of Leeds, Leeds, England, May 1979.
8. C. Lave and K. Train. A Disaggregate Model of Auto-Type Choice. Transportation Research, 1979.
9. Federal Highway Administration. Highway Statistics Summary to 1975. U.S. Government Printing Office, 1979.
10. G.R. Schink and C.J. Loxley. An Analysis of the Automobile Market: Modeling the Long-Run Determinants of the Demand for Automobiles. Wharton EFA Inc., Philadelphia, Vols. 1-3, 1977.
11. U.S. Bureau of the Census. Current Population Reports. U.S. Government Printing Office, Series P-60, No. 118, 1979.
12. Energy Modeling for Our Uncertain Future. Committee on Nuclear and Alternative Energy Systems, National Academy of Sciences, Washington, DC, Supporting Paper 2, 1978.

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State-Level Stock System Model of Gasoline Demand

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A summary overview of the specification and econometric estimation of a state-level model of highway gasoline demand is presented. The model, which was developed by Oak Ridge National Laboratory for the Energy Information Administration, was designed for policy- and technology-sensitive forecasting of gasoline use by light-duty highway vehicles over the 1980-2000 period.

This paper provides an overview of a model developed for use by the U.S. Department of Energy (DOE) in conducting policy- and technology-sensitive forecasting over a 5- to 15-year horizon of regional demand for motor fuel for light-duty vehicles. A policy- and technology-sensitive long-range gasoline demand model must integrate three major elements: (a) the demand for travel, (b) the demand for vehicles used to accomplish that travel, and (c) the technology by which those vehicles transform motor fuel into travel. Models by Difiglio and Kulash (1) and Sweeney (2) were the first to incorporate these elements into unified models for long-range forecasting of gasoline demand in the United States. Unlike these models, the model developed here takes as its theoretical basis the household production theory of consumer demand. In this framework, households are viewed as purchasing goods in the marketplace, which they transform, in conjunction with available technology, into commodities whose consumption directly yields utility [as shown, for example, by Pollak and Wachter (3)]. Thus, gasoline, or even travel, is not necessarily desired for its own sake but is rather an input to the production of something else that is.

In household production theory, demand functions exist for goods (e.g., gasoline) and have equal standing with demand functions for produced commodities (e.g., travel). As a result, it is perfectly valid to estimate direct demand equations for gasoline. Furthermore, in the short run, the demand function for gasoline will be conditional on the technology available for producing travel. These concepts form the basis for the model structure shown in Figure 1.

Given exogenous variables that include new-vehicle prices and characteristics, the demand for new vehicles by vehicle class and state is determined. Next, given existing state fleet compositions, new-car prices, and other variables, state used-vehicle holdings are determined by class and vintage. New purchases and used holdings combine to make up the fleet composition. Based on fleet composition, historical and exogenously specified data on vehicle fuel efficiencies, and state characteristics, fleet fuel efficiency is determined. Finally, fleet composition, fuel efficiencies, and other variables such as gasoline price determine the state gasoline demand.

It is not possible in this brief overview to provide full details of the specification or estimation of the model, nor is it possible to characterize the sources and construction of the data base used in its estimation and calibration. The interested reader is referred to the five-volume model documentation prepared for DOE (4), in which these issues are fully addressed.

This paper is divided into two parts: The first describes the theoretical specification of the model, and the second discusses the results of its econometric estimation.

MODEL SPECIFICATION

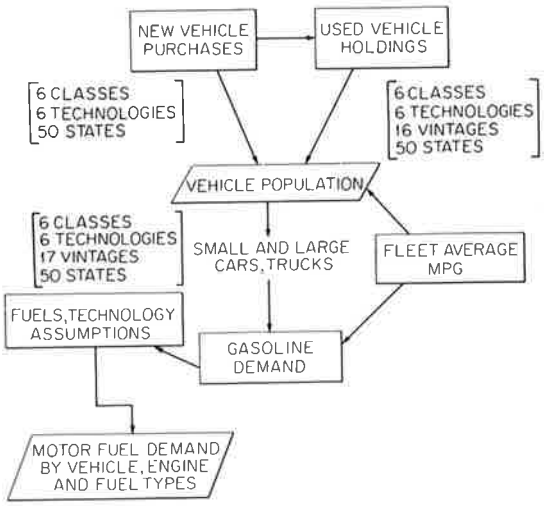
Demand for New Vehicles

The preferred approach to modeling automobile demand has, until recently, been the stock-adjustment model introduced by Chow (5) and Nerlove (6). This model specifies current sales as a function of current prices and income and lagged stock (other variables may be included):

