Article:

Wadud, Z, Graham, DJ and Noland, RB (2010) Gasoline demand with heterogeneity in household responses. Energy Journal, 31 (1). 47 - 74. ISSN 0195-6574

https://doi.org/10.5547/ISSN0195-6574-EJ-Vol31-No1-3

Gasoline demand with heterogeneity in household responses

Zia Wadud

Daniel J. Graham

Robert B. Noland

Centre for Transport Studies
Dept of Civil and Environmental Engineering
Imperial College London
London SW7 2AZ

[This is a working paper version. An updated version was later accepted for publication in the Energy Journal]

Abstract

Fuel demand elasticities are typically based on aggregate data to determine consumer responses to tax increases or price shocks. However, this fails to capture the detailed distributional effect on different socio-economic groups, which is often needed to fully understand the impact of fuel tax measures. This paper presents results from a household level gasoline demand model which accommodates variation in price and income elasticity with increasing income as well as for different socio-economic groups in the USA. We find substantial heterogeneity in price and income elasticities based on demographic groupings and income groups.

Keywords: fuel price elasticity, income elasticity, panel data, distributional effects

Introduction

The large literature on gasoline demand elasticities has generally provided estimates of price and income elasticity for an entire country. These enable an understanding of the aggregate impact on demand due to a rise in fuel price or taxes; however, they likely miss the detailed distributional effect of price changes on different socio-economic groups. Recent studies of gasoline and travel demand suggest that there could be significant heterogeneity in the price sensitivity of different socio economic groups or geographic areas (Archibald and Gillingham 1980, 1981, Greening et. al. 1995, Kayser 2000, Nicol 2003, West 2004, West and Williams 2004, Wadud et. al. 2007).[1] This paper estimates price and income elasticities of gasoline demand considering the heterogeneous responses of different demographic and geographic characteristics using household level survey data. We also examine the distribution of price and income elasticities, across the sample population.

There are many reasons to believe that households in different socio-economic groups and geographical areas would react differently to the same price stimuli. For example, rural households would possibly respond less to a price change than urban households, because of the reduced availability of alternative transport modes (e.g. Blow and Crawford 1997, Santos and Catchesides 2004, Wadud et. al. 2007).

Different income groups can clearly have differing behavioural responses to changes in fuel prices. Lower income households in urban areas may be more sensitive to price changes and be inclined to switch modes easily, resulting in a higher than average price elasticity (West and Williams 2004, Wadud et. al. 2007). On the other hand, lower income households may already be driving as little as possible because of their budget constraints and may be unable to further reduce their level of driving, resulting in a lower price elasticity than average (Kayser 2000). Wealthier households may be less sensitive to a price change because of their higher income (Robinson 1969, Gertler et. al. 1987), yet they may have more options to reduce consumption as much of their driving may be discretionary, such as for leisure trips (Wadud et. al. 2007, Kayser 2000). They are also more likely to own more than one vehicle and can use their more fuel efficient vehicle more intensively in response to an increased price. In addition they may switch to air travel if the price of motor fuel increases relative to jet fuel prices (as the latter are not taxed in most countries). All these factors suggest substantial potential heterogeneity between income groups, based on their existing travel behaviour and constraints.

[1] Detailed reviews of the gasoline demand literature is available in Dahl and Sterner (1991), Sterner and Dahl (1992), Dahl (1995), Goodwin et. al. (2004), de Jong and Gunn (2001), Graham and Glaister (2002a, 2002b) and Basso and Oum (2007).

Income elasticities can also display heterogeneity between income groups. For example, the lowest income group could have a larger than average income elasticity if the extra income is spent on traveling more or buying a new car. On the other hand, if low income households face substantial budget constraints they may spend the extra income on other necessities, resulting in a lower than average income elasticity (Wadud et. al. 2007). For higher income groups, the income elasticity could depend upon whether there is demand satiation or not. If income is not a constraint on wealthy households and these households already travel as much as they desire, extra income may not result in more fuel consumption for road travel. Because of these various possible behavioural responses, it is difficult to predict a priori, which of these effects would dominate.

Those studies that examine the impact of fuel demand for different socio economic groups tend to use cross sectional household level data. The analyses are typically based on disaggregating the data into the desired socio-economic groups and then use group means to estimate group-level elasticities. For example, for a price elasticity estimate based on income quintiles, the models will use an interaction term between income and price in the functional specification, and then will use the mean incomes of the five quintiles to determine different price elasticities for those groups. Archibald and Gillingham (1980, 1981), Kayser (2000), West (2004), Yatchew and No (2001), Blow and Crawford (1997), Santos and Catchesides (2004) all use these interactions terms between price and income.

All of these econometric models which report the variation of price elasticity with respect to income or income groups, fail to account for heterogeneity on the basis of factors other than just income.[2] A price and income interaction term tells us the difference in price elasticities of two similar households that differ in income only and assumes the households are similar in all other aspects. Yet, a higher income household, in general, will tend to be larger, is more likely to be located in a non-rural setting and is also likely to own more vehicles, compared to lower income households.[3] Thus, clustering the households on the basis of income and reporting the price elasticity on the basis of only mean income of the group could give an incorrect elasticity estimate.

Wadud et. al. (2007) modelled gasoline demand for different income quintiles using another approach. They utilized 20 years of summary expenditure data from the Consumer Expenditure

[2] The approach taken in Greening et. al. (1995) and Nicol (2003) might have been able to circumvent this issue, however they did not model demand for different income groups. West and Williams (2004) estimate group-wise models, yet because of the nature of their model, their price elasticity is a linear function of income.

[3] Pucher and Renne (2003) show that for urban households, there is a positive correlation between household income, size and car ownership.

Survey (CEX, Bureau of Labor Statistics 2005) for five US income quintiles. By employing a seemingly unrelated regression technique (Zellner 1962) they found that, for an average representative household of each quintile, a curve of the price elasticity follows a U shape, that is, the absolute value of the price elasticity initially decreases as income increases but then increases again.[4] This result is possible if the household's response to a price change depends not only on income but also on vehicle ownership, location, household size and other possible inter-quintile differences. The average representative household assumption, however, obscures the effect whether it is the income that plays a part in differing price sensitivity or some other demographic factors that are subsumed in grouping the households together.

The choice of the vehicle type to use may also vary with changes in fuel prices. Bomberg and Kockelman (2007) report that households drove their most fuel efficient vehicles more during the rise in gasoline prices in 2005. This suggests that multiple-vehicle households may be able to more readily respond to a price change than single vehicle households by switching to a more fuel efficient vehicle. Households with more than one wage earner may be able to rearrange work schedules so that they can share rides to work as a fuel saving strategy.

In this paper we attempt to estimate these heterogeneity effects in more detail. We utilize household level panel data to estimate gasoline demand elasticities. Our model incorporates various interaction terms so that the effect of different demographic and location variables on price and income elasticities can be estimated.

