RUHR

ECONOMIC PAPERS

Frank Goetzke

Colin Vance

Is Gasoline Price Elasticity in the United States Increasing? Evidence from the 2009 and 2017 National Household Travel Surveys

rwi

#765

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #765

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-893-6

Ruhr Economic Papers #765

Frank Goetzke and Colin Vance

Is Gasoline Price Elasticity in the United States Increasing? Evidence from the 2009 and 2017 National Household Travel Surveys

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at http://dnb.dnb.de

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/86788893
ISSN 1864-4872 (online)
ISBN 978-3-86788-893-6

Frank Goetzke and Colin Vance[1]

Is Gasoline Price Elasticity in the United States Increasing? Evidence from the 2009 and 2017 National Household Travel Surveys

Abstract

Drawing on the 2009 and 2017 waves of the National Household Transportation Survey, this paper models the determinants of vehicle miles traveled, with the aim of parameterizing the magnitude of the fuel price elasticity. To capture changes in this magnitude over the two years of the survey, our specification interacts the logged fuel price with a dummy indicating the 2017 survey year. We find a small but statistically significant mean elasticity of about -0.05 for the year 2009, which increases over fourfold to -0.23 by the year 2017. We explore the robustness of this result to different model specifications and estimation techniques, including instrumental variable estimation to account for the possible endogeneity of fuel prices, as well as quantile regression to account for heterogeneity according to driving intensity. A similar pattern of substantially increasing elasticity emerges across all these models. We speculate that one possible source of this pattern is economic duress from the 2008 financial crisis, which the data suggests reoriented mode choice patterns.

JEL Classification: D12, Q41, R48

Keywords: Fuel price elasticity; household VMT; heterogeneity

August 2018

1 Frank Goetzke, University of Louisville; Colin Vance, RWI and Jacobs University, Bremen. – All correspondence to: Colin Vance, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: colin.vance@rwi-essen.de

1 Introduction

Estimates of the fuel price elasticity are significant to a range of themes that have relevance for transportation policy. By measuring the responsiveness of motorists to changes in the unit costs of driving, the fuel price elasticity is useful for weighing the merits of alternative policy interventions, including those that increase driving costs, like fuel taxation, and those that decrease them, like mandated efficiency standards. The associated behavioral adjustments to such interventions, in turn, bear on a range of transportation-related externalities – not least emissions, congestion, and noise pollution – that immediately impact welfare.

The present paper provides new evidence on the fuel price elasticity in the United States, a country registering a high per capita rate of vehicle miles traveled (VMT) coupled with low fuel prices – about double and half those, respectively, of most European countries. Most evidence suggests that US motorists are relatively unresponsive to fuel price fluctuations. Elasticity estimates are typically on the order of 0.1 or below, but span a broad range that reach as high as 0.4.

This variation in estimates owes to variation in study design features, including the site of data collection, the time period of the analysis, whether the focus is on the short run or the long run, the level of data aggregation, and the definition of the dependent variable. Studies that define the dependent variable as mileage and are measured at the household level tend to yield higher elasticity estimates than those defining it as fuel consumption at the state or regional level. Such household-level estimates of the fuel price elasticity with respect to VMT contribute to our understanding by isolating the impact of the fuel price on the intensive margin, that is, on driving behavior, rather than on choices made at the extensive margin, such as those related to vehicle purchase (Gillingham et al., 2015).

In this vein, the present study develops econometric models of VMT that pool two waves of the National Household Transportation Survey (NHTS) from 2008/2009 and 2016/2017. We gauge the robustness of the results by employing three estimators, the baseline being an Ordinary Least Squares (OLS) regression, the second augmenting this estimator by instrumenting the gasoline price to address potential endogeneity, and the third using quantile regression to capture heterogeneity in the estimates by driving intensity. All models employ the household's total car mileage on the survey day as the dependent variable and the weekly local fuel price as the key explanatory variable. We interact the fuel price with a dummy variable indicating the latter survey wave to allow the estimated fuel price elasticity to vary over time.

The results of our baseline OLS model reveal a dramatic jump in the magnitude of the fuel price elasticity over the two waves of the survey, increasing over fourfold from -0.05 in 2009 to -0.23 in 2017, with similar estimates obtained from the instrumental variable (IV) model. The median estimate from the quantile model corroborates this result and additionally reveals substantial heterogeneity according to the driving intensity of the household, particularly in the 2017 survey. While the estimates corresponding to the year 2009 do not deviate markedly across quantiles, the estimates for the year 2017 are considerably higher in magnitude among households in the lower quantiles of VMT, reaching about -0.4. This magnitude abates with increases in driving intensity, becoming insignificantly different from zero by the 85% quantile.

