ELSEVIER

Energy Economics 21 (1999) 37–52

Energy Economics

Household adjustment to gasoline price change: an analysis using 9 years of US survey data

Steven L. Puller[a,*], Lorna A. Greening[b]

[a]*Department of Economics, University of California at Berkeley, 611 Evans Hall, Berkeley, CA 94720, USA*
[b]*Consultant, 2445 Rim Drive, Broomfield, CO 80020, USA*

Abstract

This paper examines the dynamics and composition of household adjustment to changes in the real price of gasoline using a panel of US households. By decomposing the demand for gasoline into the demand for vehicle miles traveled and the demand for household composite miles per gallon, we are able to add rich detail to the description of how households respond to gasoline price changes. While obtaining total price elasticity estimates well within the range found in the literature, we find that consumers initially respond to a price rise with a much larger decrease in consumption than would be indicated by the total elasticity. In addition, households respond to price changes by adjusting vehicle miles traveled more than composite miles per gallon in the year after a price change.

JEL classifications: Q41; D12

Keywords: Energy; Gasoline demand; Consumer behavior

1. Introduction

For many years, researchers and policymakers have sought to understand consumer response to changes in the price of gasoline so as to design effective energy and environmental policy. The vast majority of studies that have estimated the price elasticity of US gasoline demand have used aggregate-level data. Of the few

* Corresponding author. Tel.: +1 510 4860691; fax: +1 510 6426615.

PII: S0140-9883(98)00006-1

studies that have used micro-level data, most have measured only short-run adjustments and have failed to provide insight into the dynamics and composition of the adjustment process. This paper uses 9 years of household-level panel data to estimate longer-run elasticities of non-business gasoline demand and to analyze the timing and nature of household adjustment to changes in gasoline prices.

Studies that have used disaggregate data have found gasoline demand to be fairly inelastic. Archibald and Gillingham (1980) conducted the first major studies of gasoline demand using disaggregate household-level data. Archibald and Gillingham (1980) used the 1972–1973 Consumer Expenditure Survey to estimate an overall short-run price elasticity of -0.43. Archibald and Gillingham (1981) found that roughly three-quarters of the adjustment is to miles traveled while one-quarter is to household gasoline efficiency. Greene and Hu (1986) used National Family Opinion Poll data from 1978 to 1981 to estimate a short-run demand elasticity for one-vehicle households of -0.5 to -0.6, but note that their estimates are likely to be inflated. Walls et al. (1993) used the 1990 National Personal Transportation Survey to estimate the short-run elasticity of gasoline and found demand slightly more price elastic (-0.51) than older studies have found. Greening et al. (1995) used the 1990 Consumer Expenditure Survey and found the short-run elasticity for various socio-demographic groupings defined by cluster analysis to vary from 0.00 to -0.67. In their survey of gasoline demand elasticities, Dahl and Sterner reported the mean price elasticity for panel data studies to be -0.52 and the mean of all studies to be -0.26 in the short-run and -0.86 in the long-run (Dahl and Sterner, 1991, p. 206.)

This paper distinguishes itself from previous work in two ways. Whereas several previous studies using disaggregate data have restricted their analysis to households which do not make changes to vehicle stock, we allow vehicle stock to change and therefore our estimates include longer-run adjustments.[1] Second, households may be expected to respond to a price change with a complex adjustment process combining changes in both usage of vehicle stock and the stock itself. Previous studies which estimate demand directly may conflate the adjustments which could be separated in a two-equation model. In addition, previous studies have not estimated the dynamics of household response to price changes. We decompose the demand for gasoline into a vehicle usage and a vehicle stock equation and include lagged prices in our model so we can better analyze the composition and dynamics of the household adjustment process. We use 9 years of a rotating panel of US households to estimate the price elasticity of non-business gasoline demand.[2]

[1]Archibald and Gillingham (1980, 1981), Walls et al. (1993), and Greening et al. (1995) restrict their analyses to households which do not make changes to vehicle stock and, therefore define their elasticity estimates to be *short-run* estimates.

[2]Note, however, that our panel (the Consumer Expenditure Survey) is a rotating panel so that the window for which we view household behavior is only 1 year long. This short period of observation may limit the adjustments which we measure. However, Espey's (Espey, 1996) meta-analysis suggests that approx. 75% of the price response occurs within 1 year. Therefore we hope to capture and analyze a large fraction of the total adjustment to a change in the price of gasoline.

We obtain elasticity estimates well within the range found in the literature but find the adjustment to be neither smooth nor evenly divided between the usage of the vehicle stock and the stock itself. Our decomposition finds that households adjust the number of vehicle miles traveled more than household composite miles per gallon. In addition, we find that although gasoline demand is fairly inelastic in the year after a price change, the initial adjustment to a price rise is a rather substantial decrease in gasoline consumption.