Data

Most of our data comes from the interview survey micro data of the US Consumer Expenditure Surveys (CEX, Bureau of Labor Statistics, 1997-2002). Each household is surveyed at most for four consecutive quarters over a year and reports expenditures of the previous quarters, barring any missing interviews.[5] The survey, however, is a rolling one, implying that all households are not interviewed at the same point in time, although the interval between the interviews of the individual households is always three months. In addition to the expenditure data on various items, the survey collects information on the households' demographics, including family size, number of children, and number of earners in the household, and age, education, race and gender of the household head. Information on the number of vehicles, vehicle type, characteristics of vehicles and expenditure on fuel are also available.

[4] West's (2004) estimates of travel demand (vehicles miles of travel) show a U shaped response, but no explanation was offered.
[5] The first interview collects only demographic information and no expenditure information.

Data has been collected from 1997 to 2002 for the CEX interview surveys. Observations from the data were selected for those households that have completed all four interviews and those who have not changed their vehicle stock during all four interviews.

Heavenrich (2006) published a dataset with new vehicle fleet fuel economy according to the model year, vehicle type (automobiles, SUVs, vans) and number of cylinders present in the vehicle. This data was used to assign fuel economy for the households in the CEX data based on the vehicle model, the number of cylinders and model year. Household fuel economy is then derived as the harmonic mean[6] of such fuel economies for the personal vehicles, the assumption being that all the vehicles are driven an equal amount.[7] After the matching process, 13,251 households are left with four observations for each (from 14,441 households who have not changed their vehicle stock and have been interviewed for four consecutive quarters).

Since different households are interviewed at different time periods, we require a price matrix for the households for different quarters. This necessitates us to derive monthly price estimates for every state and average the prices faced by each household during the previous quarter, conditional upon the month of the interview. The Bureau of Labor Statistics (2007) publishes retail gasoline price data for various months, however, the dataset is for urban consumers only, and not available for all states. We therefore opt for the Energy Information Administration (2006) data on weighted gasoline prices for each month for every state as sold to retail gasoline stations. Added to this is the federal and state taxes that are applied (Federal Highway Administration 2006). The corresponding after tax prices, when averaged over the entire United States, consistently falls below the US average retail price (Bureau of Labor Statistics 2007) by around 4% to 15% (mean 7.8%), as the profit margin of the retailers has not been incorporated in our after-tax estimate. We therefore mark up our after-tax price matrix by the ratio of US average retail price to our average after tax price for each month. Three month average prices for each household are then determined based on the time of each interview and the resident state of the household.

We opt for quarterly expenditures to proxy for quarterly income in the econometric model, for two reasons. Firstly, Friedman (1957) argued that lifetime income is a better predictor of consumption than annual income, and accordingly Poterba (1991), Metcalf (1993) and West

---

[6] $\text{Mean fuel economy} = \dfrac{\text{no of vehicles}}{\sum (1/\text{ fuel economy of each vehicle})}$. This is the correct procedure to average fuel economy of a vehicle fleet.

[7] In cases where vehicle fuel economy could not be matched for missing data for one vehicle, we assigned the household the mean fuel economy of other vehicles for which data was available. We acknowledge the limitations of these assumptions, yet we believe the derived fuel economy is a better indicator of fuel consumption than the number of cylinders as used by Archibald and Gillingham (1980).

and Williams (2004) all suggest using current period expenditure to proxy for lifetime income. Secondly, CEX reports only two annual incomes, for the first and the last interview; therefore income will not show any inter-quarter change between first, second and third interviews. In the rest of the paper income refers to expenditure. Summary characteristics of the data are presented in Table 1.

Table 1 Summary statistics for the dataset

Continuous variables	Mean	Std. Dev.
Total quarterly expenditure	8379.68	6043.69
Family size	2.50	1.41
No of person less than 18 years old	0.62	1.04
No of person over 64 years old	0.42	0.70
No of wage earners	1.29	0.97
Age of household head	52.19	16.77
Nominal price of gasoline (US cents/gal)	140.83	21.61
No of cars, SUVs, vans	1.82	0.94
No of other vehicles	0.19	0.57
Quarterly gasoline consumption (gal)	221.52	180.89
Fuel economy	21.31	3.59
Discrete characteristics		**Proportion of households**
Head is female		43.33
Head is non-white		14.29
Highest education level of head is high school		36.94
Highest education level of head is some college		27.85
Highest education level of head is college graduation		29.68
Head is less than 25 years old		3.09
Head is between 25 and 44 years old		34.49
Head is between 45 and 64 years old		35.66
Head is greater than 64 years old		26.75
One child in the household		13.29
Minimum two children in the household		19.57
Located in Northeast		16.99
Located in Midwest		24.57
Located in South		34.88
Located in West		23.55
Located in rural area		10.18

The Econometric Model

Specification of the Model

Studies that use disaggregate household level data to derive gasoline demand, utilize the household production theory formulated by Becker (1965) and Lancaster (1966). Archibald and Gillingham (1980) first utilized such a framework, which was later followed by Greening et. al. (1995), Puller and Greening (1999) and Kayser (2000) as well. In this framework, a household derives utility from the transportation services produced by itself through a combination of inputs such as gasoline, number of vehicles, other goods (e.g. public transport, walking) and their own time. The gasoline demand decision is taken by maximizing their utility subject to the constraints of production technology (i.e. fuel economy, vehicle characteristics), price, income and preferences (Archibald and Gillingham 1980, 1981). This results in a demand specification which is a function of price of gasoline, income, vehicle characteristics, and household characteristics.

In order to accommodate flexibility in the specification of gasoline demand, we opt for a translog formulation (Archibald and Gillingham 1980, Basso and Oum 2007) over the Cobb-Douglas. A simple translog specification for gasoline demand with price and income as explanatory variables (without other variables) [8] is:

$$\ln \mathrm{G} = \beta_{\mathrm{Y}} \ln \mathrm{Y} + \beta_{\mathrm{P}} \ln \mathrm{P} + \beta_{\mathrm{PY}} \ln \mathrm{P} \times \ln \mathrm{Y} + \beta_{\mathrm{PP}} (\ln \mathrm{P})^2 + \beta_{\mathrm{YY}} (\ln \mathrm{Y})^2 \qquad 1$$

where G= gasoline consumption per household

Y= income per household (proxied by expenditure)

P= price of gasoline

β = corresponding parameter estimate

The price and income elasticities are:

$$\eta_{\mathrm{P}} = \beta_{\mathrm{P}} + \beta_{\mathrm{PY}} \ln \mathrm{Y} + 2\beta_{\mathrm{PP}} \ln \mathrm{P} \quad \text{and} \quad \eta_{\mathrm{Y}} = \beta_{\mathrm{Y}} + \beta_{\mathrm{PY}} \ln \mathrm{P} + 2\beta_{\mathrm{YY}} \ln \mathrm{Y} \qquad 2$$

The advantage of a translog specification is that it can capture a decrease or an increase in the absolute elasticity with an increase in the corresponding explanatory variable.[9] For example, the income elasticity (η_{Y}) can be positive through a positive value of β_{Y}, yet, with increasing income the income elasticity could decrease through a negative value of β_{YY}. Since the value and sign of β_{YY} is estimated from the data, there is no a priori structure imposed upon the variation of income elasticity. The only structure imposed by the specification on elasticity is that the variation of the elasticity will still be linear with respect to the variables chosen.