$$q_{jt} = q_j (P_t, y_t, q_{jt} - 1) \quad (1)$$

New vehicles are viewed as additions to current stock; i.e., new and used cars are assumed to be aggregatable commodities. Recent work has challenged that view. Wykoff (7) proposed the hypothesis that the services of new cars are considered by consumers to be qualitatively superior to those of used cars. In this perspective, new-car purchases are not merely additions to the existing stock but rather reflect the demand for a unique commodity, new-car services, measured independently of the existing stock of used cars. Both Wykoff and Johnson (8) found the superior-goods hypothesis performed well empirically, and Wykoff found it to be superior to the stock-adjustment approach. The superior-goods hypothesis was adopted in the model, and new and

Figure 1. Structure of state-level gasoline demand model.



used cars are treated as closely substitutable, but distinct, goods.

Another commodity aggregation issue arises with respect to vehicles of different types. The requirements of policy analysis dictate that the model be sensitive to policies aimed at changing both the technical efficiency and the vehicle mix of the fleet. The latter consideration suggests that a typology of vehicles be developed based on vehicle attributes relevant to fuel economy and consumer demand. Previous models have typically used classifications that were based on a measure of vehicle size (1) or on a combination of size and price (9) and whose boundaries were determined by judgment. A less subjective, multidimensional approach to classifying automobiles that used cluster analysis was successfully applied to 1975 model-year cars (10). The essence of this approach is to classify cars into groups that are as much alike as possible based on relevant vehicle characteristics. This approach was applied to automobiles from 1955 to 1977 in order to establish a classification that was consistent over time. Pickup trucks and vans were treated as a separate group.

Most previous models have predicted class shares by using logit-type probabilistic choice models that predict the expected fraction of new-vehicle sales for each class. To obtain sales by class, one obviously needs to have an estimate of total new-car demand. But, if the vehicle types in fact represent distinct goods, the overall demand equation will suffer to some extent from aggregation bias. A preferred approach is to estimate demand equations by vehicle class, treating the classes as close substitutes. This leads to a set of related regressions:

$$A^k = A^k\,(C_1, \ldots C_k, \ldots C_n, P, W, I, e_k, h, d, b) \tag{2}$$

where

A^k = demand for new cars of class K,
C_1-C_n = new-car costs of K and all other classes that are assumed exogenous and those of used cars,
p = vector of other goods prices used in the production of travel,
e_k = fuel efficiency of class K vehicles,

and other variables are demographic and environmental. Since vehicles within a class will have (approximately) the same prices, A^k may be expressed simply as number of cars rather than in terms of some numeraire.

Consistent with previous studies, we assume the supply of new cars to be perfectly elastic at a price established by the producers.

Demand for Used Vehicles

In the model used, vehicle supply is represented by means of scrappage functions and used-vehicle demand is represented by equations that determine used-vehicle prices. Vehicle scrappage is determined by a combination of physical deterioration, accident, and market conditions based on Parks' interpretation of scrappage as a stochastic process (11). Following Parks, we make scrappage a logistic function of prices of used cars (p), repairs (r), and age (v):

$$\lambda(P/r,v) = 1/A + \exp\{-[b_1 + b_2\,(P/r) + b_3 v]\} \tag{3}$$

If we evaluate $\partial\lambda/\partial p$ as

$$\partial\lambda/\partial p = (A + \exp\{-[b_1 + b_2(P/r) + b_3 v]\})^{-2} \cdot (b_2/r)\exp[-b_2(P/r)] \tag{4}$$

it is clear that $b_2 < 0 \rightarrow (\partial\lambda/\partial p) < 0$. That is, if $b_2 < 0$, then scrappage rates go down as prices go up. In this circumstance, λ looks very much like a vintage supply equation. Holding variables other than price constant, we may write

$$(U_t' - U_{t+1})/U_t' = \lambda'(p) \tag{5}$$

where λ' is now a function of p only and $U_t' = U_t + A_t$ (last year's used stock plus new-car sales). Rearranging gives

$$U_{t+1} = U_t'\,[1 - \lambda'(p)] \tag{6}$$

The assertion that the logistic scrappage equation derived by Parks represents the consumer as a supplier of used vehicles can be justified by an examination of the behavioral content of the equation. The consumer bases the decision as to whether to retain (supply) or scrap (not supply) a vehicle solely on the price of the vehicle relative to the cost of repairing (producing) it. If the price is greater than or equal to the cost (the "profit" is nonzero), the vehicle is retained (supplied to the market). If not, it is scrapped (supply is zero). The analogy to the standard producer's problem in microeconomic theory is straightforward. Only the formulation of costs as stochastic is substantially different.