2. Model of gasoline demand

This paper will view gasoline in the context of household production theory. A household receives utility from transportation services which are produced by the household's technology using gasoline, maintenance goods and services, and vehicle stock as factor inputs. Consequently, the demand for gasoline is derived. We model the demand for gasoline by household i in period t as:

$$g_{it} = g_{it}(p_g, I_i; c_{it}) \tag{1}$$

where p_g is a vector of contemporaneous and lagged real prices of gasoline faced by household i, I_i is the real income of household i, and c_{it} is a vector of household demographic characteristics.

One can decompose the household's demand for gasoline (g_{it}) into the demand for vehicle miles traveled (VMT_{it}) and the demand for household composite travel efficiency measured in miles per gallon (MPG_{it}) using the identity $g_{it} \equiv \mathrm{VMT}_{it}/\mathrm{MPG}_{it}$. Taking logs and differentiating with respect to the log of price, one can obtain the elasticity decomposition:

$$\eta_{g-p} = \eta_{\mathrm{VMT}-p} - \eta_{\mathrm{MPG}-p} \tag{2}$$

Therefore we can obtain the price elasticity of gasoline demand from the elasticities of vehicle miles traveled and household composite miles per gallon (MPG). In this paper, we estimate the demand for non-business gasoline directly through Eq. (1) and indirectly by estimating simultaneously the demand for vehicle miles traveled and the demand for household composite miles per gallon. The indirect estimation can tell a much richer story of how a household responds to price changes.

In order to estimate gasoline demand in this indirect fashion, we develop a model of the demand for VMT and composite MPG. Eq. (3) is a model of the household's use of its vehicle stock to produce household transport services. Households choose vehicle miles traveled based on the price per mile of travel, lagged prices of gasoline, income, the price of maintenance goods and services, and household characteristics:

$$\mathrm{VMT}_{it} = f\left(\frac{p_{g_t}}{\mathrm{MPG}_{it}}, p_{g_{t-s}}, I_i, p_{m_t}; c_{it}\right) \tag{3}$$

where VMT_{it} is the vehicle miles traveled by household i in period t, MPG_{it}, is the household's vehicle travel efficiency in period t, p_{gt} and p_{gt-s} are contemporary and lagged real prices of gasoline, p_{mt} is the price of maintenance goods and services in period t, and c_{it} is a vector of household characteristics. Eq. (4) is a model of the determination of the household's composite MPG. Households choose composite MPG (total miles/total gallons) based on the price of gas, vehicle miles traveled, income, the price of new vehicles, and household characteristics:

$$\mathrm{MPG}_{it} = f(p_g, \mathrm{VMT}_{it}, I_i, p_{\mathrm{NV}_t}; c_{it}) \tag{4}$$

where p_g is a vector of contemporaneous and lagged prices of gas and $p_{\mathrm{NV}t}$ is the price of new vehicles.

A household can adjust its miles traveled and composite MPG in a variety of ways in both the short- and long-run. First, consider the choice of VMT. In the short-run, a household can alter VMT by changing the number or the consolidation of trips, while in the long-run, a household can change the distance between its residential location and trip destinations. A household can also be expected to make short- and long-run adjustments to composite MPG. In the short-run, a household can change its driving and maintenance behavior to alter MPG (e.g. change acceleration rates, highway speeds, and car service frequency) (Archibald and Gillingham, 1981). In addition, multi-vehicle households can adjust the usage of their current stock if the vehicles differ in efficiency rating. In the long-run, a household can change vehicle stock in order to change composite MPG. We expect $\eta_{\mathrm{VMT}-p} < 0$ but $\eta_{\mathrm{MPG}-p}$ can be positive or negative (a rise in price could reduce long trips and thus reduce MPG or consolidate short trips and increase MPG). Finally, these adjustments are not expected to be smooth over time since a large component of the household response is an adjustment to a durable stock.

Several previous micro-level studies have restricted their analyses to the short-run in order to avoid more complex models involving discrete choices of vehicle number and type. We are able to estimate elasticities which include more long-run adjustments by including households that make changes in vehicle stock. We perform this estimation with Eq. (3) and Eq. (4) by restricting our analysis to two continuous dependent variables: vehicle miles traveled and household composite MPG. This implicitly ignores vehicle stock as a discrete choice variable. Although a more complete model would incorporate these discrete choices, we believe that our continuous analysis is not without good foundation because many of the short-run adjustments discussed above are continuous choices. In addition, estimating the utilization and stock equations simultaneously will avoid the misspecification problem described by Dubin and McFadden (1984) since unobserved variables which affect the usage of vehicle stock may also affect the choice of stock.