One takeaway from these findings is that the elasticity is subject to large variation over a short period of time and, in 2017, across households. That the elasticity is time-variant has already been established by earlier research, with some evidence of a decrease in its magnitude by the early 2000s (Hughes et al., 2008; Small and Van Dender, 2007). Coglianese et al. (2017) point out that this decrease in part owed to price increases after 2000 that coincided with a booming economy. Beyond validating a low elasticity as of 2009, our study documents a reversed trend thereafter, corroborating emerging evidence of a higher elasticity post 2008 (Lin and Prince, 2013; Langer et al., 2017). One possible explanation for this pattern is that economic duress from the 2009 financial crisis sensitized motorists to fuel price fluctuations. The quantile estimates suggest that households reporting low vehicle mileage were especially responsive to the fuel price, which we conclude has implications for the efficacy of fuel taxes.

2 Literature Review

The US gasoline tax has fallen in real terms over the last decades even as the transportation sector has emerged as the largest source of greenhouse gas emissions, generating about 28.8% of the total (EPA, 2018). This raises the question concerning the effectiveness of price-based interventions in decreasing VMT. As documented in Table 1, this question has been the subject of a large body of literature, which has produced empirical estimates of the fuel price elasticity in the US ranging from upwards of 0.4 to close to zero.

The following review focusses mainly on research after 2000. In addition to studies that estimate the fuel price elasticity, we also include studies that estimate the rebound effect, which measures the extent to which reductions in fuel consumption from increases in fuel economy are offset by increased driving. The rebound effect consequently has a positive sign that, as Frondel and Vance (2009) note, is, under certain conditions, expected to be of equal magnitude as the negative sign of the fuel price elasticity. This theoretical expectation traces to the fact that both effects capture changes in the unit cost of driving.

Two major literature surveys were published in the early 2000s (Graham and Glaister, 2002; Goodwin et al., 2004). Both surveys compared internationally short-run and long-run fuel elasticity with respect to either fuel consumption or vehicle miles traveled (VMT) using cross-sectional and time-series studies. Among their major results were that (1) the long-run is more responsive than the short-run and (2) fuel consumption tends to be more elastic than VMT. In addition, Graham and Glaister (2002) found that the short-run elasticity in the United States is below the OECD mean, while Goodwin et al. (2004) document that the fuel elasticity decreases post-1981. This latter finding was supported a few years later by two articles providing strong evidence that the fuel price elasticity (Hughes et al., 2008) and the rebound effect (Small and Van Dender, 2007) drop substantially in the decades leading to the new millennia. The estimates of the fuel price elasticity by Hughes et al. (2008) decrease from about -0.21 in the period 1975-1980 to -0.03 in the period 2001-2006, while those of the rebound effect from Small and Van Dender (2007) decrease from 0.22 in the period 1966-2001 to about 0.11 in the period 1997-2001.

With few exceptions, most relevant publications thereafter come to the result that fuel price responsiveness in the United States is very low. These elasticity studies bifurcate into two approaches. Some studies regress fuel demand on fuel prices (Lin and Prince, 2013; Liu, 2014, 2015; Levin et al., 2017; Coglianese et al., 2017). A larger number of papers, however, run regressions of VMT on gasoline price or fuel cost (Su, 2010, 2012; Li et al., 2014; Rentziou et al., 2012; Wang and Chen, 2014; Gillingham, 2014; Gillingham et al., 2015; Dillon et al., 2015; Langer et al., 2017; Kaechele and Slusky, 2018).

Studies investigating fuel demand typically use either aggregate time series or panel data (Lin and Prince, 2013; Liu, 2014, 2015; Levin et al., 2017; Coglianese et al., 2017). Lin and Prince (2013) run a monthly United States aggregate dynamic time-series model and show that short-run elasticity actually slightly increased between the periods 1990/2007 (-0.03) and 2008/2012 (-0.05 to -0.7). Liu (2014) and Liu (2015) employ a translog panel model for quarterly US state data and quarterly US house-

Table 1: Elasticity literature since Hughes et al. (2008) and Small and Van Dender (2007), focusing on the United States

