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Gasoline Demand in Middle-Income Countries

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Abstract

Among the policy tools available to restrict emissions from road transport are price-based instruments. To accurately gauge their effect, accurate measures of gasoline elasticities are needed. A large literature is devoted to determining the price and income elasticities related to gasoline. Using recently developed quantile regression tools on a panel of middle-income countries, we assess the heterogeneity in gasoline consumption in response to changes in gasoline prices. The estimated median elasticities are -0.7 and 0.511 for the price and income elasticities respectively. An interesting finding is the case of jointly increasing incomes and prices reduces gasoline consumption at the median while at lower quantiles this may increase gasoline consumption. This finding shows that using quantile regression offers valuable benefits for policy makers who need a thorough understanding of the markets for gasoline to evaluate various policies.

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1 Introduction

CO_2 emissions from transport are now responsible for about a quarter of total emissions from fuel combustion and still growing (IEA, 2019). Three quarters of these emissions are from the road sector. Decarbonizing transport is critical, especially road transport. A variety of methods have been suggested including taxes on fuels like gasoline since consumers respond strongly to gasoline tax changes (Li et al., 2014). A tool to assess the effectiveness of taxation policy is the price elasticity which is usually computed as an OLS estimate. This leads to interesting questions; how does the elasticity vary around the mean and if so how does higher gasoline prices translate to reducing gasoline demand within the middle-income countries. The answer to these questions are important for policy makers and energy and economic modelers when they evaluate policies relating to oil security, emission reductions, tax collection and fiscal policy and addressing other transport related externalities. As such, accurate estimates of the responsiveness are needed as policy makers attempt to model various policies to reduce gasoline consumption.

A large literature is devoted to determining the price elasticity (the relationship between fuel price and consumption) and income elasticity (the relationship between income and consumption) related to gasoline. According to a meta-analysis by Havranek et al. (2012), the long-run price elasticities ranged between -1.59 to -0.1. This range of values for the price elasticity is quite different from estimates in the recent literature. The elasticities found in Burke and Nishitateno (2013), Arzaghi and Squalli (2015), Dahl (2012), Labandeira et al. (2017), and Birol and Guerer (1993) are within a smaller range of -0.04 to -0.77. With this in mind, the aim of this paper is to explore the distributional heterogeneity of gasoline consumption.

We study a panel of 46 middle-income countries from 1998 to 2016 to assess the heterogeneity in gasoline consumption in response to changes in gasoline prices. Thus, this study contributes to the analysis of price elasticities in several aspects. First, existing studies analyze the relationship between prices and energy consumption using OLS methods focusing on the conditional mean. This approach ignores the heterogeneous effects of prices and incomes on consumption. To overcome this shortcoming quantile regression methods are employed. Quantile regression provides a full description of the conditional distribution of gasoline consumption estimating the relationship at various quantiles presenting a more thorough assessment of the impact of prices and incomes on consumption. Furthermore, quantile regression is robust to outliers and more reliable in cases when non-normal errors are present.

Second, the issue of price endogeneity often plagues cross-country studies of energy demand, see Burke and Nishitateno (2013) and Arzaghi and Squalli (2015) for a discussion. Tests reveal that endogeneity between prices and consumption is present in this panel so to overcome this issue, an instrumental variable panel quantile regression approach is used. Finally, the study limits attention to a group of countries, whom as a group represent the fastest growing consuming countries of gasoline. The change in consumption of the non-OECD was 116.4% compared to the decline of -7.6% in the OECD and the growth in non-OECD consumption is driven by middle-income countries. This last contribution represents a departure from the standard mixing of high-income countries with middle-income countries, for whom characteristics differ (Bhattacharyya and Timilsina, 2010; Labandeira et al., 2017). This study also updates previous studies including observations since the oil price collapse in 2014 and fossil fuel subsidy reforms undertaken in many countries since 2015. These advantages offer valuable benefits for policy makers who need a thorough understanding of the markets for gasoline to evaluate various policies.