[8] Since there are many socio-economic variables in the model, we do not mention them here.

[9] A semilog or linear specification cannot accommodate this behaviour. See Wadud (2007) for a discussion on functional specification in gasoline demand models.

In addition to price and income, vehicle characteristics and households' preferences also enter the demand function. It is assumed that preferences are functions of households' demographic characteristics. Demographic variables that have been found to affect the household consumption of gasoline are the size and composition of the household, number of earners in the household, age, race, gender, and education of the household, among other possible factors (Archibald and Gillingham 1980, 1981, Greening et. al. 1995, Puller and Greening 1999, Schmalensee and Stoker 1999, Kayser 2000, West and Williams 2004). We also use the number of automobiles, vans or SUV's as an explanatory variable but specify the presence of other types of vehicles through a dummy variable.[10]

Accommodating Heterogeneity

We choose not to accommodate heterogeneity through random parameters for each household, rather we determine homogenous response with respect to a few socio-economic variables. Since these socio-economic variables could be different for different households, the overall response to price and income could be different for various households in the sample. In addition, the interaction and quadratic terms in the translog form already allows the price and income elasticities to change with income and price, allowing heterogeneity in households' responses.

To accommodate the possibility that multiple vehicle households can have different price or income responses, Archibald and Gillingham (1980, 1981) separate their sample of households into two different groups based on vehicle ownership. This method of splitting the sample however reduces the sample size in both groups and may have resulted in their statistically insignificant estimate for price for the multiple-vehicle households. We instead use interactions of price and income with a dummy variable for multiple-vehicle households. This would allow the utilization of the entire sample enabling a more efficient estimation. Since, a priori, a multiple-vehicle household should be more responsive to a change in price the interaction with price should have a negative sign. Similarly interaction with income should have a positive coefficient.

The rural dummy variable is interacted with price and income to accommodate the possibility that rural households could have different elasticities than urban households. The expected sign of the price interaction term is positive, since a rural household should be less price elastic than an urban household (since they have fewer alternative travel options).

[10] The data includes fuel consumption data for recreational vehicle and boats; these are likely not major sources of quarterly fuel use and we control for their presence through a dummy variable.

Households of different sizes are also controlled for. It is also hypothesized that households with multiple wage earners could have different responses than households with single or no wage earners. To test this hypothesis, price and income are interacted with a dummy for multiple wage earner households.

Estimation of the Model

Our data traces 13,251 households over four quarters. For such a dataset, panel econometric techniques allow more efficient estimation and can control for unobservable traits of each household that may affect gasoline demand (Hsiao 2003, Baltagi 2005). Specific treatment of the unobservable variables allows us to recognize that households are heterogeneous and may differ from each other. This is certainly a more plausible representation of reality than assuming all households are similar, which is the implicit assumption in a model where all data are pooled together to estimate the parameters.

The basic framework in the panel data model is:

$$\mathrm{y}_{\mathrm{it}} = \mathbf{x}_{\mathrm{it}}^{\mathrm{T}}\boldsymbol{\beta} + \alpha_{\mathrm{i}} + \varepsilon_{\mathrm{it}} \qquad 3$$

where y_{it} = dependent variable for household i at time t

$\mathbf{x}_{\mathrm{it}}^{\mathrm{T}}$ = transpose of vector of explanatory variables for household i and time t

$\boldsymbol{\beta}$ = vector of corresponding parameters

α_{i} = household specific effect for household i

$\varepsilon_{\mathrm{it}}$ = randomly distributed error with a mean 0 and variance σ^2

When α_{i} in Eq. 3 is considered to be fixed for every household, it is known as a fixed effect or Least Squares Dummy Variable (LSDV) model (Gujarati 2003, Hsiao 2003). Fixed effect models, however, have a big disadvantage in that they cannot measure the impact of an explanatory variable which does not change with time as those variables are subsumed within the α_{i}'s (Greene 2005, Hsiao 2003). Many of our explanatory variables, such as location, region, number of vehicles within a household, and average fuel economy of the household do not vary with time within the households. These are important variables to determine gasoline demand in a household and we are principally interested in identifying the impact of some of the time invariant variables.

The LSDV model has consistent household specific effects when the time dimension is large (Greene 2005).[11] In the present case, we have only four observations for each household, which is too small to assume consistent estimates. Also, in a fixed effect model, the individual

[11] Estimates of other time-varying explanatory variables are consistent, though.

household specific fixed effects can soak up much of the variance in the dependent variable, and Meier et. al. (2001) suggest that any model which can be explained simply by a set of dummy variables with no substantive meaning is always a poor choice. This argument is applicable in our case, since we have a very large number of household specific effects.

The fixed effect model is also suitable when inference is to be made conditional on the effects present in the sample (Hsiao 2003, Baltagi 2005). The model is applicable to only the households present in the sample, and not outside of the sample (Greene 2005). Our interest, however, are not the specific households in the sample, rather, what the sample can tell us about the population. These limitations of the fixed effect model make it unsuitable for our purpose.

The random effect model, on the other hand, assumes that the individual specific effects, i.e. the α_i's, are uncorrelated with the explanatory variables and are randomly distributed across the households (Balestra and Nerlove 1966),

$$\alpha_i = \alpha + u_i \qquad 4$$

where, u_i is a randomly distributed household specific effect with mean 0 and variance σ_u^2. The random effect model is consistent with the premise that the households have been randomly drawn from the population and can be used for inference about the population (Hsiao 2003, Greene 2005). Such a model is especially attractive in the context of a large number of households with smaller time-series observations (Hsiao 2003). Random effect models can also provide estimates of the parameters for time invariant explanatory variables. The econometric estimation of a random effect model is achieved by the Generalized Least Squares (GLS) or the Maximum Likelihood (ML) method (Hsiao 2003, Baltagi 2005).

Given that quarterly observations for each household, while continuous, are not the same for each household, it is necessary to accommodate time specific effects. There is, however no reason to presume that the time specific effect will be randomly distributed as the household effects are, as done by Archibald and Gillingham (1980, 1981). Gasoline demand has been increasing over the years, therefore a time trend is more appropriate to account for the effect of time. Also the utilization of a vehicle and travel patterns may change with seasons, thereby affecting quarterly gasoline consumption. To capture the possible seasonal effect, which would be the same for every year, we therefore introduce month specific effects through dummy variables for the interview months. Thus the final model includes random household effects and fixed month effects.[12]

Results

Our estimates are based on a static random effects model.[13] We present the results of specification and model selections tests, with a special focus on the interaction terms. We then explain our parameter estimates and discuss them in the context of the gasoline demand literature, followed by the price and income elasticities of representative households in the sample. Finally we use the parameter estimates to derive the distribution of price and income elasticities of different households in the CEX sample for the year 2002.

