THE EFFECT OF CHANGES IN FUEL PRICES ON THE USE OF ROAD TRANSPORTATION IN ONTARIO

Sina Motamedi, Transportation Economics Office, Ontario Ministry of Transportation

Background

The purpose of this study is to measure the elasticity of vehicle-kilometers travelled in Ontario with respect to fuel prices. This elasticity is useful for understanding the response to road transportation use that may arise if Ontario were to implement a carbon pricing regime such as a carbon tax or cap-and-trade system, both of which would lead to a rise in fuel prices. We find that the elasticity of vehicle-kilometers travelled in Ontario with respect to the price of gasoline is within the range of -0.07 and -0.16, and our preferred model yields an elasticity of -0.12. We also found that while fuel economy negatively impacts fuel consumption with an elasticity close to -1.00, fuel economy *positively* impacts vehicle-kilometres overall with an elasticity close to 1.5. This implies that as fuel economy improves, people generally choose to use more road transportation in addition to saving on fuel consumption.

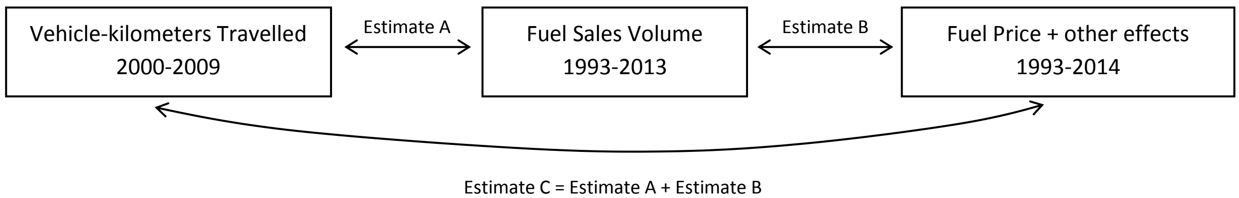
Overview

We intend to estimate vehicle kilometres travelled as a function of gasoline price (among other effects) in Ontario. Vehicle-kilometre data for Ontario exists from Statistics Canada, but is only available for 2000-2009 as the Canadian Vehicle Survey was only conducted for that time period. This limited sample period makes it difficult to adequately estimate the impact of prices and other economic variables on road transportation use directly from vehicle-kilometer data.

To work around this limited sample size, we will link Ontario vehicle-kilometers data with Ontario road-fuel consumption data, which is available from Statistics Canada for a much longer time-period (1993-2013) and will be updated going forward. Once vehicle-kilometers are adequately linked to fuel consumption, we can then estimate the impact of prices and other variables on *fuel consumption* and link these effects back to vehicle-kilometers travelled. This approach works because vehicle-kilometers are highly correlated with road-fuel consumption, thus minimizing the error associated with combining the two estimated equations. This approach will thus yield more robust estimates for vehicle-kilometers elasticities than if only the limited vehicle-kilometer data was used.

The procedure is outlined in the graphic below:

Figure 1: Overview of Estimation Process



In the end, we will have estimated two equations and combined them to create a third.

Jumping ahead, these equations will turn out to be:

$$\ln(K_t) = \alpha_0 + \alpha_1 \ln(Q_t) + \alpha_2 \ln(\eta_t) + error \tag{A}$$

$$\ln(Q_t) = \beta_0 + \beta_1 \ln(P_t) + \beta_2 \ln(\eta_t) + \beta_3 \ln(\Omega_t) + \ error \tag{B}$$

where, for period t, K_t is vehicle-kilometres travelled, Q_t is the volume of fuel consumption, η_t is fuel economy, P_t is fuel price, and Ω_t is population.