In order to estimate Eq. (1), Eq. (3) and Eq. (4), we assume that the gasoline, VMT and composite MPG demand equations take a log additive functional form. Although this functional form is somewhat restrictive, we do not believe we will obtain biased estimates due to the results of Greene and Hu (1986). Greene and Hu find the optimal Box–Cox transformation to fit disaggregate gasoline demand data and find the resulting elasticities very similar to elasticities estimated with a log additive specification. With a log additive specification of the demand functions, we can interpret the parameter estimates as elasticities.

3. Data

We use 9 years of Consumer Expenditure Survey (CES) data to estimate non-business gasoline demand. The Consumer Expenditure Survey (US Department of Labor, 1980–1990) is a rotating panel which surveys a representative sample of the US population and collects information on household consumption, demographic characteristics, and durables ownership. The CES surveys a household for five consecutive quarters with the first interview collecting only income and durables information. Although the CES has been conducted annually since 1980, the years for which vehicle stock and mileage data are available and reliable are 1980–1981 and 1984–1990. In order to obtain the fuel efficiency of each vehicle in a household, we merge on EPA (US Department of Energy, 1996) data of efficiency ratings in lab tests. We merge on the efficiency numbers using a variety of criteria including make, model, year, type of vehicle, number of cylinders and type of transmission. Then we adjust the efficiency ratings according to annual miles traveled according to Mintz et al. (1993) who found correction factors to the laboratory estimates based upon driver behavior. We restrict our analysis to vehicles which traveled over 100 miles in a quarter.

We are then able to calculate two of the variables we require for the analysis. The number of non-business gallons used by each vehicle is the number of non-business miles (provided in the CES) divided by the vehicle fuel efficiency. Total household non-business gallons is the sum of gallons across all vehicles in the household. We calculate each household's non-business composite MPG as the sum of non-business miles across all vehicles in a household divided by the sum of non-business gallons. If a household is missing data for a vehicle which traveled over 100 miles in the quarter, then the household is excluded from the analysis.

Our price data is from the Bureau of Labor Statistics (US Department of Labor, 1979–1990) Average Price data. We use BLS monthly average nominal prices of all types of gasoline for various regions and population sizes. Then we deflate by the CPI for all items, average over the months in each rotating quarter, and merge on the household data by a combination of region and size criteria. In addition, we use BLS price indexes for maintenance and new cars as instruments in the two-equation model.

After merging all the required data and performing the calculations to obtain the variables needed for the analysis, 52% of the original CES household interviews have complete data. In order to roughly test for selection, we compare the means of our sample across all the years to the means from CES tables for 1987. Because we do not observe significant differences in the means, the remaining households are ignored without any test for selection bias. Our total analysis dataset is an unbalanced sample of 95 809 quarterly interviews across 37 046 households.

4. Empirical results

Both the direct estimation of gasoline demand using Eq. (1) and the indirect estimation using Eq. (3) and Eq. (4) leave open a variety of possible model specifications. Since the data is a panel, we analyze several specifications for individual household effects. In addition, we consider a variety of lag structures for gas prices.

4.1. Individual household effects

We experiment with specifications for individual household effects on the direct one-equation model (1). First, we assume no individual effects and estimate a pooled model. Using contemporaneous price and lags ranging from zero to four quarters, we estimate impact elasticities ranging from -0.77 to -0.83 with total elasticities ranging from -0.30 to -0.39. We find the large impact elasticity to be particularly interesting. When we include only contemporary and/or 1-year lagged prices as other studies have done, we obtain total elasticity estimates in the range of -0.35. Yet when we add various quarterly lagged prices which other studies have not done, we find that the impact effect in the current quarter is much larger. These results would be consistent with consumers rescheduling activities across seasons, such as postponing vacation driving when gas prices are high.

We also estimate several random and fixed effects models but we obtain unsatisfactory results. We model several random effects specifications and obtain fairly stable price elasticity estimates which lie within the range found in the literature. However, for all specifications, a Hausman test rejects that the random effects are orthogonal to the regressors so that our parameter estimates may be inconsistent.

We also assume that individual household effects can be captured by a separate constant for each household, and analyze a fixed effects specification. Depending upon the number of lagged prices included, our estimated price elasticities range from -0.44 to -1.33, with most estimating elastic demand. An F-test rejects the null hypothesis that the individual intercept terms are equal across households. Therefore the specification tests tend to lead us to prefer the fixed effects model. Thus, we must ask whether elastic demand is plausible.[3] On the one hand, we do believe that the within-household variation is the best method to estimate price

[3]Note that elastic demand would be consistent with a market in which suppliers have market power.

elasticity since the cross-sectional variation is more likely to introduce measurement errors which could bias the estimates downward. Nevertheless, we tend not to believe the results from the fixed effects specification. The elasticity estimates are very sensitive to the number of lags whereas the pooled estimates are not sensitive.[4] Although we do not have an explanation for the high elasticity estimates under fixed effects, we note that it is not uncommon for random and fixed effects models to lead to significantly different parameter estimates when T is small and N is large (Hsiao, 1986, p. 41). Since we find the fixed and random effects specifications unsatisfactory, we will base our analysis in the remaining sections of the paper upon the results from the pooled model. Estimates for the four lag specification of the pooled, fixed effects, and random effects models are presented in Table 1.