Specification Tests and Model Selection

We perform the Breusch-Pagan (1980) test to determine the appropriateness of the household effect model over a pooled model. The corresponding Lagrange Multiplier test statistic is 13,400, which is distributed as $\chi^2[1]$. The null of no household specific effect is therefore clearly rejected. A comparison of the goodness of fit between the pooled model (Schwartz or Bayesian Information Criteria, SIC=94476.17) and the random effects model (SIC=81750.32) also shows better goodness of fit for the random effects model.

The Hausman test (1978) which is typically used to determine whether fixed or random effects is the correct method is not directly applicable here. This is because the random effects model contains many variables which are time invariant and cannot be estimated in the fixed effects model.[14] Hsiao and Sun (2000) suggest that the SIC is an alternative measure for choosing between a fixed and a random effects model; we find the random effects model has a lower SIC (Table 2) than the most comparable fixed effects model. Therefore, our rationale for using the random effects model is further supported by this goodness of fit test.

[12] The random coefficient model (Swamy 1970, Hildreth and Houck 1968), which allows the $\boldsymbol{\beta}$'s to randomly vary across households, may be more applicable to estimate heterogeneity. Such estimation requires the number of observations for each household to be fairly large and cannot be estimated with our dataset. However, through our interaction variables in the random effects model, we shall be able to capture some of the heterogeneity of the households' responses.

[13] We also estimated our model with an autoregressive error term based on Baltagi and Wu (1999). The parameter estimates were similar to the static model. We also modeled a partial adjustment model using Arellano and Bond's (1991) Generalized Method of Moments, but important specification tests could not be carried out since we only had four quarters of data for each household and these tests require at least 5 time series units.

[14] Also, the Hausman test statistic depends on the differences in the parameter estimates and variance-covariance matrices by the fixed and random effects estimations. The statistic could not be calculated since the difference matrix was not positive definite. This is not an uncommon occurrence in the practical application of the Hausman test to panel data (see http://www.stata.com/help.cgi?hausman)

Table 2 Choice between random and fixed effects model

	Degrees of freedom	SIC
Random Effects	45	81750.32
Fixed Effects	13284	190662.30

In estimating the random effects model, we carry out statistical tests to compare the translog specification (base model) with a Cobb-Douglas specification (Model A). Since the Cobb-Douglas model is nested within the translog model, the likelihood ratio (LR) test can be performed to detect the significance of the additional interaction variables of price and income. Results are shown in Table 3. The translog model is a significant improvement over the Cobb-Douglas specification (Model A). We also tested a Cobb-Douglas formulation with price and income interaction (Model B), but it was inferior to the translog specification based on the LR test. In addition, to accommodate the finding by Wadud et. al. (2007) that price elasticity may decrease at higher income quintiles, we estimate another model (Model C) that contains an additional interaction term $\mathrm{lnprc} \times (\mathrm{lninc})^2$ over the translog specification (base model). The addition of this interaction term, however, does not significantly improve the fit. We therefore conclude that the translog specification gives the best fit for our data to estimate the demand for gasoline.

Previous work in this area has not examined the interaction of price and income with other factors such as location or vehicle ownership to examine heterogeneity between households. We therefore test whether the interactions are useful in explaining gasoline demand or not. Since all the candidate models without the interaction are nested within the base model, the LR test can be used to examine these effects (Table 3). Model D drops all the price and income interactions with the dummy variables for rural location, multiple-earner households and multiple-vehicle households. The LR test indicates that the fit does not improve compared to the base model. This is also true for models E, F and G which drop the price and income

Table 3 Choice between Cobb-Douglas vs. translog specification, significance of interaction terms (all random effects model, estimated by Maximum Likelihood, likelihood at null -46488.76 for all models)

Model No.	Description of the variables in the model	Degrees of freedom	log likelihood	SIC	LR statistic
<u>Basic model</u>					
Base	Translog in price and income, interaction of price and income with dummies for (a) rural area, (b) multiple earner, (c) multiple vehicle	45	-40630.40	81750.32	
<u>Functional specification</u>					
A	No translog in price and income Cobb-Douglas price and income	42	-40735.75	81928.38	210.70(p=0.000)
B	No translog in price and income Cobb-Douglas in price and income, price and income interaction	43	-40725.55	81918.86	190.29(p=0.000)
C	Interaction of price and quadratic income	46	-40630.33	81761.06	0.14(p=0.707)
<u>Significance of interaction terms</u>					
D	No interaction of price and income with (a) rural dummy, (b) multiple earner, (c) multiple vehicles	39	-40707.38	81839.00	153.95 (p=0.000)
E	No interaction of price and income with rural dummy	43	-40636.58	81740.91	12.35(p=0.000)
F	No interaction of price and income with multiple earner	43	-40644.00	81755.75	27.19(p=0.000)
G	No interaction of price and income with multiple vehicle	43	-40681.56	81830.88	102.31(p=0.000)

interactions with rural dummy, multiple-earner dummy and multiple-vehicle dummy variables respectively. Once again the base model, which includes interaction terms, provides the best fit to our data.

Since we have utilized interaction terms among variables in the econometric model, there is a possibility of multicollinearity affecting the estimates. A large dataset however allows the parameters for most of our interaction variables to be estimated with small standard errors. To test the effect of multicollinearity, we randomly dropped 1% of the sample and re-estimated the model and found negligible differences in the parameter estimates. This indicates that multicollinearity did not adversely affect our estimation.[15]

Parameter Estimates

Parameter estimates for the translog random effects model (the base model) for the entire sample of 13,251 households are presented in Table 4. Since dummy variables are used in the models to represent different demographic characteristics of the household a reference household is defined. Our reference household is headed by a white male, of the age between 45 and 64, with elementary school or no school experience. The household is located in an urban area in the northwest region of the USA. The reference household has a single personal vehicle, no other types of vehicle and a maximum of one earning member. Interpretation of all dummy variables can be made with respect to this reference household.

Parameter estimates for price and income (expenditure)[16] have expected signs. The parameter estimate for the interaction between price and income is positive indicating that the absolute value of the price elasticity decreases with an increase in income. This is also consistent with the theoretical literature (Robinson 1969, Gertler et. al. 1987). A negative parameter estimate for the quadratic term in income (expenditure) means that the income (expenditure) elasticity decreases with higher income. This confirms our a priori hypothesis that higher income households may already maximize their travel (via car) and do not increase this much with a further increase in income.

