings from the full sample. Again, there are points in

**Figure 7:** *Impact of prevalence of children in single-car households (N=2,042)*

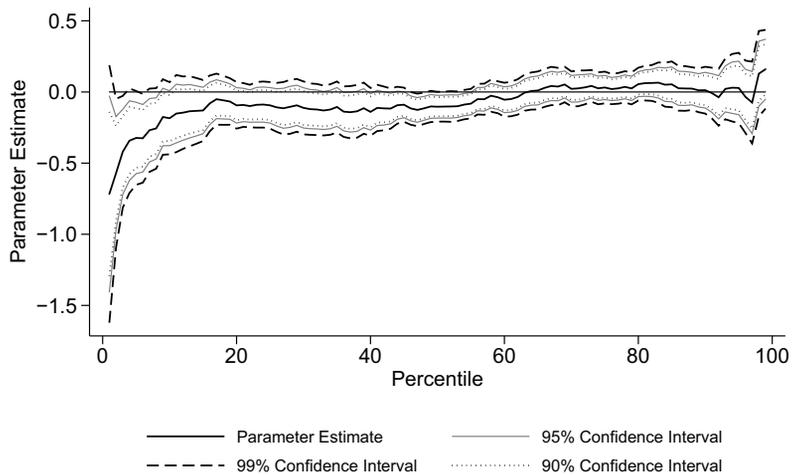


the center of the conditional distribution of the response at which the control variable has significance. However, the impact is small from an economic point of view. Therefore, the estimate for the effect of employment on the subsample of single-car households confirms the findings from the full sample.

The same is also true for the income variable. A statistically or economically significant effect can neither be found in the sample including (Figure 5) nor in the sample excluding multi-car households (Figure 9), with the exception of a few parameter estimates beyond the 90th percentile. Therefore, the insights made with respect to income are robust, too.

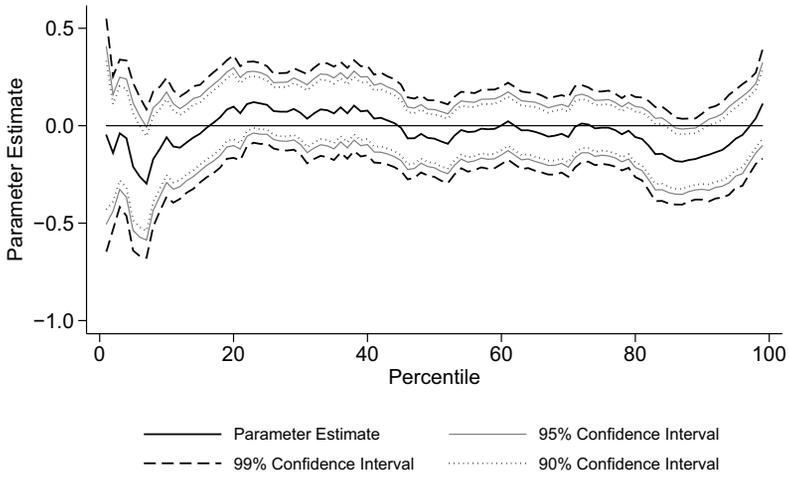
Figure 10 indicates that taking the car on vacation has a relatively high and stable impact for households in the lower part of the conditional distribution of car mileage, while it tapers off in the upper half of the distribution. Comparing the estimates from the sample of single-car households to the sample including multi-car households (Figure 2), we see that the impact