4.2. Lag structure

Our most general model of the lag structure would be to place no restrictions on the parameters and include up to four quarters of lagged prices. The results from this general pooled model are reported in column 1 of Table 1. The estimated dynamics of the adjustment process from this unrestricted specification can be seen in Fig. 1. The parameter estimates seemingly suggest that households do not adjust smoothly to price changes. However, this unexplainable waviness is likely due to strong collinearity rather than sporadic adjustment by households. Therefore this general model may estimate more of the quixotic nature of the data than the actual adjustment process. As a result, we impose restrictions on parameters to purge the estimates of the wavy patterns of lagged parameter estimates, but remain cautious not to impose invalid restrictions on the underlying behavioral model. As our criteria, we seek restrictions which avoid the unexplainable waviness, but do not change the estimate of the total adjustment (the sum of the price parameter estimates).

We consider several possible sets of restrictions. Previous conservation studies have suggested that demand for a variable input may have a large negative impact multiplier followed by a snap-back effect as households adjust durable stock.[5] To allow for this possibility, we allow the impact parameter to be free, but require that lagged parameters (or the snap-back effect) lie along a line (first-order polynomial). Also, we estimate a specification where the impact parameter is free and the four lagged parameters are required to be equal. Finally, studies have modeled the lagged coefficients as lying along an inverted-V. Accordingly, we require all parameter estimates (contemporary as well as lagged) to lie along a second-order polynomial.

[4]One plausible explanation is that the fixed effects estimates are biased due to the omitted time invariant covariates. However, we run the pooled model excluding the variables with no within household variation and obtain elasticity estimates very close to the original pooled results.

[5]An example of this effect applied to automobile stock is Greene (1992).

The OLS results from these three specifications of the one-equation model are shown in Table 2 and Fig. 1. All three models clear up much of the waviness of the unrestricted parameter estimates without changing the estimates of the total

Table 1
Single equation model with four lagged prices (regression coefficients with standard errors in parentheses)

Variable	Variable definition	Regression		
		Pooled	Fixed effects	Random effects
lngas	Log of contemporary real gas price	−0.826	−1.283	−1.006
		(0.054)	(0.053)	(0.042)
lngas11	Log of 1 qtr. lagged real gas price	0.094	−0.106	0.010
		(0.086)	(0.063)	(0.060)
lngas12	Log of 2 qtr. lagged real gas price	1.577	1.799	1.781
		(0.089)	(0.064)	(0.061)
lngas13	Log of 3 qtr. lagged real gas price	−2.017	−2.218	−2.113
		(0.085)	(0.062)	(0.059)
lngas14	Log of 4 qtr. lagged real gas price	0.843	0.743	0.881
		(0.054)	(0.052)	(0.043)
ln_incatx	Log of household income after tax	0.023	0.000	0.015
		(0.001)	(0.002)	(0.001)
childu18	No. of children under 18 in household	−0.014	−0.022	−0.016
		(0.003)	(0.016)	(0.005)
no_earnr	No. of earners in household	0.249	0.063	0.191
		(0.005)	(0.010)	(0.006)
urban	1 = Urban household	−0.208		−0.207
		(0.011)		(0.016)
refwhite	1 = Reference person white	0.257		0.266
		(0.011)		(0.016)
ref_fem	1 = Reference person female	−0.340		−0.333
		(0.008)		(0.011)
ref_hs	1 = Reference person high school educ.	0.132		0.129
		(0.010)		(0.014)
ref_scol	1 = Reference person some college	0.201		0.193
		(0.011)		(0.015)
ref_col	1 = Reference person college grad.	0.222		0.219
		(0.012)		(0.017)
ref_grad	1 = Reference person beyond college educ.	0.187		0.196
		(0.013)		(0.018)
totwkwrk	No. of weeks worked by head and spouse	0.001	0.001	0.001
		(0.000)	(0.000)	(0.000)
age_ref	Age of reference person	0.042	0.022	0.045
		(0.001)	(0.011)	(0.002)
agerefsq	Age squared of reference person	0.000	0.000	−0.001
		(0.000)	(0.000)	(0.000)
retired	1 = Member of household is retired	0.275	0.077	0.212
		(0.014)	(0.025)	(0.017)
intercept		3.248		3.299
		(0.035)		(0.046)