Since both equations (A) and (B) have simple log-linear forms, they can be easily combined to express our final equation:

$$\boxed{\ln(K_t) = \gamma_0 + \gamma_1 \ln(P_t) + \gamma_2 \ln(\eta_t) + \gamma_3 \ln(\Omega_t) + error} \tag{C}$$

By design, the coefficients in equation (C) represent elasticities of vehicle-kilometers and, in particular, γ_1 is the elasticity of vehicle-kilometres with respect to the price of fuel. Note that fuel economy η_t appears as an independent variable in both equations (A) and (B). Since fuel economy η_t should have opposite impacts on vehicle-kilometres (positively) and fuel consumption (negatively), including η_t in both equations (A) and (B) allows the proper, separate estimation of both impacts. The overall fuel economy impact on vehicle kilometres becomes known once equations (A) and (B) are combined to create equation (C).

(A) Estimating Vehicle-Kilometers from Road Fuel Consumption

With an overview of our methodology summarized, we can now begin the actual work of obtaining estimates. We start by first estimating vehicle-kilometres travelled from fuel sales volume by now more formally writing equation (A), but with properly defined variables and error term:

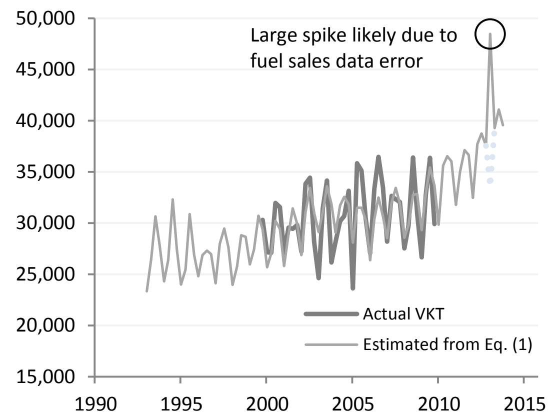
$$\ln(K_t) = \alpha_0 + \alpha_1 \ln(Q_t) + \alpha_2 \ln(\eta_t) + \kappa_t \tag{1}$$

where K_t is vehicle-kilometres travelled in Ontario, Q_t is the volume of fuel purchased for road-use in Ontario, η_t is a proxy for average fuel economy in the US, and $\kappa_t \sim \text{WN}(0, {\sigma_\kappa}^2)$. The OLS estimates for equation (1) are displayed in Table A1.1 in Appendix 1.

Table 1: OLS Estimates for Eq. (1)

$\ln(K_t) \sim$	Coefficient Estimate	t-Test P-value
α_0	-12.76	0.058
$\alpha_1 \ln(Q_t)$	1.63	0.000
$\alpha_2 \ln(\eta_t)$	3.22	0.051
DW P-value	0.11	
Ljung-Box P-value	0.39	
Time Period	1999Q1 – 2009Q4	
Frequency	Quarterly	
Sample Size	41	
R^2	0.49	
Adjusted R^2	0.46	

Figure 2: Actual and Fitted VKT from Eq. (1)



Note that the coefficient estimates for fuel consumption and fuel efficiency are both positive as would be expected from economic theory.

From Figure 2 above, notice that the original vehicle-kilometer data exhibits irregular seasonal patterns: the third quarter usually has the highest incidence of road travel but in some years is displaced by either the second or fourth quarter. Furthermore, notice that the vehicle-kilometer data exhibits higher seasonality than what would be expected if we had looked *only* at fuel volume consumption. That is, fuel volume consumption varies *much less* than vehicle-kilometers travelled. This is a strange result as these two series *should* be very correlated, nearly one-for-one, especially in the short-run, assuming that fuel mileage is consistent throughout the seasons. There are some possible explanations for why these seasonal inconsistencies exist. For one, some periods may experience higher road traffic and congestion, thus reducing the distance one can achieve from a given volume of fuel. This however is not consistent with the vehicle-kilometer data, since congestion in peak travel periods should cause vehicle-kilometers to be *less* varied than what is suggested by the fuel consumption data since vehicles will experience lower fuel efficiency in peak congestion periods and higher fuel efficiency in congestion troughs. A more likely explanation is that this discrepancy is due to the nature of the trips taken: longer, more leisure road trips taken in the summer are more fuel efficient and thus achieve higher fuel mileage in peak travel periods – resulting in higher seasonal variability in vehicle-kilometres travelled. This, however, still does not explain the seasonal irregularity observed in the vehicle-kilometres data.