	Type	Obs. level	Time	Dep. variable	Ind. variable	Findings
Hughes et al. (2008)	Time series OLS	Monthly US	1975 - 2000	Fuel demand/capita	Gas price	Elasticity: -0.335
			2001 - 2006			Elasticity: -0.042
Lin and Prince (2013)	Dynamic time series	Monthly US	1990 - 2007	Fuel demand/capita	Gas price	SRE: -0.028
			2008 - 2012			SRE: -0.052 to -0.068
Liu (2014)	Semiparametric translog	Qrtly US states	1994 - 2008	Fuel demand/capita	Gas price	Elasticity: -0.013 to -0.117
Liu (2015)	Dynamic translog model	Qrtly US HH	1997 - 2002	HH fuel demand	Gas price	Elasticity: -0.23 to -0.39
Coglianese et al. (2017)	IV FE panel (monthly)	US states	1989 - 2009	State fuel demand	Gas price	Elasticity: -0.190 to -0.192
Levin et al. (2017)	FE panel (daily/monthly)	MSA	2006 - 2009	Fuel demand/capita	Gas price	Elasticity: -0.295 to -0.364
Small and Van Dender (2007)	Simultaneous equations	US states	1966 - 1989	State VMT	Fuel cost/mile	SRE: -0.0465 to -0.0819
	(pooled cross-section)		1997 - 2001		(rebound)	SRE: -0.0197 to -0.0366
Su (2010)	Dynamic panel (annual)	US metro areas	1991 - 2001	Metro VMT/capita	Gas price	SRE: -0.0629
Su (2012)	Quantile regression (daily)	US vehicles	2008 - 2009	Vehicle VMT	Fuel cost/mile	Elasticity: -0.1141[1] to -0.193
Li et al. (2014)	OLS (daily)	US households	1995 - 2009	Household VMT	Gas price	Elasticity: -0.052 to -0.196
Rentziou et al. (2012)	SURE panel model (annual)	US states	1998 - 2008	State VMT	Gas price	Elasticity: -0.035 to -0.088
Wang and Chen (2014)	SEM (daily)	US vehicles	2008 - 2009	Household VMT	Gas price	Elasticity: -0.0941[1] to -0.406
Gillingham (2014)	Quantile regression	CA vehicles	2001 - 2009	Vehicle VMT	Gas price	Elasticity: -0.17 to -0.33
Gillingham et al. (2015)	IV FE panel (annual)	PA vehicles	2000 - 2010	Vehicle VMT	Gas price	Elasticity: -0.099
Dillon et al. (2015)	SEM (daily)	South. CA HH	2008 - 2009	Household VMT	Gas price	Elasticity: -0.0661[1] to -0.171
Langer et al. (2017)	FE panel (monthly)	OH vehicles	2009 - 2013	Vehicle VMT	Fuel cost/mile	Elasticity: -0.150
Kaechele and Slusky (2018)	OLS (daily)	MSA HH	1995 - 2009	Household VMT	Gas price	Elasticity: -0.316 to -0.393
Dimitropoulos et al. (2016)	Lit. review/meta-analysis	25 US studies	1983 - 2016	Fuel demand & VMT	Gas price	Elasticity: -0.099 to -0.250

[1] Elasticity estimate is not significantly different from zero.

hold data, respectively, finding elasticities anywhere between -0.01 (Liu, 2014) and -0.39 (Liu, 2015). Coglianese et al. (2017) develop an instrumental variable fixed-effects model with leads to control for anticipatory behavior. They find a fuel elasticity of around -0.19. Levin et al. (2017) discovers that the lower the aggregation level, the higher the elasticity. Including day-of-week and city-level fixed effects, they estimate elasticity values between -0.295 to -0.364.

Research focusing on VMT is based mostly on disaggregate cross-sectional household or vehicle observations. Among studies using the 2009 NHTS data, Su (2012) develops a quantile regression for daily vehicle VMT. He estimates, depending on the quantile, a rebound effect between 0.11 and 0.19, with the middle-range of VMT being the most price-responsive and the low range the least. Li et al. (2014) pool the 1995, 2001 and 2009 NHTS data and run OLS regressions resulting in elasticity values between -0.05 and -0.20. Wang and Chen (2014) estimate a structural equation model (SEM) using the 2009 NHTS data to determine elasticity depending on household income. They find values from -0.09 (statistically not significant) to -0.40, higher income households being the most price responsive and middle income the least.

Other studies have focused on regional data or have isolated elasticities in urban areas. Using US state panel data, Rentziou et al. (2012) build a seemingly unrelated regression equations model and estimate an elasticity between -0.05 and -0.09. Su (2010) estimates a 20-year annual dynamic panel model for 84 American urban areas, finding a short-run elasticity of -0.06. Gillingham (2014) follows new vehicles in California to their first smog check, and in a subsequent paper (Gillingham et al., 2015) tracks vehicles in Pennsylvania through their annual emission inspection tests. The 2014 paper presents a quantile regression and finds elasticity values increasing from -0.17 for the low VMT quantile to -0.33 for the high VMT quantile. The 2015 paper utilizes a fixed-effects panel model and estimates an elasticity of 0.10. In a structural equation model (SEM) exploiting a Southern California 2009 NHTS subsample of households, Dillon et al. (2015) estimate a statistically insignificant elasticity that ranges from -0.07 to -0.171. Taking advantage of private driving records from the State Farm Automobile Insurance Company, Langer et al. (2017) estimates an elasticity of -0.15 applying a fixed-effects panel model with monthly vehicle VMT observations. Using the same data set as Li et al. (2014), which includes the 1995, 2001 and 2009 NHTS, Kaechele and Slusky (2018) finds for major cities a relatively high elasticity between -0.316 and -0.393.

Finally, a meta-regression study by Dimitropoulos et al. (2016) summarizes 79 publications with elasticity estimates and finds a range between -0.099 and -0.250, depending on whether the estimation method is OLS or, alternatively, various panel or weighted least square approaches. What all the reviewed literature has in common is that elasticity values are relatively low, but with a tendency to increase as the aggregation level of the data set moves from national to state to metro area to household level. With the exception of Su (2010), the highest elasticities are observed in subsets in metropolitan areas (Dillon et al., 2015; Levin et al., 2017; Kaechele and Slusky, 2018). This updated literature review confirms the finding of previous literature surveys that fuel consumption is more price responsive than vehicle miles traveled. Also of note is that elasticity appears to be higher in the analyses focusing on the time after 2008/09 (Lin and Prince, 2013; Langer et al., 2017), which is supported by the evidence presented in the current application.