The demand side of the used-car problem is specified in terms of demand relative to last period's stock. Assume that the survival rate of used-car stock (U_{t+1}/U_t) is a function of price (p) and other factors (z). Consumer theory suggests that these other factors would be income and the prices of substitutes (new cars) and complements (such as gasoline). The functional form

$$U_{t+1}/U_t' = 1/\{1 + \exp[-(a_0 + a_1 p + a_2 z)]\} \tag{7}$$

has the desirable property of being bounded by 0 and 1. Rearranging gives

$$p = -(1/a_1)\{\ln[(U_t'/U_{t+1}) - 1] + a_0 + a_2 z\} \tag{8}$$

which is the demand equation in terms of price. In contrast to the scrappage equation, this equation includes income and prices of other goods. An advantage of this formulation is that it permits a detailed accounting of the actual number of vehicles by class and vintage within the context of a supply and demand model. By virtue of this, we can also

keep track of changes in vehicle efficiencies or even vehicle technologies as they are introduced and penetrate the vehicle fleet.

Conditional Demand for Gasoline

The vehicle demand equations derived above are long-run, static equilibrium equations. They describe the behavior of the consumer when all inputs to the household production process are variable and are thus a function only of goods prices and income. In the short run, the individual consumer may be able to turn over his or her vehicle stock rather quickly. However, the aggregate stock, by virtue of the value embodied in it, remains virtually constant. Thus, both the number of vehicles and their characteristics are essentially fixed, which makes the demand for gasoline conditional on them and independent of vehicle prices. This gives the model a sequential structure in which gasoline demand is conditional on the outputs of the motor-vehicle demand models.

The gasoline demand functions for states as fully specified include gasoline price (p^g), a vector of prices of other inputs (p^o), wage and nonwage income (w,I), a vector of vehicle ownership by efficiency-size classes (Q^v), a vector of vehicle characteristics (X), household size (h), working- and driving-age population (d), and other state characteristics (z):

$$q_{st} = q_s\,(P_{st}{}^g, P_{st}{}^o, w_{st}, I_{st}, Q^v{}_{st}, X_{st}, h_{st}, d_{st}, z_{st}) \tag{9}$$

where the subscripts s and t index state and time period, respectively.

Throughout, we have spoken as if the only highway motor fuel for light-duty vehicles were gasoline; in the future, however, there may be significant fuel substitution. The distribution between gasoline and other fuels is "shared out" according to the distribution of engine technologies in the vehicle fleet.

ESTIMATION OF ECONOMETRIC RELATIONS

This section of the paper first describes the five automobile classes used in modeling new-car demand and then considers the estimation of the six new vehicle demand equations, the results of the estimation of the used-car supply and demand equation, and, finally, the estimation of the gasoline demand model itself. Issues of functional form and regional parameter estimates as well as price and fuel-efficiency elasticities are addressed. Data for all 50 states and the District of Columbia for the 1967-1977 period were used in estimating the model (4).

Vehicle Classification

The five-group vehicle classification used in estimating class demand equations is described in Table 1. Based on their mean or centroidal values on each of eight variables, the groups can be described as follows:

Class	Vehicle Type
M1	High-performance, luxury sports cars
M2	Large luxury cars
M3	Small economy cars
M4	Medium-sized economy cars
M5	Large economy cars

New-Vehicle Demand

The model for new-vehicle demand consists of five automobile classes plus all light trucks with a gross vehicle weight of less than 10 000 lb. Each variable actually included in the estimated equations is described below. Detailed descriptions of primary data and sources are given elsewhere (4).

Table 1. Centroid values for five-group classification.

Variable Group	Group M1	M2	M3	M4	M5
Membership	50	135	251	304	234
Market shares (%)	5.1	13.9	25.8	31.2	24.0
Wheelbase (in)	96.4	123.0	95.6	112.8	120.7
Roominess factor (ft^3)	63.3	124.1	89.7	111.3	147.0
Curb weight (lb)	2780	4740	2308	3517	4410
Manufacturer's list price ($)	8063	7682	3606	4412	5214
Number of passengers	2.56	5.85	4.27	5.52	6.65
Displacement (in^3)	202	438	119	301	365
Price to number of passengers ($)	3115	1323	884	815	789
Horsepower to weight	0.0462	0.0499	0.0336	0.0407	0.0383

After considerable experimentation, annual payments cost was selected as the vehicle price variable. This variable was computed from the manufacturer's list price and the interest rate for loans on new or used automobiles, as appropriate, by using the following formula:

$$C_{it} = MLP_{it}/\sum_{k=1}^{3}(1+r)^{-k} \tag{10}$$

where

C_{it} = annual payment for a class i car purchased new in year t,
MLP = manufacturer's list price, and
r = finance rate for new-automobile loans.