Our results show both short-run elasticities are inelastic, the median price elasticity is -0.7 and the median income elasticity is 0.511, consistent with past research on this topic. An interesting finding is that the price elasticities become more elastic moving towards the median from the lower quantiles. This highlights that in the lower quantiles, there is less price sensitivity; fuel taxation may have more success near the median country while less effectual at lower quantiles. In addition, at the lower quantiles the income elasticity suggests that increasing incomes and prices simultaneously may increase gasoline consumption over some ranges of price increases whereas at the median and upper quantiles these ranges lead to a fall in consumption. This interesting situation is hidden using conventional OLS methods demonstrating the value in using quantile regression methods.

The rest of this article is organized as follows: the next section presents the methodology and data description. Section three compares the results from baseline OLS methods with those from the instrumental variable quantile regression. The final section concludes.

2 Method and data

2.1 Method

The main goal of this paper is to explore the distributional heterogeneity of gasoline demand. Our primary tool is quantile regression which has several advantages over OLS and fixed effects. First, it moves beyond central moments. Second, it is robust to outliers and heavy tails. Third, it provides a summary of the conditional distribution; offering more insight into the relationships between dependent and independent variables (Koenker, 2005). The basic demand equation to estimate the price and income elasticities is

$$\log(Qpc)_{it} = \beta_1 + \beta_2 \log(Price_{it}) + \beta_3 \log(GDPpc_{it}) + \beta_4 \log(popdens_{it}) + \epsilon_{it}, \qquad (1)$$

with Qpc_{it} is gasoline consumption per capita, $GDPpc$ is GDP per capita proxying for income, $Price_{it}$ is the real pump price of gasoline, and the control variable $popdens$ is population density for country i and year t. This specification was used by Burke and Nishitateno (2013).[1]

As a general quantile regression for log gasoline consumption (setting $y_{it} = \log(Qpc)_{it}$) is

$$Q_{y_{it}}(\tau | d_{it}, x_{it}, \alpha_i) = d'_{it}\delta(\tau) + x'_{it}\beta(\tau) + \alpha_i(\tau) \qquad (2)$$

[1]There is support for this specification using the the method described in Parker (2018).

where τ is a quantile, d is the price variable, x are the exogenous income and density variables and α_i is the country effects. Harding and Lamarche (2009) show that in a fixed effects with endogenous regressor model the objective function for the conditional instrumental quantile relationship is:[2]

$$R(\tau, \delta, \beta, \gamma, \alpha) = \sum_{t=1}^{T} \sum_{i=1}^{N} \rho_\tau [y_{it} - d'_{it}\delta - x'_{it}\beta - \alpha_i - \hat{w}'_{it}\gamma], \tag{3}$$

where $\rho_\tau = u(\tau - I(u \leq 0))$ is the quantile loss function, τ is a quantile, $\hat{w}$ is the OLS projection of the endogenous variable d on the instruments w, and x are the exogenous variables. Harding and Lamarche (2009) use a two-step approach; first minimizing the above objective function for β, γ, and α as functions of τ and δ,

$$\left\{\hat{\beta}(\tau, \delta), \hat{\gamma}(\tau, \delta), \hat{\alpha}(\tau, \delta)\right\} = arg \min_{\beta,\gamma,\alpha} R(\tau, \delta, \beta, \gamma, \alpha), \tag{4}$$

then, secondly, estimate the coefficient on the endogenous variable d by finding the value of δ which minimizes the weighted distance function defined on γ:

$$\hat{\delta}(\tau) = arg \min_{\delta} \hat{\gamma}(\tau, \delta)' \mathbf{A} \hat{\gamma}(\tau, \delta), \tag{5}$$

with positive definite matrix $\mathbf{A}$. The standard errors needed to do inference are obtained from the covariance estimates outlined in Koenker (2004) and Harding and Lamarche (2009).[3]

2.2 Data

The data used in this analysis are sourced primarily from the IEA energy balances (IEA, 2018). We obtain motor gasoline consumption in the road sector measured in ktoe, national output measured as GDP (billion 2010 USD using PPPs), and population in millions (POP). We use per capita consumption figures for GDP and fuel consumption (divide by population). Local pump prices for gasoline and the national CPIs are from the World Bank Development Indicators (World Bank, 2017). The CPIs were used to deflate the price series. The fuel prices are reported every two-years (biennial) limiting the size of the panel.[4] Two control variables, population density and urban population percentage, were also collected from the World Bank Development Indicators but only population density proved to be relevant.[5]

Figure 1 shows a simple plot of gasoline consumption to prices and incomes with two simple regression estimates. The solid line shows the OLS estimates while the dashed line shows the median regression. In the case of national income, the two lines are close and nearly parallel

[2]This section closely follows the exposition in Harding and Lamarche (2009).