Table 1 (*Continued*)

Variable	Variable definition	Regression		
		Pooled	Fixed effects	Random effects
R^2		0.151	0.785	0.641
Sum of price coefficients (elasticity estimate)		−0.329	−1.065	−0.477

Sample size: 95 809.
F-test on pooled vs. fixed effects: $F_{37\,045,58\,750} = 4.90$; $P > F = 0.0000$.
Hausman test: χ^2 (18) = 668.78; $P = 0.0000$.

effect.[6] The snap-back model suggests a large impact effect followed by a snap-back which peaks after one quarter and then declines. Both the second-order polynomial and constant lagged coefficients models suggest a smaller negative impact effect followed a slightly positive lagged effect. Under these two models, however, the impact effect appears to be biased. As a result, we prefer the first-order snap-back model. Therefore we conclude from our one-equation model that the impact effect of a gas price change is significantly larger than the total effect. A 1% rise in the price of gasoline will decrease consumption by 0.76% in the current quarter, but then consumption will snap-back in the following quarter by 0.40% and be followed by progressively smaller rises in consumption in subsequent quarters. The overall effect of a 1% price rise in the year following the price change is a 0.34% fall in consumption.

4.3. Two-equation model

We now apply these model specifications to the two-equation model in order to tell a richer story about the household's adjustment process. The two-equation model allows us to decompose the adjustment from the one-equation model into the adjustment of the number of miles traveled and the adjustment of the household's composite MPG. Using two-stage least squares, we estimate Eq. (3) and Eq. (4) with four unrestricted lagged prices and estimate a slightly higher gasoline price elasticity (−0.47) than in the one-equation model. Regression results are reported in the first two columns of Table 3. We find that the elasticity of VMT with respect to the price of gasoline is −0.69 while the elasticity of composite MPG is −0.22. This negative elasticity of composite MPG would be consistent with households reducing the number of high efficiency miles such as vacation trips. The larger elasticity of VMT suggests that households make the

[6]Although each of these sets of restrictions are rejected at all standard testing levels, we believe such restrictions do not impose invalid restrictions on the behavioral model and are necessary to deal with the collinearity.

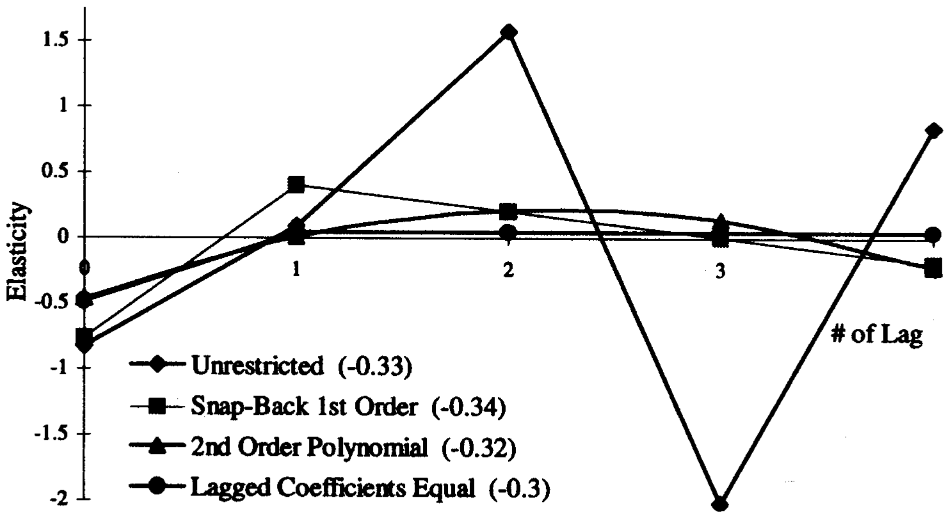

Fig. 1. One-equation model with four lagged prices: lagged coefficient estimates under the four different lag specifications for the one-equation model of gasoline demand with total elasticity estimates shown in parentheses.

largest adjustment within 1 year of a price change by reducing miles traveled. However, the resulting decrease in gasoline consumption is mitigated by a small reduction in household composite MPG.