Initially, individual prices of new and used vehicle substitutes were tested in the equations. Not surprisingly, multicollinearity problems were horrendous. Therefore, price indices for other new cars and for used cars were constructed by weighting class prices proportionally to their budget shares. The base year used for budget shares was 1967. The formula for the other-new-car price index (CIND) in the class i equation is as follows:

$$CIND_{it} = \sum_{j\neq i} C_{jt}\cdot C_{j67}\cdot A_{j67}/\sum_{j\neq i} C_{j67}\cdot A_{j67} \tag{11}$$

where A_{j67} is the sales of class j cars in 1967.

Gasoline price was entered as gasoline cost per mile, except in the light-truck equation. Income is simply measured as personal disposable income per household. Unemployment is the unemployment rate (in percent). All monetary variables were deflated to temporally and spatially constant dollars by using the regional cost-of-living index described elsewhere (4). Two demographic variables were included: household size (average number of persons per household) and the number of persons per household between the ages of 18 and 44 inclusive, the prime age group for drivers. Two rather crude measures of state spatial structure were included: (a) gross population density in persons per square mile and (b) urbanization measured as the percentage of population living in standard metropolitan statistical areas (SMSAs).

In theory, three vehicle price variables should appear on the right-hand side of each vehicle demand equation: (a) own price, (b) the price index of other new cars, and (c) the price index of used cars. The problem is that all three variables are strongly correlated as confirmed by simple as well as multiple correlation coefficients.

Solutions to the multicollinearity problem are few and generally "painful" (12). Of the possible solutions, we have resorted to (a) dropping the used-car price variable and (b) using extraneous information about the values of parameters. Extraneous information is used in an innovative way that allows an explicit trade-off of changes in the least-squares parameter estimate toward an a priori more desirable estimate for increases in the mean squared error (MSE) of the model. This was done by mapping the MSE of each regression equation as a function of arbitrarily fixed values of the own-price elasticities.

The equations were estimated in double log form. The coefficient of the log of own price was constrained by transforming the log dependent variable (y) by adding b_{1x1} where $-b_1$ is our first estimate of the price elasticity; $y + b_{1x1}$ may then be regressed against the remaining variables in the model (all but x_1). It is relatively easy to show that in an ordinary-least-squares (OLS) regression the value of b_1 that minimizes the error sum of squares for the transformed dependent variable regression is exactly the OLS estimate that would be obtained by performing the OLS regression of y on the full set of explanatory variables. By repeatedly selecting values of b_1, one can describe the relation between b_1 and the error sum of squares.

The equations were estimated in logarithms by using the variance-components procedure of the SAS79 program (TSCSREG) (13). National-level slope coefficients were estimated with state intercept terms computed from the equations' residuals.

Five-year dummy variables were included in the class 3 equation. Foreign cars--in fact, small cars in general--were an innovation during the 1960s in the United States. It was not until 1970 that Ford (Pinto) and General Motors (Vega) began to produce class 3 vehicles. The five dummy variables account for the shift in the demand curve as class 3 vehicles penetrated the U.S. market. By 1972, this penetration appears to have been complete. Time dummies for 1972 and afterward proved to be nonsignificant. A 1977-year dummy variable was also included in the class 4 and class 5 equations. The reason for this is that a significant redesign of large vehicles, called "downsizing", first occurred in 1977.

In general, the results were encouraging. In five out of six cases, the optimal own-price coefficient was negative, as expected. Only in the case of class 4 cars was this not the case. (Although it is not possible to offer a definitive explanation for this, it may well be that the omission of used-car prices had a greater effect on this equation.) This approach includes three criteria for deciding on the "best" value for the own-price elasticity: (a) the cost in increased error sum of squares of deviations from the optimum, (b) the effect of changes in the own-price coefficient on the values of other parameter estimates, and (c) a priori knowledge about parameter values. Based on such considerations, the final equations presented in Table 2 were chosen. There is no doubt that this approach involves subjective judgment as well as a priori knowledge about parameters. However, the technique we have adopted is certainly no less intelligent than ignoring the statistical problems and simply letting the chips fall where they may.