Gasoline consumption is lower when the household head is female and higher when the household head is non-white. This finding is similar to Archibald and Gillingham (1980), who reported parameter estimates of -0.22 for female and 0.22 for nonwhite household head. Estimates from our random effects model are -0.044 and 0.036 for female and nonwhite head of households respectively. This could indicate that the effect of gender and race on driving

[15] Results are available in Wadud (2007)
[16] Recall that we proxy income via the expenditure variable; we refer to it as the income

may have fallen substantially over the years.[17] In this regard, Pucher and Renne (2003) report that women and men are becoming more alike in terms of their urban travel behaviour. Converting the parameter estimates to percentage change, households with female heads consume 4.3% less gasoline than households with male heads.[18] Similarly, nonwhite vehicle owning households consume 3.7% more as compared to white vehicle owning households.

Effect of educational attainment of the head of the household was insignificant for two groups, although educated (college graduate) households tend to use 3.8% less fuel for driving. Archibald and Gillingham (1980) also report that households with higher education tend to use less fuel.

Households with younger heads tend to drive more, with the youngest (less than 25 years) driving around 6.4% more than the reference household. Older household heads, on the other hand drive 17.5% less than the reference household. Observing the trend of results for the dummy variables for the age of household head, households consume successively smaller quantities of fuel with increasing age. Model specifications which use age explicitly, however, are split with the effect of age. Kayser (2000) reports a negative effect and Yatchew and No (2001) report positive effects for younger ages and negative effects for middle aged households.[19] Our results thus are consistent with Kayser's (2000) findings for the USA.

Overall family size has a significant positive effect on gasoline consumption. However, this is offset slightly when there are two or more children in a household, which lowers gasoline consumption by around 5.6% (one child in the household has no statistically significant effect). Kayser (2000) also reported lower consumption for the presence of several children, although her estimates were not statistically different from zero. West and Williams (2004) report that the presence of children increases the share of gasoline in a households budget, which is in apparent contradiction to our findings. There is however a difference between the explanatory variables in the two econometric specifications. West and Williams (2004) consider one or two adult households, and children are additional to these adults in the household. In our specification, family size contains all members in the household therefore giving each of them equal weight. Thus for a family size of three, presence of two children would reduce the consumption of gasoline compared to no children in the family. Our findings with respect to children are therefore consistent with those in the literature.

---

[17] Archibald and Gillingham (1980) use 1972 CEX data. Our specification is different from their's, therefore we acknowledge that this interpretation could be spurious.

[18] Halvorsen and Palmquist (1980) show that percentage change effect for a dummy variable is given by e^{β}-1, where β is the parameter estimate for the dummy variable. Generally, e^{β}-1 and β tend to be close in magnitude, as in this case, but they need not be (Kayser 2000).

[19] Yatchew and No's (2001) dataset is for Canada and they used a flexible semiparametric functional form for age.

Table 4 Gasoline demand parameter estimates by disaggregate model

Model type	Panel Random Effect	
Household specific effect	Yes-random	
	Coef.	Std. err.
Ln(expenditure)†	0.661**	0.184
Ln(price)	-4.859**	1.168
Ln(price)×Ln(expenditure)	0.210**	0.033
$(\text{Lnprice})^2$	0.264**	0.115
Ln(expenditure)^2	-0.081**	0.006
Dummy for gender of household head (male =0)	-	-
Dummy for female household head	-0.044**	0.008
Dummy for race of household head (white=0)	-	-
Dummy for nonwhite household head	0.036**	0.011
Dummy for education of household head (no school =0)	-	-
Dummy for some school experience	-0.013	0.017
Dummy for school graduate and some college experience	-0.019	0.018
Dummy for college graduate	-0.039**	0.019
Dummy for age of household head (age between 45 and 64=0)	-	-
Dummy for age of household head less than 25 years	0.062**	0.021
Dummy for age of household head between 25 and 44 years	0.045**	0.010
Dummy for age of household head above 64	-0.192**	0.011
Ln(family size)	0.176**	0.013
Dummy for the presence of children (no children = 0)	-	-
Dummy for the presence of 1 child	-0.011	0.013
Dummy for the presence of more than 1 child	-0.058**	0.016
Dummy for regional location (northeast=0)	-	-
Dummy for Midwest region	0.013	0.013
Dummy for Southern region	0.077**	0.012
Dummy for Western region	-0.035**	0.013
Dummy for urban or rural location (nonrural=0)	-	-
Dummy for rural location	-1.365**	0.415
Interaction between ln(price) and dummy for rural location	0.250**	0.077
Interaction between ln(expenditure) and dummy for rural location	0.024	0.018
Ln(number of cars)	0.245**	0.021
Interaction of ln(price) and dummy for multiple vehicles	-0.152**	0.021
Interaction of ln(expenditure) and dummy for multiple vehicles	0.100**	0.012
Dummy for the presence of other vehicles	0.099**	0.013
Ln(fuel economy in mpg)	-0.442**	0.025

** Statistically significant at 95%, * statistically significant at 90%

† Expenditure is a proxy for income

Table 4 (cont.) Gasoline demand parameter estimates by disaggregate model

Model type	Panel Random Effect	
Household specific effect	Yes-random	
	Coef.	Std. err.
Ln(no of earners in the household)	0.355**	0.032
Interaction between ln(price) and dummy for multiple earners	-0.084**	0.021
Interactions between ln(expenditure) and dummy for multiple earners	0.042**	0.011
Time	0.000	0.000
Dummy if the interview month was February	0.006	0.013
Dummy if the interview month was March	-0.001	0.013
Dummy if the interview month was April	0.030**	0.009
Dummy if the interview month was May	0.046**	0.013
Dummy if the interview month was June	0.023*	0.013
Dummy if the interview month was July	0.032**	0.009
Dummy if the interview month was August	0.048**	0.013
Dummy if the interview month was September	0.056**	0.013
Dummy if the interview month was October	0.048**	0.009
Dummy if the interview month was November	0.022*	0.013
Dummy if the interview month was December	0.007	0.013
Intercept	14.529**	3.147
Model diagnostics		
Adj. R^2	0.417	
Log-likelihood	-40630.4	
AIC	81350.81	
SIC	81750.32	
N	53004	

** Statistically significant at 95%, * statistically significant at 90%

Households located in the Midwest region consume similar amounts of gasoline as those in the Northeast region. Households in the Southern region, on average, consume 8% more gasoline than those in the Northeast. Western households, however, consume 3.4% less gasoline than those in the Northeast. Archibald and Gillingham (1980) and Schmalensee and Stoker (1999) both report that Western households consume less gasoline.[20]

Households in rural regions consume more gasoline than those in urban areas. The statistically significant positive parameter estimate for the interaction of price with the rural dummy

[20] The classification of the regions are based on the CEX data regional classifications (http://www.bls.gov/cex)

variable indicates that gasoline demand for rural households is less price elastic than for urban households. This finding is similar to the estimates by Wadud et. al. (2007) for the USA. Blow and Crawford (1997) and Santos and Catchesides (2004) also found similar results for the UK. The lower price elasticity is likely the result of a lack of alternate transport modes in rural areas. Interaction of the rural dummy with expenditure was statistically insignificant, indicating that income elasticities do not differ significantly between urban and rural households.