[3]The analysis is done in R using the packages `quantreg` (Koenker, 2018) and `plm` (Croissant and Millo, 2008).

[4]The CPI data was missing for some country-year combinations further limiting the panel size. The final panel is balanced.

[5]The appendix and supplementary sections have the data definitions and country lists.

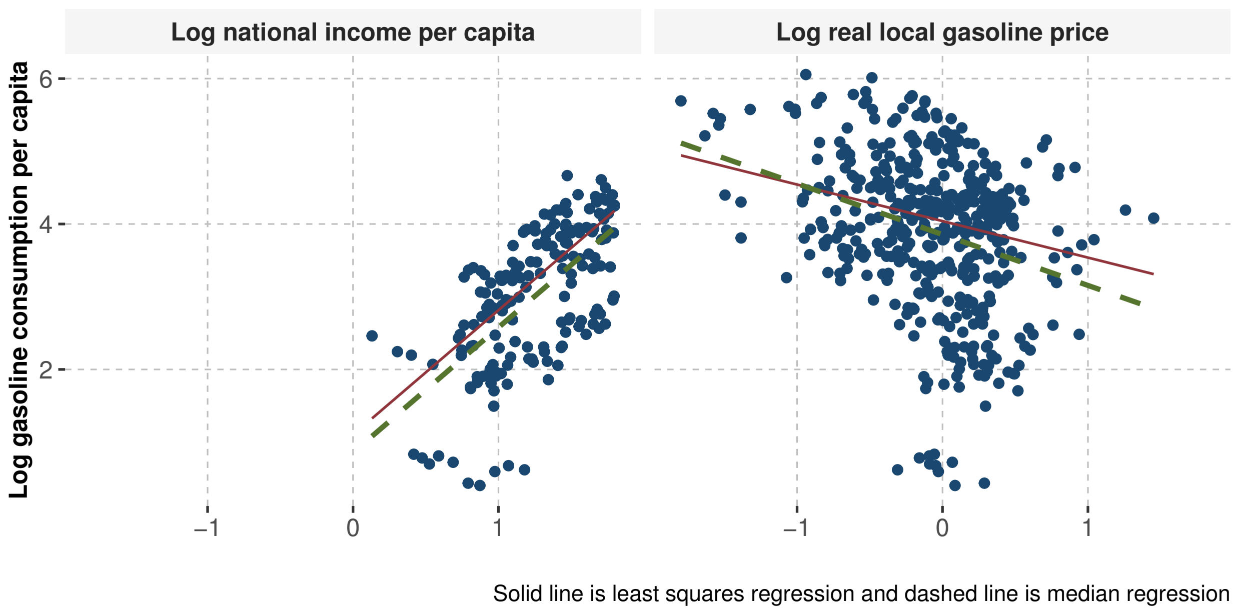

Figure 1: Differences between mean regression and median regression for gasoline consumption

but for prices the two lines have different slopes. This suggests, that the simple OLS line is being influenced by outliers and the median regression will provided better results of price elasticity. Furthermore, Table 1 shows the summary statistics for the dataset and we note that the Jarque-Bera test rejects the notion of normality for gasoline consumption, further casting doubt on the suitability of OLS for this dataset.

Table 1: Summary statistics for 2016

Variable	Mean	Median	Std dev.	Maximum	Minimum	1st Quartile	3rd Quartile	Jarque Bera
log gasoline consumption	4.1800	4.2577	0.9811	6.0556	0.6197	3.5588	4.7350	17.05***
log gasoline price	-0.5018	-0.4411	0.4510	0.1868	-2.0388	-0.6965	-0.1872	16.02***
log national income	2.2105	2.3559	0.6196	3.2254	1.0534	1.7940	2.6419	2.42
log population density	4.3802	4.4336	1.1170	7.1013	1.3380	3.9807	4.9557	3.3

Note:
Data are in logs. Std dev. refers to the standard deviation. Jarque Bera refers to the Jarque Bera test for normality. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively. N = 46 .