**Figure 8:** *Impact of the number of employed in single-car households (N=2,042)*

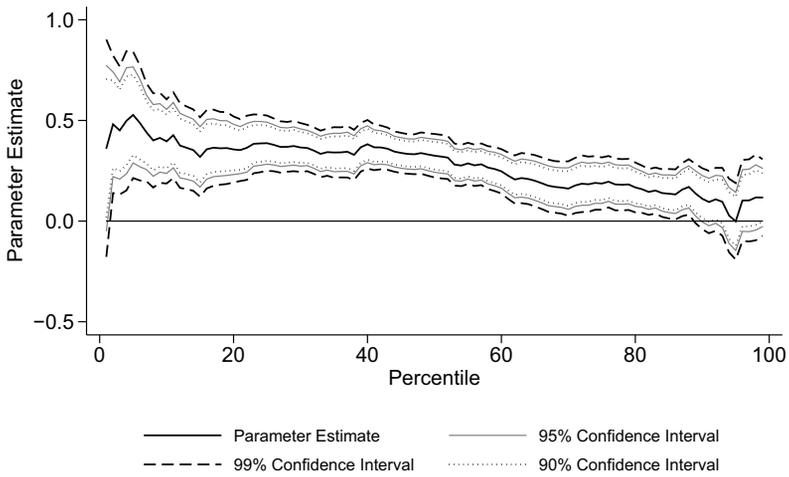


of taking the car on vacation is somewhat smaller in the multi-car sample, although there is no statistically significant difference between both.

**Figure 9:** *Impact of income in single-car households (N=2,042)*



**Figure 10:** *Impact of taking the car on vacation in single-car households (N=2,042)*



## 5 Policy implications

Altogether, the empirical evidence found with respect to fuel price elasticities from the quantile panel estimations can be regarded as robust. Irrespective of whether single- or multi-car households are considered, the regressions indicate that the higher the car mileage demand, the lower the price elasticity. For households that exhibit a car mileage demand equal to or higher than the median, the elasticity estimates are mostly insignificant, indicating that their elasticities are too small in magnitude to be distinguishable from zero.

Taking account of the richness of the quantile panel regression results, it becomes clear that an average estimate of fuel price elasticities is not a particularly good approximation of reality: Reactions to fuel prices vary markedly across the conditional distribution of car mileage. Especially at the low end of this distribution, fuel tax increases lead to decreases in car mobility, reducing the mobility of the least mobile households.

In sum, the quantile panel estimates that control for unobserved heterogeneity highlight that fuel price elasticities of households are mostly small. This has far reaching consequences with respect to the efficacy of fuel taxation as a policy instrument: Among those households that contribute most to total car mileage, no price reaction can be discerned, so that a price instrument is ineffective as a means to lower car mileage and, hence, pollution. It is, however, a very efficient instrument with respect to generating tax revenues. The low and insignificant fuel price elasticities indicate that car-dependent households are not responsive to fuel price fluctuations.

Including emissions from German road traffic into the European emissions trading system might be an efficient alternative to fuel taxes. Gas stations, for example, could be held responsible to buy emission certificates equal to the carbon content of the fuel they sell. This would ensure that total emissions are limited to the amount of emission certificates issued under a cap determined by policy-makers. Increases in road traffic would trigger increases in certificate prices that in turn lead to emission reductions in other sectors under the regulation of the emissions trading system.

## 6 Conclusions

This article shows that employing quantile panel methods in the field of fuel price elasticity estimates reveals important insights that would otherwise be overlooked using conventional approaches. The results clearly indicate that there is a very high elasticity in the lower part of the conditional distribution of car mileage demand in Germany: Households that drive little are highly sensitive to fuel prices.

At the same time, there is virtually no statistically significant fuel price elasticity for most of the remaining households. Compared to fixed effects mean regression, the quantile panel estimator by Abrevaya and Dahl (2008) advanced by Bache et al. (2011) to handle unbalanced panels allows for a more nuanced interpretation of the results that better captures the heterogeneity of fuel price elasticities.

These findings have implications for whether governments should pursue the taxation of fuel when driving down emissions from vehicles is concerned. Finding that households with a low car mileage demand are price elastic, while households with a high car mileage demand are not, implies that fuel taxation generates high revenues while the impact on total mileage demand on the national level is probably small. Accordingly, the effect on pollution, congestion, or noise from traffic is also small. Instead of increasing fuel taxes, including emissions from German road traffic into the European emissions trading system might prove an efficient and easy to implement alternative to fuel taxes.

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