Our results show that more wage earners in a household increases gasoline consumption. Puller and Greening (1999) also find that the consumption of gasoline increases with the number of wage earners in a household. Kayser (2000) found that in households where the head and spouse do not work they consume less gasoline.

Multiple wage earner household interactions are also statistically significant for both price and income. Parameter estimates when price is interacted is negative, suggesting that these households may become more efficient in their travel behaviour with an increase in gasoline price. Income elasticities of multiple wage earner households are also higher. Households with multiple vehicles are also more price elastic, supporting the proposition that these households increase use of their more fuel efficient vehicle in response to a price increase. In general, the presence of multiple vehicles has a larger effect on the price and income elasticities than the presence of multiple earners in a household.

Elasticities of Gasoline Demand

Gasoline demand elasticities with respect to price and income for different household characteristics are presented in Table 5. The statistical significance of the elasticity parameters and standard errors of the elasticity are also reported. Income and price are kept constant at the national average to determine the first set of elasticities. These elasticities therefore are for households that have similar income and are facing similar prices, but are different in terms of their locations, vehicle holdings or number of wage earners. Urban households in general are more price elastic than rural households. Urban multiple-vehicle, multiple wage earner households are the most price responsive (-0.577), whereas single earner, single vehicle rural households are the least responsive (-0.091). It is therefore clearly evident that the price elasticity of different types of households can be very different. Multiple wage earner and multiple-vehicle households also have higher income elasticities.

We also calculate the elasticites of these household types at their mean income and mean price for each group. These are the second set of elasticities in Table 5. Urban multiple wage earner, multiple-vehicle households are still the most responsive (-0.490), although the price elasticity is not much different for urban multiple-vehicle single earner households (-0.484). Calculation of elasticities by group means also reduces the variation of the elasticities among the households from the first set of elastiticites estimated at national mean income and price for all households. Income elasticities also show less variation. It is however, still evident that the response to a price or income change varies across household type.

Table 5 Price and income elasticities for households with differing characteristics (Standard errors in parentheses)

Household charactersitics			Elasticities			
Location	Car ownership	Earners	Price and income fixed at sample (national) average		Price and income fixed at respective group average	
			Price	Income	Price	Income
Urban	Single	Zero or one	-0.341** (0.029)	0.273** (0.009)	-0.414** (0.031)	0.329** (0.009)
Urban	Single	Multiple	-0.425** (0.033)	0.314** (0.0129)	-0.401** (0.033)	0.304** (0.013)
Urban	Multiple	Zero or one	-0.493** (0.030)	0.373** (0.010)	-0.484** (0.030)	0.365** (0.010)
Urban	Multiple	Multiple	-0.577** (0.030)	0.414** (0.010)	-0.490** (0.031)	0.351** (0.010)
Rural	Single	Zero or one	-0.091 (0.077)	0.297** (0.019)	-0.236** (0.076)	0.391** (0.019)
Rural	Single	Multiple	-0.175** (0.078)	0.338** (0.021)	-0.238** (0.077)	0.362** (0.021)
Rural	Multiple	Zero or one	-0.243** (0.076)	0.397** (0.019)	-0.325** (0.075)	0.445** (0.019)
Rural	Multiple	Multiple	-0.327** (0.075)	0.438** (0.019)	-0.321** (0.075)	0.423** (0.019)

** Statistically significant at 95%

The elasticity estimates in this work shed some light on Wadud et. al.'s (2007) unique finding of a U-shaped price elasticity with increasing income quintile. Their work used an aggregate, time series gasoline demand model for different income quintiles. In this work, we find that the absolute value of price elasticity decreases with increasing income. However, more households belonging to the higher income quintile live in urban areas and higher income quintiles also have a consistently higher proportion of multiple-vehicle and multiple wage earner households. Since both these factors are associated with larger price elasticities, it is plausible that these effects could counteract the decrease in price elasticity with increasing income and thus result in higher price elasticities in the highest income quintiles (when aggregate data is used as in

Wadud et. al. 2007). We, however, found that the effect of income (expenditure) was more pronounced in the 2002 CEX micro dataset (Table 5) and as such no evidence of a U shaped curve could be established for the 2002 dataset. This is also directly evident from the parameter estimates in Table 4, where the parameter estimates for the price interactions with income are larger than the estimates for price interaction with dummies for multiple-vehicle or multiple wage earner households.

The variation of our price elasticity estimates between five income quintiles (Table 6) is smaller than those reported in West and Williams (2004), which is possibly a result of our specific attention to other demographics. Our median parameter estimates (-0.473, next section) are also very similar to Archibald and Gillingham's (1980), who used 1972 CEX data to derive a price elasticity of -0.43. The similarity of the results for two different periods of analysis could indicate that the price elasticities of households may have not changed significantly as reported in some of the recent literature (Hughes et. al. 2007). It is however, important to note the differences in the two modeling approaches. We have used disaggregate household level data, which always gives higher price elasticity estimates than aggregate data, as used by Hughes et. al. (2007).[21]

Table 6 Median price elasticity for expenditure quintiles

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Reported income (before tax) quintiles (current work)	-0.510	-0.513	-0.474	-0.454	-0.397
Expenditure quintiles (current work)	-0.596	-0.517	-0.484	-0.454	-0.334
Expenditure quintiles (West and Williams 2004)	-0.724[a]	-0.689	-0.549	-0.448	-0.180[a]

[a] statistically insignificant

Distribution of Price and Income Elasticities

The elasticities in Table 5 are for representative households and still do not capture the full distribution of elasticities among various households since both the price of gasoline a household faces and their income will vary. Fig. 1 presents the price elasticity of gasoline demand for all individual households in the CEX interview survey micro data for the year 2002. The elasticity of every household is calculated from its total expenditure (as a proxy for income), the number of vehicles in the household, the number of wage earners in the

[21] See Sterner and Dahl (1992), Basso and Oum (2007), Wadud (2007).

household, which state the household is located in (to determine the price they face for gasoline) and whether the household is located in an urban or rural setting.[22] The median of the distribution is -0.473 and the mean -0.469.[23] We interpret these price elasticities as intermediate to long run, since most of the explanatory power in variation in the data is derived from inter-household differences (54.2%) and only a small component is from intra-household differences over the four quarters (3.6%).[24,25] The distribution (Fig. 1) has a few households (<0.25%) with a positive price elasticity as a result of some unique combinations of price and income. Fig. 1 clearly shows that there could be a wide variation in the elasticities if household characteristics are allowed to affect the elasticity values. These household elasticities can be used to determine the distribution of welfare among households as a result of a policy that increases the price of gasoline.