There are two prevailing views about the potential of gasoline price endogeneity. The first is that prices and quantities are determined jointly, the factors that determine the price are also those that determine consumption. The second view is that prices are determined in the international oil market and there is a separation between prices and quantities. This latter view has become the default, primarily due to a lack of valid instruments to tackle the endogeneity issue (van Benthem and Romani (2009); Arzaghi and Squalli (2015)). Burke and Nishitateno (2013) takes a cautious approach with endogeneity demonstrating that real world oil price is a satisfactory instrument for local prices, and this is the approach used in this paper.

3 Results

The results are grouped into three sections. In the first subsection we present baseline regression estimates using standard panel techniques. This provides a baseline to assess the average elasticities. These estimates are only a starting point, and the following subsection reports the results from the fixed effects quantile regressions. The last subsection discusses the results.

3.1 Baseline results

The baseline results are shown in Table 2. Four estimations are shown; pooled OLS (column 1), mean fixed effects (column 2), median fixed effects (column 3), and instrumental variables fixed effects (column 4).[6] The fixed effects models include country effects and global real oil prices are used to instrument for local gasoline prices for the model in column four. It can be clearly seen that the price and income elasticities are all statistically significant and have the expected sign. The mean and median fixed effect models report minor differences between them—the median results are slightly more elastic. These two models have the most inelastic price elasticities of the four models.

Table 2: Baseline regression estimates of gasoline demand

		Fixed Effects		
Variables	Pooled	Mean	Median	IV
log gasoline price	-0.402***	-0.123**	-0.179***	-0.776***
	(0.047)	(0.051)	(0.034)	(0.179)
log per capita income	1.149***	0.47***	0.581***	0.413***
	(0.048)	(0.114)	(0.096)	(0.091)
log population density	-0.186***	0.764***	0.459***	0.125
	(0.028)	(0.224)	(0.156)	(0.268)
Adj. R-Squared	0.703	0.318		0.102

Note:
***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively. Figures in parentheses are double clustered standard errors. Median fixed effect regression use sandwich standard errors. IV is fixed effects with instrumental variable estimation (Generalized two-stage least squares method). Real oil price is used as instrument for log fuel price. Number of observations is 460. FE models have country fixed effects.

[6] Generalized two-stage least squares method used.

Table 3: Quantile fixed effects instrumental regression estimates of gasoline demand

Variables	0.25	0.5	0.75
log gasoline price	-0.322***	-0.7***	-0.673***
	(0.107)	(0.085)	(0.07)
log per capita income	0.491**	0.511***	0.454***
	(0.211)	(0.049)	(0.047)
log population density	0.535***	0.391***	0.292
	(0.201)	(0.136)	(0.269)

Note:
***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively. Figures in parentheses are standard errors computed with the quantile regression sandwich formula. Real oil price is used as instrument for log fuel price.

The IV estimates are the largest in absolute value (|-0.78|) being the most elastic estimate. The income elasticities of the fixed effects models are similar, in the range 0.41 and 0.58 while the pooled income elasticity is elastic (1.15). A test of poolability reveals that the fixed effects model should be preferred over the pooled model. Turning to the issue of price endogeneity testing reveals that prices are indeed endogenous in this dataset, and the model in column four is preferred. The first stage regression was sound; correctly signed coefficients and the real global oil price should not be considered a weak instrument.

3.2 Quantile regression results

Table 3 presents the results from the instrumental variable fixed effects quantile regression for the first (column 1), second (column 2), and third (column 3) quartiles. The standard errors are computed with the quantile regression sandwich formula. As was the case for the results in Table 2, the price and income elasticities are significant and correctly signed. The income elasticities do not change much, although the median is slightly larger than the first and third quartiles. While increasing gasoline prices decreases gasoline consumption, its effects are more inelastic at lower consumption levels than at higher consumptions levels. Overall, the results suggest that the impact of prices on consumption are heterogenous.