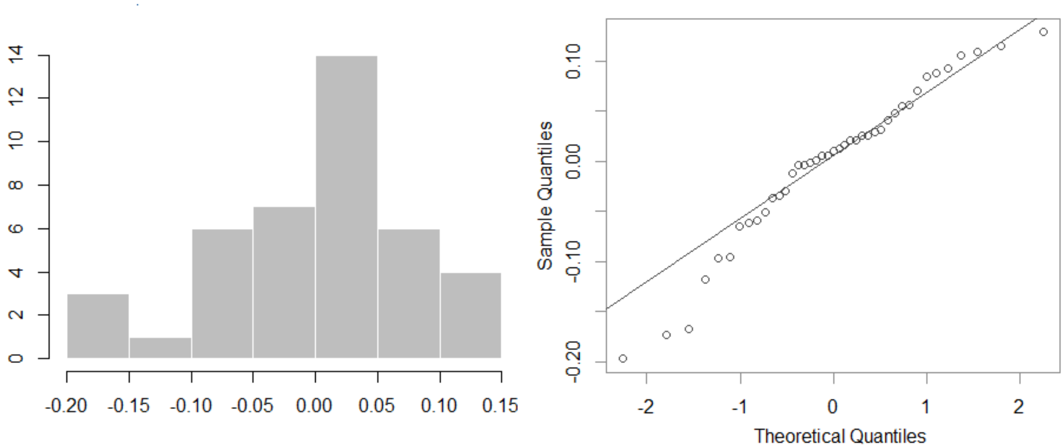
Lastly, the seasonal discrepancies may be due to the nature of the vehicle-kilometres data source, which is based on surveying drivers and is thus susceptible to memory bias. In particular, there may be a significant risk of some survey respondents incorrectly reporting their dates and distance of travel, which could cause *both* irregular and exaggerated seasonality in the vehicle-kilometer data. We suspect that this is at least somewhat true. If so, and if pervasive enough, the fitted vehicle-kilometer values from equation

(1) may be estimating short-run seasonal fluctuations *better* than the original vehicle-kilometer data – though this claim is only speculative.

Regardless of the reason, we do not need to be too concerned with these seasonal discrepancies observed in the vehicle-kilometre data as long as the discrepancies average out to zero, because we will then still be obtaining efficient regression estimates for the coefficients we are interested in measuring.

To check that equation (1) is well-specified, we can inspect the characteristics of its residuals. To start, both the Durbin-Watson and the Ljung-Box tests (listed in Table 1) show little evidence of autocorrelation in the residuals, so we need not worry about that. To analyze the distribution of the residuals, we can inspect the histogram and QQ-plot.

Figure 3: Histogram and QQ-plot of Residuals from Eq. (1)



Inspecting the histogram and QQ-plot above, we can see that, though noisy due to the limited sample size, the residuals are mostly well-behaved. There is evidence of negative skewness, however we are not too concerned with this result. Note that we believe that fuel consumption and fuel economy are highly significant to vehicle-kilometres *a priori* and are merely attempting to measure the magnitude of the relationship, as opposed to testing whether a relationship exists at all. Since the distribution of the residuals does not affect the efficiency of the model estimates, only the corresponding P-values used to test significance, we are not very concerned with whether the residuals from equation (1) are exactly normally distributed. We thus proceed with equation (1) in hand.