The distribution of income elasticities is presented in Fig. 2. Once again there are variations to be observed among the households. The median and mean of the distribution are 0.342 and 0.340 respectively. For a very few households, income elasticity is negative (<0.16%), which is again possibly not realistic, but is a result of variation in the data. The red lines refer to a normal distributional plot.

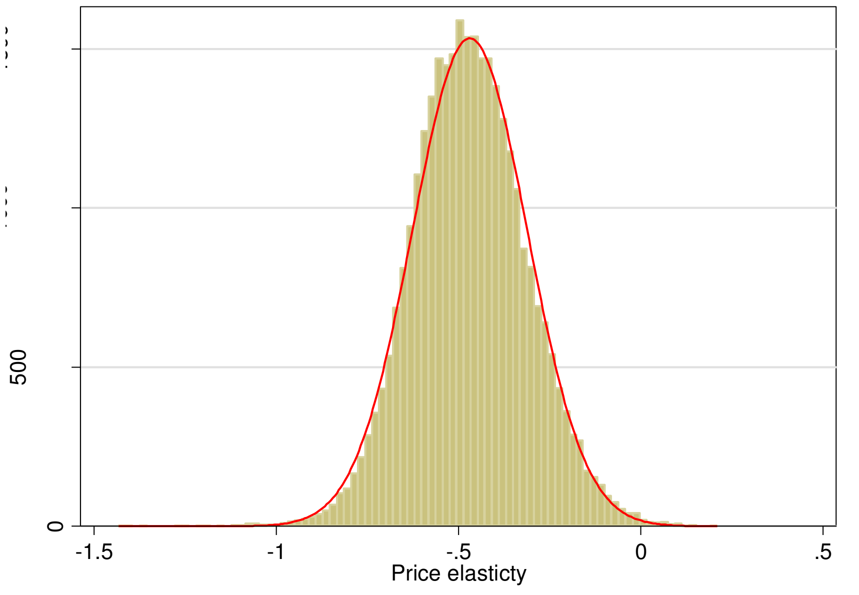

Fig. 1 Distribution of price elasticities of gasoline demand for all 2002 households

[22] Households without vehicles are assigned the elasticity of similar one vehicle households.
[23] Strictly speaking, mean elasticity does not have a physical meaning, since different households face different prices.
[24] These numbers are from inter and intra household R^2 of the panel estimation process.
[25] Sterner and Dahl (1992) also argued that panel data gives intermediate to long run price elasticity estimates.

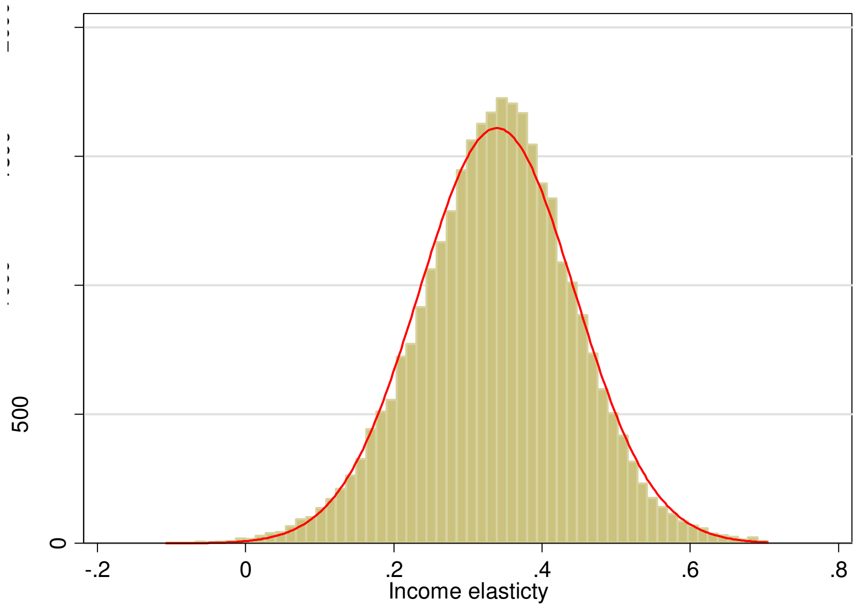

Fig. 2 Distribution of income elasticities of gasoline demand for all 2002 households

Conclusions

An econometric model using a large household level panel dataset was estimated to investigate the demand for gasoline in the USA. We proceeded with the hypothesis that the price and income elasticities of different households depend not only on the income of the households but also on other demographic and locational characteristics. In modeling gasoline demand, we interacted price and income with several demographic characteristics. This allowed for the estimation of heterogeneous responses of individual households to a change in price or income. We found evidence of heterogeneity as shown in the significance of various interaction terms as well as in the distribution of our elasticity results, by household. In particular, a household's price and income elasticity depends on the number of vehicles owned, the number of wage earners and the location of the household.

Income elasticity decreases as income increases, possibly suggesting demand satiation at a higher income level. Ceteris paribus, multi-car households consume more fuel compared to those with only one car, as income increases. Households with multiple wage earners also drive more than zero or single wage earner households if their income increases. Rural households, however, do not show any significant difference compared to urban households in response to an increase in their income.

We also conclude that households with multiple vehicles are more price elastic. This could be due to their ability to switch to a more efficient secondary vehicle. Multiple wage earner households have higher price elasticities than single wage earner households. One possible explanation is that these households have greater flexibility in rearranging their travel patterns.

Rural households consume more gasoline, yet, these households are less responsive to a price change, which could reflect a lack of alternative modes available to rural households. In general, multi-car, multi-wage earner, urban households have the largest response to a price change and a single car, single (or no) wage earner, rural household has the lowest.

We have also presented the distribution of income and price elasticities for households in the 2002 CEX survey. We believe these disaggregate elasticities would allow a more precise estimation of welfare distribution due to a change in gasoline price arising from various policies, which we are currently investigating.

Acknowledgments

This research benefited from funding provided by the Commonwealth Scholarship Commission.

References

Archibald R, and Gillingham R 1980. An analysis of short-run consumer demand for gasoline using household survey data, The Review of Economics and Statistics, 62(4), pp. 622-628.

Archibald R, and Gillingham R 1981. A decomposition of the price and income elasticities of the consumer demand for gasoline, Southern Economic Journal, 47, pp. 1021-1031.

Arellano M and Bond S R 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies, 58, pp. 277-297.

Balestra P and Nerlove M 1966. Pooling cross section and time-series data in the estimation of a dynamic model: The demand for natural gas, Econometrica 34, pp. 585-612.

Baltagi B H 2005. Econometric analysis of panel data, John Wiley & Sons Ltd, West Sussex.

Baltagi B H and Wu P X 1999. Unequally spaced panel data regressions with AR(1) disturbances, Econometric Theory, Vol. 15, No. 6, pp. 814-823.