3 Data

This study pools the trip files of both the 2009 and 2017 National Household Travel Survey (NHTS). The surveys were conducted by the Federal Highway Administration (FHA) from March 2008 through April 2009 and April 2016 through April 2017, respectively. To our knowledge, this is the first research based on 2017 NHTS data to estimate the fuel price elasticity; the 2009 NHTS data was previously used by Su (2012); Li et al. (2014); Wang and Chen (2014); Dillon et al. (2015) as well as Kaechele and Slusky (2018).

The dependent variable is the sum of VMT undertaken on the survey travel day, aggregated by household. In order to avoid any abnormality, since we have only one travel day, we excluded all weekend travel and any individual trip greater than 75 miles. As the main study variable, we use the fuel price, which is included in the NHTS as the price of gasoline on the travel week. The price of gasoline was not directly surveyed, but later added based on Energy Information Administration (EIA) data reported by Census regions. We deflate fuel price by applying the consumer price index, with 2010 as the base year.

Table 2: Descriptive Statistics

	Mean	**Standard deviation**
VMT	46.106	41.816
Fuel price	2.524	0.760
Poor	0.148	0.356
Upper middle class	0.253	0.435
Wealthy	0.203	0.402

Based on the reported household income intervals, we developed three income categories: We included the upper 15 percent into the wealthy group, which was in 2009 greater than \$100,000 and in 2017 more than \$125,000. The next 20 percent, in 2009 between \$60,000 and \$100,000 and in 2017 between \$75,000 and \$125,000, were put into the upper middle-class group. The lowest 32.5 percent, which was in 2007 under \$25,000 and in 2017 below \$35,000, became the poor group. The remaining observations are in the omitted middle-income category.

Table 2 summarizes the descriptive statistics of the main variables. Additional variables not included in Table 2 are the following control variables: Household type dummies are based on ten life-cycle categories, which combine the number of adults with the children of different ages. These variables also proxy for both number of licensed drivers and number of household vehicles. Nine census divisions account for regional differences. Six city size, four urban type and eight population density variables control for destination opportunity and transportation mode alternatives. We also include monthly unemployment measured at the state level to capture macroeconomic conditions, which deteriorated sharply over the first survey year as the financial crisis hit. The specification is completed with dummies indicating the month of the survey to further control for macroeconomic fluctuations and account for seasonal differences in travel demand resulting from holidays and summer vacation time.

For 2009, we started out with 1,167,321 trips covering all modes. We deleted all non-automotive and weekend trips, as well as trips exceeding 75 miles. We also dropped records with missing data. At the end, we had daily 517,396 trips across 82,334 households, or 6.3 trips per household. The average length of an included single trip is 7.7 miles, and the mean of the sum of all household trips is 48.3 miles. In 2017, we had 923,572 trips. After excluding non-automotive, weekend trips, and trips greater than 75 miles, as well as all records with missing data, we end up with 473,997 trips across 82,334 households, or 5.8 trips per household. The average length of an included single trip is 7.5 miles, and the mean of the sum of all household trips is 43.9 miles.

4 Methodology

To gauge the robustness of the results to differing assumptions about the data generation process, we present three econometric models. Following the tradition of past fuel elasticity analysis, our baseline model is a double-log regression that is estimated using Ordinary Least Squares. We investigate whether the elasticity varies over time by including a dummy variable for the year 2017 ($year17$) that is interacted with the logged fuel price via the following specification:

$$ln(VMT_i) = \beta_0 + \beta_1 year17 + \beta_2 ln(fuelprice_i) + \beta_3 year17 * ln(fuelprice_i) + X_i' \beta_z + \epsilon_i \tag{1}$$

The dependent variable, $ln(VMT_i)$, is the natural log of the total household VMT. The dummy $year17$ has the value of 1 for the year 2017 and is zero otherwise. The policy variable is $ln(fuelprice_i)$. X_i is the vector of all the control variables, β's are the regression coefficients and ϵ_i is the error term.

The question of causality is an issue that looms large in analyses of fuel price responsiveness owing to the potential endogeneity of fuel prices. Indeed, variation in whether and how studies account for endogeneity is likely to be one of the sources of the high degree of variation in estimates documented in the literature review. As suggested by Liu (2016), and demonstrated empirically by Gillingham et al. (2015), estimates of the price elasticity that ignore endogeneity may be subject to bias. This bias can be attenuated by an instrumental variable approach (IV) in which at least one instrumental variable is employed for the potentially endogenous variable. For the IV approach to be a reasonable identification strategy, the instrumental variable z_i should be correlated with the fuel price, i. e. $Cov(fuelprice_i, z_i) \neq 0$, while it should not be correlated with the error term ϵ_i: $Cov(z_i, \epsilon_i) = 0$. If either of these two identification assumptions is violated, employing z_i as an instrument for $fuelprice_i$ is not a viable approach.