Before moving on, take note of the large spike in the fitted vehicle-kilometers value in the first quarter of 2013. This spike in the expected vehicle-kilometers value is a direct result of a spike in fuel sales volume data for the same period, which we strongly believe to be a data error. As a result, we will be excluding the 2013Q1 fuel sales volume data point from our analysis by including an indicator variable for 2013Q1 when appropriate. For a detailed discussion as to why we believe this data point is an error, see Appendix 2.

(B) Estimating Road Fuel Consumption from Fuel Price

We now turn to estimating road-fuel consumption Q_t as a function of fuel price and other economic and demographic variables – that is, equation (B). For consistency with equation (1), and simplicity in interpretation, we again use an equation with log-linear form. Our base model form is:

$$\ln(Q_t) = \beta_0 + \beta_1 \ln(P_t) + \sum_X \beta_X X_t + \varphi_t \tag{2}$$

where P_t is the average *real* price of gasoline in Toronto in period t, $\{X\}$ are yet-to-be-determined variables, and $\varphi_t \sim \mathrm{WN}(0, {\sigma_\varphi}^2)$.

Estimates for various versions of equation (2) can be found in Appendix 1. Our preferred version of equation (2) is:

$$\ln(Q_t) = \beta_0 + \beta_1 \ln(P_t) + \beta_2 \ln(\eta_t) + \beta_3 \ln(\Omega_t) + \sum_D \beta_D \mathbf{1}_t(D) + \varphi_t \tag{3}$$

where η_t is a proxy for average fuel economy in the US in period t, Ω_t is the population of Ontario in period t, and $\mathbf{1}_t(D)$ are indicator variables for each quarterly period D. The quarterly indicators $\mathbf{1}_t(D)$ are used to capture seasonal effects that are inherent in the use of road transportation and, thus, fuel consumption.

The Durbin-Watson and Ljung-Box tests on the OLS residuals of equation (3) both show strong evidence of autocorrelation. To correct for this autocorrelation, we introduce an AR(1) term ϕ_t into equation (3):

$$\ln(Q_t) = \beta_0 + \beta_1 \ln(P_t) + \beta_2 \ln(\eta_t) + \beta_3 \ln(\Omega_t) + \sum_D \beta_D \mathbf{1}_t(D) + \phi_t \tag{4}$$

where $\phi_t \equiv \rho\phi_{t-1} + \varphi_t \sim \mathrm{AR}(1)$ with autocorrelation ρ.

To estimate equation (4), we employ maximum-likelihood estimation which is commonly used for estimating ARIMA models. See Table A1.2 for the estimation results of equation (4).

Note that the coefficient estimates of our preferred model of equation (4), which include an AR(1) term, are very close to the corresponding coefficient estimates of equation (3). This robustness in the coefficient estimates strengthens our confidence in them.

(C) Vehicle-Kilometers as a Function of Gasoline Prices

With equation (4) in hand, we can obtain an equation for $\ln(K_t)$ that is dependent on the same variables by combining equation (4) with equation (1):

$$\ln(K_t) = \gamma_0 + \gamma_1 \ln(P_t) + \gamma_2 \ln(\eta_t) + \gamma_3 \ln(\Omega_t) + \sum_D \gamma_D \mathbf{1}_t(D) + \varepsilon_t \tag{5}$$

where $\gamma_0 \equiv \alpha_0 + \alpha_1\beta_0$, $\gamma_1 \equiv \alpha_1\beta_1$, $\gamma_2 \equiv \alpha_2 + \alpha_1\beta_2$, $\gamma_3 \equiv \alpha_1\beta_3$, $\gamma_D \equiv \alpha_1\beta_D$, $\varepsilon_t \equiv \alpha_1\phi_t + \kappa_t$, and $\varepsilon_t \equiv \alpha_1\phi_t + \kappa_t \sim$ ARMA(1,1).

Equation (5) is our final equation for vehicle-kilometres travelled and represents the demand function for road transportation. This is the equation which we are most interested in even though it is not being directly estimated. Note that the coefficients in equation (5) represent the elasticities of vehicle-kilometers and that, in particular, γ_1 is the elasticity of vehicle-kilometres with respect to the price of gasoline. See Appendix 1 for the estimation results of equation (5).