Table 2
Single equation pooled model with four lagged prices (price coefficients with standard errors in parentheses)

	Regression			
	Unrestricted	Snap-back 1st order	2nd order polynomial	Lagged coefficients equal
lngas	−0.826	−0.764	−0.464	−0.485
	(0.054)	(0.046)	(0.036)	(0.035)
lngas11	0.094	0.403	0.011	0.045
	(0.086)	(0.039)	(0.017)	(0.009)
lngas12	1.577	0.204	0.211	0.045
	(0.089)	(0.019)	(0.029)	(0.009)
lngas13	−2.017	0.006	0.136	0.045
	(0.085)	(0.010)	(0.017)	(0.009)
lngas14	0.843	−0.192	−0.212	0.045
	(0.054)	(0.027)	(0.036)	(0.009)
Elasticity estimate	−0.33	−0.34	−0.32	−0.30

Table 3
Two-equation pooled model with four lagged prices (regression coefficients with standard errors in parentheses)

Variable	Variable definition	Unrestricted model		Snap-back model	
		Eq. (3) LN (VMT)	Eq. (4) LN (MPG)	Eq. (3) LN (VMT)	Eq. (4) LN (MPG)
lngas	Log of contemporary real gas price	−0.859 (0.056)	−0.131 (0.110)	−0.869 (0.050)	−0.112 (0.013)
lngas11	Log of 1 qtr. lagged real gas price	0.010 (0.088)	−0.041 (0.021)	0.327 (0.041)	−0.018 (0.010)
lngas12	Log of 2 qtr. lagged real gas price	1.528 (0.091)	0.042 (0.190)	0.114 (0.022)	−(0.026) (0.005)
lngas13	Log of 3 qtr. lagged real gas price	−2.009 (0.086)	−0.095 (0.252)	−0.099 (0.016)	−0.033 (0.002)
lngas14	Log of 4 qtr. lagged real gas price	0.727 (0.060)	−0.023 (0.095)	−0.312 (0.031)	−0.040 (0.007)
ln_mpg	Log of non-business miles per gallon	0.409 (0.325)		−0.403 (0.330)	
ln_vmt	Log of non-business VMT		−0.047 (0.125)		−0.016 (0.010)
ln_incatx	Log of household income after tax	0.025 (0.001)	0.003 (0.003)	0.026 (0.001)	0.002 (0.000)
pr_main	Price index of maintenance	0.004 (0.002)		0.005 (0.002)	
pr_new	Price index of new cars		−0.005 (0.000)		−0.005 (0.000)
chidu18	No. of children under 18 in household	−0.027 (0.008)	−0.024 (0.005)	−0.045 (0.008)	−0.023 (0.001)
no_earnr	No. of earners in household	0.256 (0.007)	0.025 (0.033)	0.266 (0.068)	0.017 (0.003)
urban	1 = Urban household	−0.194 (0.014)	0.016 (0.023)	−0.173 (0.014)	0.022 (0.003)
refwhite	1 = Reference person white	0.261 (0.011)	0.016 (0.033)	0.265 (0.011)	0.008 (0.004)
ref_fem	1 = Reference person female	−0.311 (0.018)	0.034 (0.037)	−0.272 (0.018)	0.043 (0.003)
ref_hs	1 = Reference person high school educ.	0.151 (0.014)	0.038 (0.021)	0.175 (0.014)	0.033 (0.003)
ref_scol	1 = Reference person some college educ.	0.246 (0.026)	0.086 (0.035)	0.304 (0.027)	0.077 (0.004)
ref_col	1 = Reference person college grad	0.293 (0.040)	0.131 (0.043)	0.386 (0.04)	0.121 (0.004)
ref_grad	1 = Reference person beyond college	0.275 (0.050)	0.163 (0.042)	0.394 (0.050)	0.152 (0.004)
totwkwrk	No. of weeks worked by head and spouse	0.001 (0.000)	0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
age_ref	Age of reference person	0.039 (0.003)	−0.005 (0.005)	0.033 (0.003)	−0.006 (0.000)

Table 3 (*Continued*)

Variable	Variable definition	Unrestricted model		Snap-back model	
		Eq. (3) LN (VMT)	Eq. (4) LN (MPG)	Eq. (3) LN (VMT)	Eq. (4) LN (MPG)
agerefsq	Age squared of reference person	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
retired	1 = Member of household is retired	0.286	0.026	0.296	0.017
		(0.015)	(0.037)	(0.015)	(0.004)
intercept		4.588	3.826	6.959	3.632
		(1.143)	(0.776)	(1.163)	(0.065)
R^2		0.164	0.110	0.154	0.117
Elasticity		−0.69	−0.22	−0.75	−0.22

Unfortunately, collinearity again gives us uninterpretable waves which we would like to purge from our estimates (see Fig. 2). When we apply the first-order snap-back, second-order polynomial, and constant lagged coefficients model to the two equations, we smooth the parameter estimates but obtain slightly larger (in absolute value) gasoline price elasticities (see Figs. 3–5). When we estimate the snap-back and second-order polynomial models, we obtain VMT elasticities of