Following Liu (2016), one candidate instrument is the price for West Texas Intermediate (WTI) crude, as this price reflects world oil prices and hence is likely to be correlated with the gasoline price, which we confirm empirically below. Whether WTI is uncorrelated with the error term cannot be empirically verified and indeed, scenarios are plausible in which oil price shocks are transmitted to driving, thereby biasing the IV estimate. Nevertheless, our inclusion in the specification of monthly fixed effects as well as a control for the unemployment rate serves to eliminate the main channels through which spurious correlation could emerge. Because the gas price is interacted with the year dummy for 2017, instruments are also required for this term. Drawing on the discussion in Wooldridge (2010) (pp. 121-122), a natural instrument is the interaction of WTI with other exogenous variables in the model. To this end, we interact WTI with the year dummy as well as with dummies indicating the nine geographical divisions of the US. The resulting interactions allow differential effects of WTI on the gas price by region, which could arise from the spatial distribution of refinery operations and associated differences in transport costs.

This set-up leads to a system of two equations estimated by two-stage least squares (2SLS), implemented using the Stata command *ivreg2* (Baum et al., 2007). In the first stage, both endogenous variables ($fuelprice_i, fuelprice_i * Y16$) are independently regressed on all the instrumental variables plus the elements in X_i, from which predicted values are generated. The IV estimates are then obtained in the second stage by estimating structural equation (1) using the predicted- instead of the observed values of the endogenous variables.

One potentially restrictive feature of the OLS and IV estimators is their focus on the conditional expectation function, which precludes the ability to estimate differential effects of an explanatory variable at different points in the conditional distribution of the dependent variable. As several recent studies have identified, the distribution of VMT may be characterized by substantial dispersion. This raises the question of whether the effects of the determinants of VMT vary by the level of VMT, that is, by the intensity of driving. This question cannot be addressed by standard mean-regression approaches.

The quantile regression estimator, introduced by Koenker and Bassett Jr (1978), avoids this restriction by allowing estimation of the impact of a regressor at any point in the conditional distribution of the response, not just the conditional mean. Following the introduction of Koenker and Hallock (2001), the starting point for quantile regression are the unconditional quantiles, obtained by minimizing the sum of asymmetrically weighted residuals with an accordingly chosen constant b:

$$Q_\tau(y) = \min_{(b \in \Re)} \rho_\tau \sum (y_i - b) \tag{2}$$

where τ specifies the percentile in the distribution of the dependent variable y_i. The weighing scheme $\rho_\tau(.)$ is the absolute value function that takes on different slopes depending on the sign of the residuals and the quantile of interest. Moving from the unconditional to the conditional quantiles is achieved by substituting the b by the parametric function $b(X_i, \beta)$ and minimizing the following equation using linear optimization:

$$Q_\tau(y) = \min_{(b \in \Re)} \rho_\tau \sum (y_i - b(X_i, \beta)) \tag{3}$$

with the vector X_i containing the control variables while β is the corresponding parameter vector. The solution to this minimization problem yields estimates of the impact of the controls across all points in the conditional distribution of the response. As Frondel et al. (2012) note, quantile regression methods provide for a richer characterization of mobility data by allowing investigation of the impact of a regressor such as fuel prices on the full distribution of the dependent variable or any particular percentile, not just the conditional mean. We can thereby explore whether the elasticity varies according to driving intensity.

5 Regression Results

Table 2 catalogues the results from the OLS, 2SLS, and quantile regressions. We focus our attention on the estimates of the fuel price elasticity and the indicators for income class; the inclusion of the other control variables is indicated in the lower panel. Robust standard errors using the Huber-White estimates of variances are presented for the OLS and 2SLS models, while the standard errors for the quantile models are calculated by bootstrapping.

Table 3: Regression Results

	OLS		**2SLS**		**Quantile (median)**	
	Coef	SE	Coef	SE	Coef	SE
Fuel price	-0.039**	(0.016)	-0.044***	(0.017)	-0.026	(0.017)
Year 2017 dummy	0.838***	(0.252)	0.795	(0.426)	0.911***	(0.247)
Fuel price X year 2017 dummy	-0.195***	(0.055)	-0.186***	(0.093)	-0.210***	(0.054)
Poor	-0.275***	(0.008)	-0.275***	(0.008)	-0.249***	(0.009)
Upper middle class	0.190***	(0.006)	0.190***	(0.006)	0.180***	(0.007)
Wealthy	0.254***	(0.007)	0.254***	(0.007)	0.252***	(0.007)
Constant	2.656***	(0.102)	2.804***	(0.107)	2.740***	(0.109)
Household type	yes		yes		yes	
Census division	yes		yes		yes	
MSA type	yes		yes		yes	
Urban classification	yes		yes		yes	
Population density	yes		yes		yes	
Unemployment rate	yes		yes		yes	
Month of the year	yes		yes		yes	
Observations	163,580		163,580		163,580	
R^2	0.188		0.188		0.120	
First stage F-Statistic (Kleibergen-Paap rk Wald)			>14,000***			
Hansen J statistic			11.927			
Hausman statistic			1.097			

Note: * denotes significance at the 5%-level, ** at the 1%-level and *** at the 0.1%-level, respectively.