Figure 2 presents the quantile plots of the elasticities. The horizontal lines are the IV estimates from Table 2 with a two standard error band indicated by the dashed lines. The price elasticities fall across the quantiles, but this is not constant. There is a decline from the lowest quantiles to the median value, then it levels off until about the third quantile where it starts to decline again. Most of the quantile estimates lie above the IV mean estimator and are enclosed in the corresponding confidence band. The income elasticity lies within the two standard error confidence band except at the upper extreme quantiles. Just like the price elasticities, most of the estimates lie above the IV estimator.

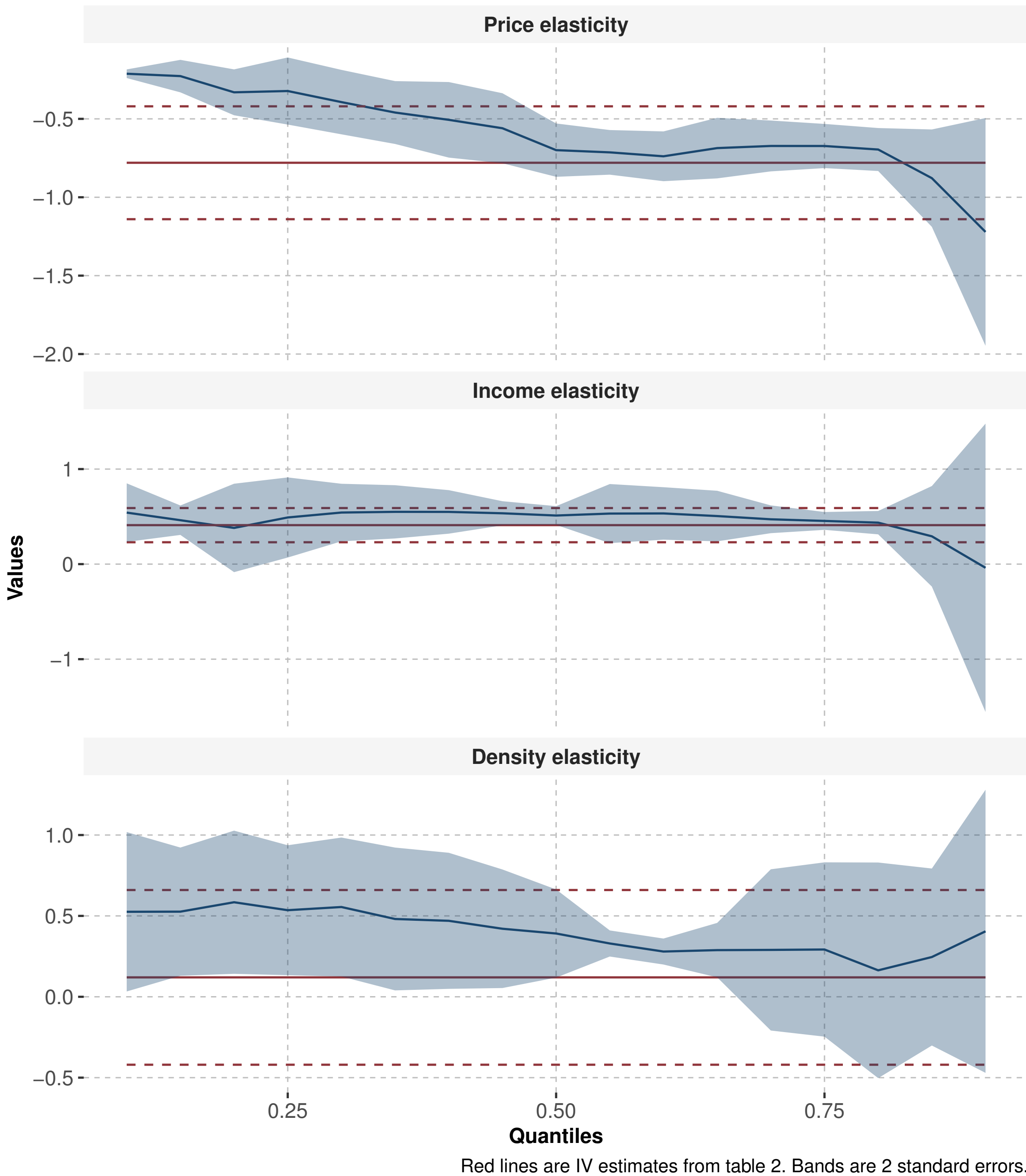

Figure 2: Change in quantile coefficients

3.3 Discussion

The price elasticities reported in this paper are mid-range compared to the range reported in Havranek et al. (2012) (short-run -0.96 to 0.08). However, they are larger than Havranek et al.'s estimate (-0.23) and those reported in Birol and Guerer (1993) and Arzaghi and Squalli (2015).[7] Furthermore, the results across the quantiles are consistent with the view that lower priced gasoline in developing countries has less reactive behavior than higher priced countries, such as the OECD countries. The range of income elasticities reported in the literature is quite wide; Havranek and Kokes (2015) reports a range of -1.13 to 2.98, the estimates from this paper are in the middle of this range. Developing country elasticities are expected to be higher due faster economic growth. There was less support for this from our data as the income elasticities were similar across all the quantiles. The income elasticities in this paper are similar in magnitude to those in Birol and Guerer (1993) which are less than those in Burke and Nishitateno (2013). The distribution of price elasticities varies more than the income elasticities in our sample. Whether this result is observed in other samples is unknown and is under investigation. In summary, the price elasticities in this paper are larger than some recent studies and are quite heterogenous; they become more elastic moving towards the median from the lower quantiles.