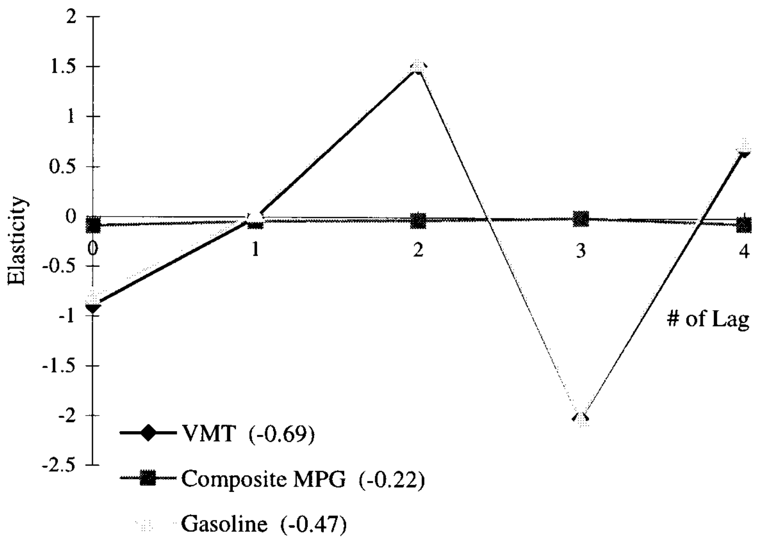

Fig. 2. Two-equation model with four unrestricted lags: elasticity estimates of VMT, composite MPG, and gasoline demand for each lagged price with total elasticity shown in parentheses.

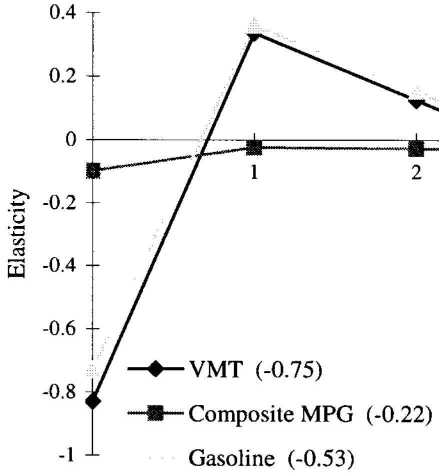

Fig. 3. Two-equation model with four lags: snap back first-order. Elasticity estimates of VMT, composite MPG, and gasoline demand for each lagged price with total elasticity in parentheses.

approx. -0.75 and MPG elasticities of -0.22 for a total gasoline elasticity approx. -0.54. The snap-back model again finds the larger response in VMT with a one-quarter snap-back in VMT (see Fig. 3). The VMT snap-back declines after the first quarter and eventually becomes negative. As for the constant lagged coefficients model, the initial effect is larger for both VMT and MPG and is followed by

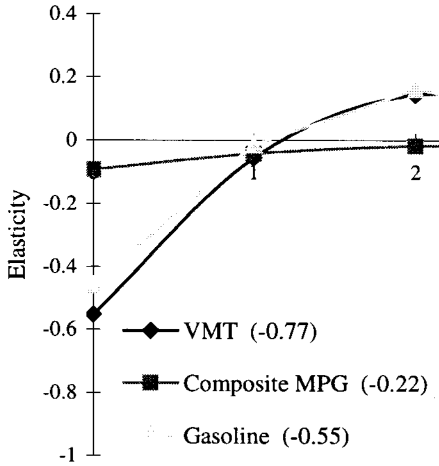

Fig. 4. Two-equation model with four lags: second order polynomial. Elasticity estimates of VMT, composite MPG, and gasoline demand for each lagged price with total elasticity shown in parentheses.

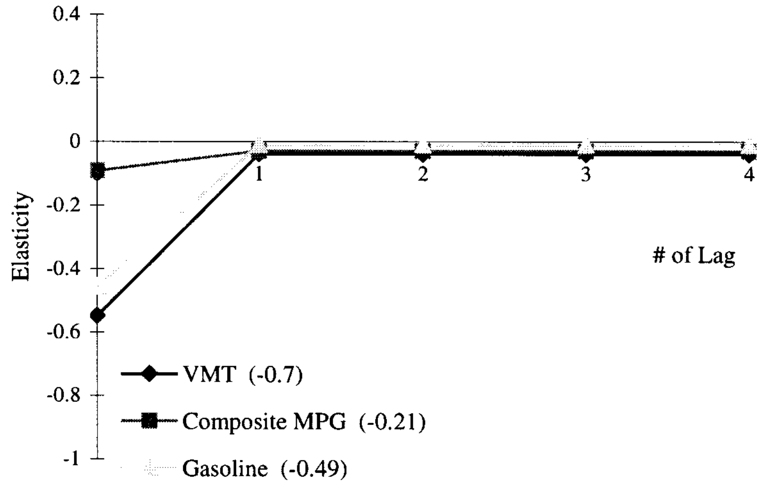

Fig. 5. Two-equation model with four lags: lagged coefficients equal. Elasticity estimates of VMT, composite MPG, and gasoline demand for each lagged price with total elasticity shown in parentheses.

smaller but still negative lagged effects (see Fig. 5). Again, we prefer the snap-back model because it appears not to significantly bias the impact effect. Qualitatively it suggests that households make the largest adjustment to vehicle miles traveled rather than to household MPG. MPG has a negative elasticity which is consistent with households primarily reducing the driving of more fuel efficient miles such as long trips. In addition, the snap-back effect is largest in the quarter following a price change.