In our preferred model, the elasticity of vehicle-kilometers travelled with respect to the price of gasoline is -0.12 and is in line with previous studies in other jurisdictions. Reviewing other estimated model specifications (see Appendix 1), the gasoline price-elasticity ranges between -0.10 to -0.18, which is again in line with previous studies in other jurisdictions.

Discussion and Final Remarks

We have found that the elasticity of vehicle-kilometers travelled in Ontario with respect to the price of gasoline ranges from -0.07 to -0.16, with our preferred estimate being -0.12. We have also found that while fuel economy negatively impacts fuel consumption with an elasticity close to -1.00, fuel economy *positively* impacts vehicle-kilometres overall with an elasticity close to 1.5. This implies that as fuel economy improves, people generally choose to "spend" some of their fuel economy savings on more road transportation.

The work described in this paper is ongoing and other areas for further analysis are still being explored. Deeper analysis of freight vehicle-kilometres travelled, in particular, would help to better understand the link between fuel price, fuel consumption and carbon emissions. Exploratory analysis of trucking data in Ontario, using the same data sources used in this study, has yielded fuel price elasticities for freight vehicle-kilometre that are zero or, strangely, positive. We have little confidence in these preliminary estimates, however, because freight vehicle-kilometres are less behaved than for the general fleet and the limited sample period makes it difficult to adequately glean inference. Based on a review of previous studies as well as our own, we suspect that the price elasticity of vehicle-kilometres is likely to be smaller for freight vehicles than for the general vehicle fleet and possibly near zero. This is an area we are interested in and are still actively exploring. ▪

APPENDIX 1: Estimates of Model Specifications

Table A1.1: OLS Estimates for Eq. (3)

$\ln(Q_t) \sim$	**Preferred**	**Model 2**	**Model 3**	**Model 4**
β_0	-8.28 [0.000]	-17.74 [0.000]	-4.38 [0.000]	-
$\beta_1 \ln(P_t)$	-0.08 [0.001]	-0.16 [0.000]		-
$\beta_2 \ln(\eta_t)$	-0.99 [0.000]		-1.10 [0.000]	-
$\beta_3 \ln(\Omega_t)$	1.19 [0.000]	1.59 [0.000]	0.97 [0.000]	-
$\beta_4 \ln(U_t)$				-
Quarterly Indicators	Included	Included	Included	-
Indicator of 2013Q1 Outlier	Included	Included	Included	-
Durbin-Watson P-value	0.002	0.000	0.000	-
Ljung-Box P-value	0.000	0.000	0.000	-
Time Period	1995-2013	1995-2013	1995-2013	-
Frequency	Quarterly	Quarterly	Quarterly	-
Sample Size	84	84	84	-
R^2	0.96	0.93	0.96	-
Adjusted R^2	0.96	0.92	0.96	-

Note: Two-sided p-values in square brackets.

Table A1.2: MLE Estimates for Eq. (4)

$\ln(Q_t) \sim$	**Preferred**	**Model 2**	**Model 3**	**Model 4**
β_0	-7.87 [0.000]	-13.80 [0.000]	-4.46 [0.000]	11.44 [0.000]
$\beta_1 \ln(P_t)$	-0.07 [0.027]	-0.08 [0.096]		-0.04 [0.137]
$\beta_2 \ln(\eta_t)$	-1.00 [0.000]		-1.10 [0.000]	-1.08 [0.005]
$\beta_3 \ln(\Omega_t)$	1.17 [0.000]	1.35 [0.000]	0.98 [0.000]	
$\beta_4 \ln(U_t)$				
$\phi_t \sim \text{AR}(1)$	0.28 [0.007]	0.67 [0.000]	0.35 [0.001]	
$\phi_t \sim \text{AR}(4)$				Not listed.
Quarterly Indicators	Included	Included	Included	Captured by AR(4).
Indicator of 2013Q1 Outlier	Included	Included	Included	Included
Time Period	1995-2013	1995-2013	1995-2013	1995-2013
Frequency	Quarterly	Quarterly	Quarterly	Quarterly
Sample Size	84	84	84	84
R^2	0.97	0.95	0.96	0.94
Adjusted R^2	0.96	0.95	0.96	0.94

Note: Two-sided p-values in square brackets. See Glossary in Appendix 5 for variable descriptions.