To understand some implications of the results, we identify the minimum gasoline price taxes needed to reduce gasoline consumption across all quartiles based on various changes in income. The changes in income are collected from the World Bank national accounts data for three middle-income groups: lower middle-income, middle-income, and upper middle-income (World Bank, 2019). The results are shown in Table 4. At an income change of 4.3% the gasoline price change needs to be larger than 6.5% whereas at a change of 5.5% the price change needs to exceed to 8.4%. Policy analysts would need to consider whether the size of these would be acceptable to consumers.

Table 4: Minimum tax rate needed to ensure reduced gasoline consumption for various income changes

	Upper middle-income	Middle-income	Lower middle-income
Q1	0.00	0.00	0.00
Q2	-2.39	-2.55	-3.07
Q3	-2.46	-2.62	-3.16
Growth rate (2018)	4.30	4.60	5.50
Tax rate	6.55	7.00	8.40

[a] Growth rates are from the World Bank (World Bank, 2019)

[7] Birol and Guerer (1993) reports elasticities between -0.04 and -0.29 for six developing countries. Arzaghi and Squalli (2015) studied 32 fuel subsidizing countries and report an elasticity of -0.25.

4 Summary and concluding remarks

How gasoline demand reacts to changes in prices and income has important ramifications associated with climate change, optimal taxation and energy security. As such, this paper investigates the distributional heterogeneity of gasoline consumption of middle-income countries . A sample of 46 middle-income countries with biennial observations between 1998 and 2016 was studied. The results find that the short-run median income elasticity is 0.511 while the short-run median price elasticity around -0.7. The reported price elasticities are larger than those in some recent studies. An interesting finding is that the price elasticities become more elastic moving towards the median from the lower quantiles.

The estimated price elasticities are inelastic, reflecting the lack of close substitutes for gasoline in transport. What is revealing is that lower consumption countries tend to have lower price responsiveness than the higher consumption countries. This indicates a gasoline taxation policy, is likely to be ineffective in some countries to reduce gasoline consumption. In fact, at the lower quantiles the elasticities suggest that if both incomes and prices increase jointly, for some price changes, gasoline consumption may increase whereas at the median and upper quantiles gasoline consumption will fall. Therefore, in low response countries, a shift policy (moving commuters to public transportation) may have better results and be more acceptable at reducing gasoline consumption.