Basso L J and Oum T H 2007. Automobile fuel demand: A critical assessment of empirical methodologies, Transport Reviews, 27(4), pp. 449-484.

Becker G 1965. A theory of the allocation of time, Economic Journal, September, pp. 493-517.

Blow L, and Crawford I 1997. The distributional effects of taxes on private motoring, The Institute for Fiscal Studies Commentary 65, London.

Bomberg M and Kockelman K M 2007. Traveler response to the 2005 gas price spike, Proceedings of the 86th Annual Meeting of the Transportation Research Board, Washington DC

Bureau of Labor Statistics 1997-2002 [online]. Consumer Expenditure Survey: Public Use Micro Data, US Department of Labor, available at <http://www.bls.gov/cex/home.htm>

Bureau of Labor Statistics 2005 [online]. Consumer Expenditure Survey: Current Standard Tables: 1984-2003, US Department of Labor, available at <http://www.bls.gov/cex/home.htm>

Bureau of Labor Statistics 2007 [online]. Consumer Price Indexes, US Department of Labor, available at <http://www.bls.gov/cpi/home/htm>

Dahl C 1995. Demand for transport fuels: A survey of demand elasticities and their components, the Journal of Energy Literature I(2).

Dahl C, and Sterner T 1991. Analysing gasoline demand elasticities: A survey, Energy Economics, 13, pp. 203-210.

de Jong G, and Gunn H 2001. Recent evidence on car cost and time elasticities of travel demand in Europe, Journal of Transport Economics and Policy, 35(2), pp. 137-160.

Energy Information Administration 2006 [online]. Motor gasoline sales to end users prices, US Department of Energy, available at <http://tonto.eia.doe.gov/dnav/pet/pet_pri_top.asp>, accessed July 2006.

Federal Highway Administration 2006 [online]. Monthly motor fuel reported by states, various years, US Department of Transportation, available at < http://www.fhwa.dot.gov/ohim/mmfr/ mmfrpage.htm>, accessed July 2006

Friedman M 1957. A Theory of the Consumption Function, Princeton University Press, National Bureau of Economic Research, Princeton, NJ.

Gertler P, Locay L, and Sanderson W 1987, Are user fees regressive? The welfare implications of healthcare financing proposals in Peru. NBER Working paper, No. 2299.

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), pp. 275-292.

Graham D J, and Glaister S 2002a. The demand for automobile fuel: A survey of elasticities, Journal of Transport Economics and Policy, 36(1), pp. 1-26.

Graham D J, and Glaister S 2002b. Review of income and price elasticities of demand for road traffic, Department for Transport, London.

Greene W H 2005. Econometric Analysis, Fifth edition, Pearson Education Inc., New Delhi.

Greening L A, Jeng H T, Formby J P, and Cheng D C 1995. Use of region, life-cycle and role variable in the short-run estimation of the demand for gasoline and miles travelled, Applied Economics, 27, 643-656.

Gujarati D N 2003. Basic Econometrics, McGraw Hill Companies, Inc., New York, pp. 478.

Halvorsen R and Palmquist R 1980. The interpretation of dummy variables in semilogarithmic equations, American Economic Review, 70(3), pp. 474-475

Hausman J A 1978. Specification tests in Econometrics, Econometrica, Vol. 46, pp. 1251-1371

Heavenrich R M 2006. Light-duty automotive technology and fuel economy trends: 1975 to 2006, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, Ann Arbor.

Hildreth C and Houk J P 1968. Some estimators for a linear model with random coefficients, Journal of the American Statistical Association, 63, pp. 584-595

Hsiao C 2003. Analysis of Panel Data, Cambridge University Press, Cambridge.

Hsiao C and Sun B H 2000. To pool or not to pool panel data, in Panel Data Econometrics: Future Directions, Papers in Honor of Professor Pietro Balestra, Krishnakumar J and Ronchetti E (eds.), Amsterdam: North Holland, pp. 181-198

Hughes J E, Knittel C R and Sperling D 2007. Evidence of a shift in the short-run price elasticity of gasoline demand, Proceedings of the 86th Annual Meeting of the Transportation Research Board, January, Washington, DC

Kayser H A 2000. Gasoline demand and car choice: estimating gasoline demand using household information, Energy Economics, 22, pp. 331-348.

Lancaster K 1966. A new approach to consumer theory, Journal of Political Economy, April, pp. 132-157.

Meier K J, Eller W S, Winkle R D and Polinard J L 2001, Zen and the art of policy analysis: A response to Nielsen and Wolf, The Journal of Politics, 63(2), pp. 616-629

Metcalf G E 1993, The Lifetime Incidence of State and Local Taxes: Measuring Changes During the 1980s, NBER Working Paper No. 4252, Cambridge, Massachusetts.

Nicol C J 2003. Elasticities of demand for gasoline in Canada and the United States, Energy Economics, 25, pp. 201-214.

Poterba J 1991, Is the Gasoline Tax Regressive? Tax Policy and the Economy, 5, pp. 145-164.

Pucher J and Renne J L 2003. Socioeconomics of urban travel: evidence from the 2001 NHTS, Transportation Quarterly, 57(3), pp. 49-77

Puller S L and Greening L A 1999. Household adjustment to gasoline price change: an analysis using 9 years of US survey data, Energy Economics 21, 37-52.

Robinson J 1969. The Economics of Imperfect Competition, London: MacMillan.

Santos G and Catchesides T 2004. Distributional consequences of gasoline taxation in the United Kingdom, Transportation Research Record: Journal of the Transportation Research Board, 1924, pp. 103-111.

Schmalenesee R and Stoker T M 1999. Household gasoline demand in the United States. Econometrica, 67(3), pp. 645-662.

Sterner T and Dahl C A 1992. Modelling transport fuel demand, in: Sterner, T. (Ed.), International Energy Economics, Chapman and Hall, London, pp. 65-79.

Swamy P A V B 1970. Efficient inference in random coefficient regression model, Econometrica, 38, pp. 311-323.

Varian H R 2006. Intermediate Microeconomics, 7th Ed., New York: W W Norton.

Wadud Z 2007. Personal tradable carbon permits for road transport: Heterogeneity of demand responses and distributional analysis, PhD Dissertation (under preparation), Imperial College London.

Wadud Z, Graham D J and Noland R B 2007. Modelling fuel demand for different socio-economic groups, Proceedings of the 86th Annual Meeting of the Transportation Research Board, Washington DC.

West S E 2004. Distributional effects of alternative vehicle pollution control policies, Journal of Public Economics, 88, pp. 735-757.

West S E, and Williams III R C 2004. Estimates from a Consumer Demand System: Implications for the Incidence of Environmental Taxes, Journal of Environmental Economics and Management, 47(3), pp. 535-558.

Yatchew A, and No J A 2001. Household gasoline demand in Canada, Econometrica, 69(6), 1697-1709.

Zellner A 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias, Journal of the American Statistical Association, 57(298), pp. 348-368.