Overall, the point estimates across the models are highly stable. Turning first to the OLS model, the estimated fuel price elasticity corresponding to the year 2009 is -0.048 and is statistically significant at the 1% level. While small, the magnitude of the estimate corresponds to the lower bound estimates of several other household studies of VMT from roughly the same time period. A sizeable – and statistically significant – jump in magnitude is seen by 2017, when the elasticity reaches approximately -0.23 (= -0.039 + -0.195). In this year, a 10% increase in the fuel price would correspond to a roughly 2.3% decrease in VMT.

The coefficients of the income class dummies confirm the intuition that wealthier households have higher VMT. Households in the highest income class designated by the indicator wealthy have approximately 28% (=exp(0.25)-1) higher VMT than those in the lower middle class, the base category. Households designated as poor have 24% lower VMT than the lower middle class households.

Alternative specifications of the OLS model were explored (but not presented) to assess the robustness of the results to the omission of particular variables. For example, recognizing that urban classification and population density are attributes that may draw people to settle in a particular local based on their transportation preferences, and hence may be endogenous, we estimated models that omitted these controls. This omission had no substantial bearing on the estimates.

Of course, interpretation of the estimates from the OLS regression is also subject to the caveat that they may be biased from the potential endogeneity of the gasoline price. We address this issue with the application of the two-stage least squares model presented in column 2. The validity of this approach depends on the strength of the instruments, measured here by the WTI price and its interaction with the regional dummies and the dummy indicating the year 2017. An initial indication is given by the highly significant coefficient estimates of the instruments originating from the first stage, with t-statistics that are in all instances larger than 100 (not presented). A more formal gauge of the strength of the instruments is given by the Kleibergen-Paap Wald rk F statistic (Kleibergen and Paap, 2006), the critical values for which are taken from Stock and Yogo (2002). The F-statistic from the test is greater than

14,000, leading to the rejection of the hypothesis that the second-stage equation is weakly identified. Given that our set up includes more instruments than endogenous variables, we also test the null hypothesis that the model is not over-identified. Based on a chi-square value of the Hansen J-statistic of 11.9 (p=0.17), we fail to reject this hypothesis, providing further support that the instruments are valid.

Referring to the coefficients of the 2SLS model, the estimates are largely in line with those of the OLS regression. The estimate of the fuel price elasticity for the year 2009, at -0.044, is only marginally higher in magnitude, while the estimate on the interaction term has a somewhat lower magnitude. This pattern carries over to an estimated fuel price elasticity in 2017 of -0.23, which is the same magnitude as the OLS regression. The similarities in the estimates on the income indicators are likewise pronounced, leading us to conclude that whatever bias may be induced by endogeneity is moderate. This was also confirmed by the application of a Hausman test, which failed to reject the null hypothesis that the gas price is exogenous. In this regard, we note that one channel through which endogeneity may otherwise arise is via different travel patterns over the course of the year owing to holidays and weather, which is controlled for here by the month dummies. In fact, we find that if these dummies are excluded from the model, then the null hypothesis of exogeneity is rejected.

The final column of Table 3 presents the estimates from the quantile regression corresponding to the 50 percent quantile, alternatively referred to as median regression. The estimated fuel price elasticity for the year 2009, at-0.027, is statistically indistinguishable from zero at the 5% level of statistical significance. Conversely, the interaction effect is highly significant, yielding an elasticity estimate for the year 2017 of -0.23, in exact accordance with the other estimates.

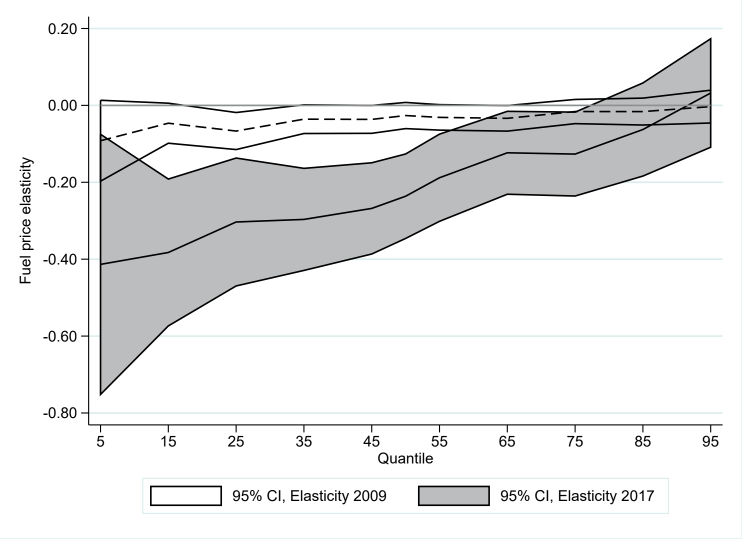
Moving beyond a focus on the 50 percent quantile, Figure 1 presents a graphical depiction of the point estimates of the coefficients along with the 95% confidence intervals across all quantiles of the dependent variable for the years 2009 and 2017. The vertical axis shows the magnitude of the fuel price elasticity while the horizontal axis shows the corresponding quantile of VMT. Several insights can be gleaned from the figure.