5. Conclusions

This paper estimates household adjustment to changes in the real price of non-business gasoline. We estimate the demand for gasoline with a one-equation model, and then decompose the demand for gasoline into the demand for vehicle miles traveled and the demand for household fuel efficiency measured in miles per gallon.

Our one-equation pooled model yields gasoline price elasticity estimates which are consistent with the literature and support the claim that gasoline demand is relatively inelastic in the year following a price change. The interesting result is that the impact in the current quarter is much larger than previous studies have estimated. When we use contemporaneous prices and 1-year lags as other studies have used, we obtain elasticity estimates in the range of -0.35, which is consistent with the literature. However, when we uses various specifications of quarterly lagged prices, we find that the impact elasticity is consistently approx. -0.8.

Our two-equation results suggest that households reduce both vehicle miles traveled and household composite MPG in the year after a price change. The net adjustment to miles traveled is 3.5 times larger than the net adjustment to MPG. Our finding that $\eta_{MPG-p} < 0$ might suggest that households adjust composite MPG more by reducing high efficiency miles than by altering driving and maintenance behavior or by changing household vehicle stock. In the snap-back model, our preferred model of the lag structure, we find that both VMT and household MPG fall in the quarter of a price rise. However, in subsequent quarters, VMT snaps back while household MPG continues to gradually decline.

This paper offers insights into the dynamics and composition of household response to changes in the real price of gasoline. As in previous studies, gasoline demand is estimated to be relatively inelastic. However, we find that in the year following a price change, the adjustment is neither smooth nor evenly divided between adjustments to vehicle miles traveled and adjustments to household composite miles per gallon.

Acknowledgements

This research was supported by Shell Oil Company, General Motors, and Ford Motor Company. Additional support was provided by the Deputy Assistant Secretary for Transportation Technologies through Contract Number DE-AC03-765F00098. We are grateful to Kenneth Train for suggestions about the adjustment process and to Dan McFadden for his valuable comments.

References

Archibald, R., Gillingham, R., 1980. An analysis of the short-run consumer demand for gasoline using household survey data. Rev. Econ. Stat. LXII, 622–628.

Archibald, R., Gillingham, R., 1981. A decomposition of the price and income elasticities of the consumer demand for gasoline. South. Econ. J. 47, 1021–1031.

Dahl, C., Sterner, T., 1991. Analysing gasoline demand elasticities: a survey. Energy Econ. 13, 203–210.

Dubin, J., McFadden, D., 1984. An econometric analysis of residential electric appliance holdings and consumption. Econometrica 52, 345–362.

Espey, M., 1996. Explaining the variation in elasticity estimates of gasoline demand in the United States: a meta-analysis. The Energy J. 17, 49–60.

Greene, D., 1992. Vehicle use and fuel economy: how big is the 'rebound' effect? The Energy J. 13, 117–143.

Greene, D., Hu, P., 1986. A Functional Form Analysis of the Short-Run Demand for Travel and Gasoline by One-Vehicle Households. Transportation Research Record 1092. Transportation Research Board, National Research Council, Washington, D.C., pp. 10–15.

Greening, L., et al., 1995. Use of region, life-cycle and role variables in the short-run estimation of the demand for gasoline and miles travelled. Appl. Econ. 27, 643–656.

Hsiao, C., 1986. Analysis of Panel Data. Cambridge University Press, New York.

Mintz, M., Vyas, A., Conley, L., 1993. Differences Between EPA-Test and In-Use Fuel Economy: Are the Correction Factors Correct? Transportation Research Board 72nd Annual Meeting, Washington, D.C.

United States Department of Energy, 1996. Fuel Economy Guide, DOE/EE-0102. Government Printing Office.

United States Department of Labor. Consumer Expenditure Survey. Bureau of Labor Statistics, Washington, D.C., surveys from 1980–1990.

United States Department of Labor. CPI detailed report. Bureau of Labor Statistics, Washington, D.C., issues from 1979–1990.

Walls, M., Krupnick, A., Hood, C., 1993. Estimating the Demand for Vehicle-Miles-Traveled Using Household Survey Data: Results from the 1990 Nationwide Personal Transportation Survey. Resources for the Future Discussion Paper ENR 93–25, Washington, D.C.