References

Arzaghi, M., Squalli, J., 2015. How price inelastic is demand for gasoline in fuel-subsidizing economies? Energy Economics 50, 117–124. https://doi.org/10.1016/j.eneco.2015.04.009

Bhattacharyya, S.C., Timilsina, G.R., 2010. Modelling energy demand of developing countries: Are the specific features adequately captured? Energy Policy 38, 1979–1990. https://doi.org/10.1016/j.enpol.2009.11.079

Birol, F., Guerer, N., 1993. Modelling the transport sector fuel demand for developing economies. Energy Policy 21, 1163–1172. https://doi.org/10.1016/0301-4215(93)90267-J

Burke, P.J., Nishitateno, S., 2013. Gasoline prices, gasoline consumption, and new-vehicle fuel economy: Evidence for a large sample of countries. Energy Economics 36, 363–370. https://doi.org/10.1016/j.eneco.2012.09.008

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: The plm package. Journal of Statistical Software, Articles 27, 1–43. https://doi.org/10.18637/jss.v027.i02

Dahl, C.A., 2012. Measuring global gasoline and diesel price and income elasticities. Energy Policy 41, 2–13. https://doi.org/10.1016/j.enpol.2010.11.055

Harding, M., Lamarche, C., 2009. A quantile regression approach for estimating panel data models using instrumental variables. Economics Letters 104, 133–135. https://doi.org/10.1016/j.econlet.2009.04.025

Havranek, T., Irsova, Z., Janda, K., 2012. Demand for gasoline is more price-inelastic than commonly thought. Energy Economics 34, 201–207. https://doi.org/10.1016/j.eneco.2011.09.003

Havranek, T., Kokes, O., 2015. Income elasticity of gasoline demand: A meta-analysis. Energy Economics 47, 77–86. https://doi.org/10.1016/j.eneco.2014.11.004

IEA, 2019. Tracking clean energy progress, Transport (TCEP) [WWW Document]. URL https://www.iea.org/tcep/transport/ (accessed 9.30.2019).

IEA, 2018. World Energy Balances 2017. International Energy Agency. https://doi.org/10.1787/world_energy_bal-2017-en

Koenker, R., 2018. Quantreg: Quantile regression.

Koenker, R., 2005. Quantile regression, Econometric society monographs. Cambridge University Press. https://doi.org/10.1017/CBO9780511754098

Koenker, R., 2004. Quantile regression for longitudinal data. Journal of Multivariate Analysis 91, 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Labandeira, X., Labeaga, J.M., López-Otero, X., 2017. A meta-analysis on the price elasticity of energy demand. Energy Policy 102, 549–568. https://doi.org/10.1016/j.enpol.2017.01.002

Li, S., Linn, J., Muehlegger, E., 2014. Gasoline taxes and consumer behavior. American Economic Journal: Economic Policy 6, 302–42. https://doi.org/10.1257/pol.6.4.302

Parker, S., 2018. Transport fuel demand for non-OECD countries. USAEE Working Paper 18-334.

van Benthem, A., Romani, M., 2009. Fuelling growth: What drives energy demand in developing countries? The Energy Journal 30, 91–114. https://doi.org/10.2307/41323369

World Bank, 2019. World Bank national accounts data (ny.gdp.mktp.kd.zg). The World Bank.

World Bank, 2017. World Development Indicators. The World Bank.

Appendix

Table 5: Variable definitions

Variable	Definition	Units	Source
Gasoline consumption	Per capita road motor gasoline consumption excl. biofuels	Kilograms of oil equivalent	IEA World Energy Balances
Gasoline price	Real pump price for gasoline	US$ per liter	World Development Indicators
Income	Per capita GDP	Thousand 2010 USD using PPPs	IEA World Energy Balances , Indicators
Population density	Population density	people per sq. km of land area	World Development Indicators
Population	Population	Million papers	IEA World Energy Balances , Indicators

Note:
All of the data are biennial over the period 1998-2016.

Table 6: Country groupings

	Income group	
Region	Upper middle-income	Lower middle-income
Europe & Central Asia	9	1
Middle East & North Africa	2	3
Sub-Saharan Africa	2	7
Latin America & Caribbean	8	3
South Asia	1	3
East Asia & Pacific	3	4