To begin, there is relatively little variation in the estimates for the year 2009, though they tend to be somewhat higher in magnitude in the lower quantiles. The largest statistically significant estimate of -0.06 is found at the 25th quantile; thereafter the estimates fall to -0.03 or smaller, with the 95% confidence interval consistently straddling zero by the 65 percent quantile. In short, we find a small elasticity for 2009 that varies little, irrespective of driving intensity.

Conversely, the estimates for 2017 are subject to considerable heterogeneity. Over most quantiles, they have a higher magnitude but also a higher standard error than the estimates from 2009. Similar to the analysis by Frondel et al. (2012) of the rebound effect using household data from Germany, we find an inverse relationship between driving intensity and the fuel price elasticity. Households in the lower quantiles of VMT are considerably more responsive to fuel prices. Between 25th and 5th quantiles, the elasticity varies between -0.3 and just larger than -0.4. Its magnitude abates, however, with higher VMT. By the 60th quantile, the magnitude is about -0.15, and by the 75th quantile it becomes statistically indistinguishable from zero.

One possible explanation for the higher fuel price elasticity in 2017, at least among households under the median quantile of VMT, may be a reorientation of mobility patterns owing to the financial crisis in 2008. Household expenditures on gasoline comprise a sizeable share of pre-tax income, about 4%, so it is plausible that mode switching may have occurred in response to economic duress. Confirmation of this explanation would require more in depth analysis of work status and income, extend-

Figure 1: Quantile estimates of the fuel price elasticity



ing beyond the scope of the present study. Nevertheless, anecdotal evidence in support of mode switching is seen with reference to the public transit modal share documented in the NHTS, which increases from 1.9% in 2009 to 3.6% in 2017. This large, statistically significant jump, may be indicative of a higher willingness to switch from car to public transit travel in response to fuel prices.

With regard to the efficacy of fuel taxation as a tool to address transport-externalities, the results from the mean regressions suggest that by 2017, policy makers had gained substantially more leverage to reduce car travel via higher fuel taxes. Closer scrutiny of the quantile estimates, however, suggests that the actual effectiveness of taxation may be muted by the fact that those who drive the most are the least responsive to price changes, while those who drive the least are the most responsive. A back-of-the-envelope calculation using the VMT values for the year 2017 serves to illustrate the implications. If we were to assume a 2.3% decrease in driving across all households, as would result from a 10% increase in the gas price according to the mean regression, the average absolute reduction in daily VMT would amount to slightly over one mile. Repeating the calculation using instead the quantile-specific elasticities yields a considerably lower reduction of 0.75 miles. Thus, assuming a uniform elasticity of -0.23 is likely to substantially overestimate the reduced car travel resulting from a fuel price increase.

6 Conclusion

Using the 2009 and 2017 waves of the National Household Transportation Survey, this paper has estimated the magnitude of the fuel price elasticity with respect to vehicle miles traveled. Three econometric estimators were employed to this end: OLS, two-stage least squares, and quantile regression. Each model was specified so as to allow the magnitude of the fuel price elasticity to differ between the 2009 and 2017 survey waves.

Four insights emerge from the analysis:

- Based on the OLS regression, there is a large and statistically significant jump in the magnitude of the elasticity between the two survey waves, increasing from -0.05 in 2009 to -0.23 in 2017.

- This finding is validated by the two-stage least squares regression. In fact, we fail to reject the null hypothesis that the fuel price elasticity is endogenous, a result that is predicated on the inclusion of month dummies in the model to control for fluctuations in driving behavior over the course of the year.

- The quantile regression confirms a large increase in the elasticity between the survey waves, but additionally reveals substantial heterogeneity in its magnitude for the 2017 wave. Specifically, the results show that elasticity depends inversely on the household's driving intensity: households with low vehicle mileage exhibit price elasticities that are substantially larger than those of households with high vehicle mileage.

- The pattern of estimates produced by the quantile regression has important implications for judging the effectiveness of fuel price taxation. Through a simple numerical calculation, we demonstrated that the predicted average decrease in VMT resulting from a 10% increase in the fuel price is substantially higher when using the uniform elasticity from the OLS regression than when using quantile-specific elasticities. This finding owes to the fact that those households who are most responsive to fuel prices are those who drive the least, a pattern that is obscured by the results of the mean regressions.