Table A1.3: Induced Estimates for Eq. (5)

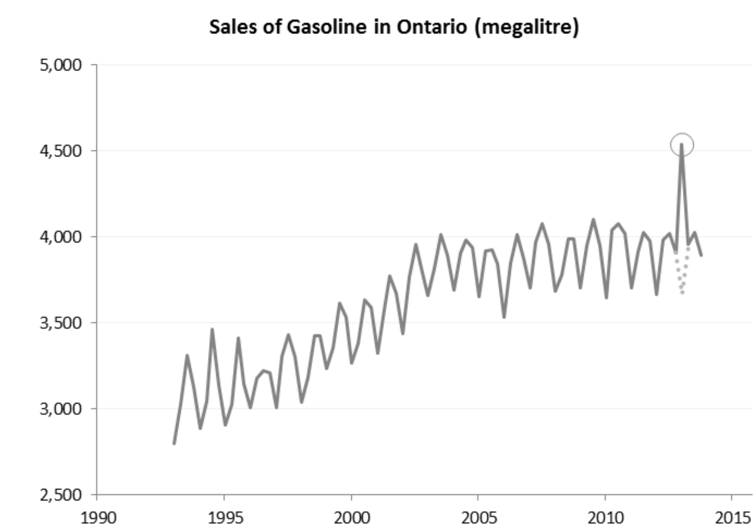
$\ln(K_t) \sim$	**Preferred**	**Model 2**	**Model 3**	**Model 4**
γ_0	-12.83	-22.52	-7.28	18.67
$\gamma_1 \ln(P_t)$	-0.12	-0.12		-0.07
$\gamma_2 \ln(\eta_t)$	1.59		1.43	1.46

$\gamma_3 \ln(\Omega_t)$	1.91	2.20	1.60	
$\gamma_4 \ln(U_t)$				
Quarterly Indicators	Included	Included	Included	Captured by ARMA(4,4).
Indicator of 2013Q1 Outlier	Included	Included	Included	Included
AR part of ARMA(1,1)	0.28	0.67	0.35	ARMA(4,4) components not computed.
MA part of ARMA(1,1)	4.16	1.99	3.45	
Time Period	1995-2013	1993-2013	1993-2013	1995-2013
Frequency	Quarterly	Quarterly	Quarterly	Quarterly
R^2	0.37	0.40	0.32	0.36
Adjusted R^2	0.25	0.32	0.22	0.33

Note: See Glossary in Appendix 5 for variable descriptions.

APPENDIX 2: Data Error in Sales of Gasoline in 2013Q1

We are highly skeptical of Statistics Canada's road-fuel sales data for 2013Q1, which experiences an unusual spike, and highly suspect it to be an error in the data.



From a consumer behaviour point of view, this spike is unusual since it occurs in the quarter that historically has the least volume of fuel sold each year (January to March). From a data quality point of view, this spike is also unusual since the source of this data is expected to be very reliable. We have explored several possible causes for this spike in fuel sales, including possible changes in provincial and federal fuel tax rates which could cause a response by both consumer consumption and by producers' bookkeeping for tax purposes (which is the original source of the road-fuel data). Unfortunately, we were unable to find any plausible explanations from either the consumer or producer side. We suspect that the spike in road-fuel volume sales seen in 2013Q1 is an error from Statistics Canada.