Future research should probe further into the sources of the increased elasticity following 2009 that is demonstrated in this analysis and other work. We speculate that one explanation may relate to the effect of the financial crisis in changing mobility habits, but this explanation should be subjected to further empirical scrutiny. To this end, models that couple the quantile estimator with specifications that include interactions to allow the effect of fuel price to vary according to socioeconomic attributes, such as income, hold much promise.

References

Baum, C. F., Schaffer, M. E., and Stillman, S. (2007). ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML, and k-class regression. Boston College Department of Economics, Statistical Software Components S425401. Available at: `http://ideas.repec.org/c/boc/bocode/s425401.html`.

Coglianese, J., Davis, L. W., Kilian, L., and Stock, J. H. (2017). Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand. *Journal of Applied Econometrics*, 32(1):1–15.

Dillon, H. S., Saphores, J.-D., and Boarnet, M. G. (2015). The impact of urban form and gasoline prices on vehicle usage: Evidence from the 2009 National Household Travel Survey. *Research in Transportation Economics*, 52:23–33.

Dimitropoulos, A., Oueslati, W., and Sintek, C. (2016). The Rebound Effect in Road Transport: A Meta-Analysis of Empirical Studies. *OECD Environment Working Papers*, 113.

EPA (2018). Sources of Greenhouse Gas Emissions. Washington D.C.: United States Environmental Protection Agency. Available at: `https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions`.

Frondel, M., Ritter, N., and Vance, C. (2012). Heterogeneity in the rebound effect: Further evidence for Germany. *Energy Economics*, 34(2):461–467.

Frondel, M. and Vance, C. (2009). Do high oil prices matter? Evidence on the mobility behavior of German households. *Environmental and Resource Economics*, 43(1):81–94.

Gillingham, K. (2014). Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California. *Regional Science and Urban Economics*, 47:13–24.

Gillingham, K., Jenn, A., and Azevedo, I. M. (2015). Heterogeneity in the Response to Gasoline Prices: Evidence from Pennsylvania and Implications for the Rebound Effect. *Energy Economics*, 52:41–52.

Goodwin, P., Dargay, J., and Hanly, M. (2004). Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review. *Transport Reviews*, 24(3):275–292.

Graham, D. J. and Glaister, S. (2002). The Demand for Automobile Fuel: A Survey of Elasticities. *Journal of Transport Economics and Policy*, 36(1):1–25.

Hughes, J., Knittel, C., and Sperling, D. (2008). Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand. *The Energy Journal*, 29(1):113–134.

Kaechele, A. and Slusky, D. J. (2018). With and without the tracks: how railroad access impacts gas price elasticity. *Applied Economics Letters*, 25(16):1113–1116.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, 133(1):97–126.

Koenker, R. and Bassett Jr, G. (1978). Regression Quantiles. *Econometrica*, 46(1):33–50.

Koenker, R. and Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, 15(4):143–156.

Langer, A., Maheshri, V., and Winston, C. (2017). From Gallons to Miles: A disaggregate Analysis of Automobile Travel and Externality Taxes. *Journal of Public Economics*, 152:34–46.

Levin, L., Lewis, M. S., and Wolak, F. A. (2017). High Frequency Evidence on the Demand for Gasoline. *American Economic Journal: Economic Policy*, 9(3):314–47.

Li, S., Linn, J., and Muehlegger, E. (2014). Gasoline Taxes and Consumer Behavior. *American Economic Journal: Economic Policy*, 6(4):302–42.

Lin, C.-Y. C. and Prince, L. (2013). Gasoline Price volatility and the Elasticity of Demand for Gasoline. *Energy Economics*, 38:111–117.

Liu, W. (2014). Modeling Gasoline Demand in the United States: A flexible semiparametric Approach. *Energy Economics*, 45:244–253.

Liu, W. (2015). Gasoline Taxes or Efficiency Standards? A heterogeneous Household Demand Analysis. *Energy Policy*, 80:54–64.

Liu, W. (2016). Estimating the elasticities of gasoline demand: an instrumental variable approach. *Applied Economics Letters*, 23(16):1153–1156.

Rentziou, A., Gkritza, K., and Souleyrette, R. R. (2012). VMT, Energy Consumption, and GHG Emissions Forecasting for Passenger Transportation. *Transportation Research Part A: Policy and Practice*, 46(3):487–500.

Small, K. A. and Van Dender, K. (2007). Fuel efficiency and motor vehicle travel: the declining rebound effect. *The Energy Journal*, 28(1):25–51.

Stock, J. H. and Yogo, M. (2002). Testing for weak instruments in linear IV regression. National Bureau of Economic Research Cambridge, Mass., USA.

Su, Q. (2010). Travel Demand in the US Urban Areas: A system dynamic panel data approach. *Transportation Research Part A: Policy and Practice*, 44(2):110–117.

Su, Q. (2012). A quantile regression analysis of the rebound effect: Evidence from the 2009 National Household Transportation Survey in the United States. *Energy Policy*, 45:368–377.

Wang, T. and Chen, C. (2014). Impact of fuel price on vehicle miles traveled (VMT): do the poor respond in the same way as the rich? *Transportation*, 41(1):91–105.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press.