Data References

Variable	Description	Period	Source
K_t	Vehicle-kilometers travelled in Ontario	1999Q1-2009Q4	Statistics Canada, CANSIM Table 405-0008
Q_t	Road-use Fuel Consumption (megalitres)	1993Q1-2013Q4	Statistics Canada, CANSIM Table 405-0003
Pump Price	Average Price of Gasoline in Toronto	1993Q1-2014Q4	Statistics Canada, CANSIM Table 326-0009
CPI	Ontario Consumer Price Index	1993Q1-2014Q4	Statistics Canada, CANSIM Table 326-0020
P_t	Average *Real* Price of Gasoline in Toronto	1993Q1-2014Q4	$\equiv \frac{\text{Pump Price}}{\text{CPI}}$
Θ_t	Population of Ontario	1993Q1-2014Q4	Statistics Canada, CANSIM Table 051-0005
η_t	Proxy for Average Fuel Economy (miles per gallon)	1993Q1-2014Q4	Estimated using A_t and ξ_t. See Appendix 3 for details.
A_t	Average Age of US Vehicle Fleet	1995-2013	US Department of Transportation, National Transportation Statistics, Table 1-26
ξ_t	Average Adjusted Fuel Economy of New Gasoline and Diesel Vehicles in the US (miles per gallon)	1975-2014	US Environmental Protection Agency, "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2014," Table 2.1
U_t	Unemployment rate in Ontario	1993Q1-2014Q4	Statistics Canada, CANSIM Table 282-0085

References

Barla, P., Gilbert-Gonthier, M. and Kuelah, J.T. (2014). “The demand for road diesel in Canada.” *Energy Economics* 43, pp. 316-322.

Brons, M., Nijkamp, P., Pels, E. and Rietveld, P. (2006). “A Meta-analysis of the Price of Elasticity of Gasoline Demand. A Systems of Equations Approach.” Tinbergen Institute Discussion Paper.

Dahl, C.A. (2012). “Measuring global gasoline and diesel price and income elasticities.” *Energy Policy* 41, pp. 2-13.

De Borger, B. and Mulalic, I. (2012). “The determinants of fuel use in the trucking industry – volume, fleet characteristics and the rebound effect.” *Transport Policy* 24, pp. 284-295.

Hughes, J.E., Knittel, C.R. and Sperling, D. (2008). “Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand.” *The Energy Journal* 29(1), pp. 93-114.

Hymel, K.M., Small, K.A., and Van Dender, K.V. (2010). “Induced demand and rebound effects in road transport.” *Transportation Research Part B: Methodological* 44(10), pp. 1220-1241.

Johansson, O. and Schipper, L. (1997). “Measuring the Long-run Fuel Demand of Cars.” *Journal of Transport Economics and Policy* 31(3), pp. 277-292.

Noland, R.B. and Cowart, W.A. (2000). “Analysis of Metropolitan Highway Capacity and the growth in vehicle miles of travel.” *Transportation* 27(4), pp. 363-390.

Small, K.A. and Van Dender, K. (2007). “Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect.” *Energy Journal* 28(1), pp. 25-52.

Small, K.A. and Verhoef, E.T. (2007). *The Economics of Urban Transportation.* New York: Routledge. Print edition.

US Environmental Protection Agency (2014). "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2014." Table 2.1, pp. 5. US EPA-420-R-13-001, Office of Transportation and Air Quality, October 2014.
http://www.epa.gov/fueleconomy/fetrends/1975-2014/420r14023a.pdf

Wang, T. and Chen, C. (2013). “Impact of fuel price on vehicle miles traveled (VMT): do the poor respond in the same way as the rich?” *Transportation* 41(1), pp. 91-105.

Winebrake, J.J., Green, E.H., Comer, B., Chi, L., Froman, S. and Shelby, M. (2015). “Fuel price elasticities in the US combination trucking sector.” *Transportation Research Part D: Transport and Environment* 38, pp. 166-177.