Although standard errors are given in Table 2, they should not be taken literally since they do not take into account that the value of the own-price coefficient was fixed outside of the regression analysis. Strictly speaking, the error of these exogenous estimates (which is unknown) should be taken into account.

Used-Car Demand

Equation 4 was estimated by means of a nonlinear least-squares routine [the SAS79 NLIN procedure was used (13)]. Equations were estimated for all states. Separate scrappage equations were estimated for classes 2, 4, 5, and 6, which are predominantly domestically manufactured vehicles. For classes 1 and 3, the equations for 2 and 4 were substituted, respectively. Individual equations could not be estimated for classes 1 and 3, since these consist primarily of imported cars and only the first seven vintage-year observations were available in the data base for imported cars in operation. Vehicles do not even begin to be scrapped in significant numbers until they are at least five or six years of age. In all, more than 200 separate equations were estimated with satisfactory results.

Prices of one-year-old used cars were estimated as a simple linear function of new-car prices. This simplification of the theoretical used-car demand model was used because of time and resource constraints. Preliminary experimental attempts to estimate the fully specified equation, however, indicated that new-car price was the only statistically significant variable. The used-car price equations were estimated at the national level by means of ordinary least squares [the SAS79 GLM procedure was used (13)]. Prices are purchase prices in 1967 constant dollars. The results are given in Table 3.

Gasoline Demand Equation

The variables used in estimating the gasoline demand equation are as follows:

1. Gasoline price--State prices were derived from data for 55 cities.
2. Income--Wage rate and nonwage income as well as disposable household income were used in alternative estimations. Disposable income was preferred because of its greater usefulness for applications of the model in forecasting. However, the choice of income measure had a minimal effect on the coefficient estimates of other variables. All money variables were converted to constant spatial dollars by means of a state cost-of-living index (4).
3. Persons per household under 18 years of age--Persons per household under 18 years of age accounts for state-to-state differences in the aggregate household composition by individuals not of driving age.
4. Workers per household--Workers per household largely measures a time trend of increasing labor-force participation rates for household members.
5. Urbanization--The urbanization variable is percentage of state population residing in SMSAs.
6. Population density--Population density is measured in persons per square mile.
7. Small cars--Number of small cars, roughly subcompact or smaller (i.e., classes 1 and 3), per household was used.
8. Large cars--Number of large cars per household, roughly compact or larger (i.e., classes 4, 5, and 2), was used.
9. Light trucks--Number of trucks of less than 10 000 lb weight per household was used.
10. Fuel efficiency--The fuel-efficiency measure used is estimated realized fuel economy of the state light-duty-vehicle fleet in miles per gallon.

The dependent variable used in this analysis is the Federal Highway Administration (FHWA) annual series of state highway gasoline use (taken from FHWA Table MF-26). This total includes private and commercial use and use by all types of vehicles. In

Table 2. Variance-components estimates of new-car class demand equations that use transformed dependent variable technique.

Vehicle Class	Intercept		Own Price		Cross Price		Gasoline		Income		Household Size		Age 18-44	
	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE
1	-6.370	3.609	-0.7	-	0.289	0.456	0.326	0.196	1.428	0.195	-1.425	0.457	-	-
2	4.035	2.413	-2.5	-	1.406	0.267	-0.094	0.167	0.808	0.136	-	-	-1.903	0.198
3	4.929	2.073	-0.7	-	0.330	0.189	0.209	0.149	0.334	0.153	-0.912	0.435	1.951	0.243
	-1.308[a]	0.078[a]	-1.091[b]	0.076[b]	-0.864[c]	0.073[c]	-0.453[d]	0.065[d]	-0.192[e]	0.620[e]				
4	2.314	2.082	-0.4	-	0.417	0.209	-0.090	0.142	0.060	0.111	0.902	0.264	-	-
	0.306[f]	0.193[f]												
5	-0.658	2.535	-2.5	-	2.226	0.258	-0.162	0.163	0.427	0.142	2.244	0.381	-1.887	0.235
	-0.504[f]	0.156[f]												
6	1.318	2.273	-1.2	-	1.138	0.251	-0.006	0.192	0.332	0.137	-1.300	0.354	0.609	0.224

Note: C = coefficient and SE = standard error.
[a]Year 1967.
[b]Year 1968.
[c]Year 1969.
[d]Year 1970.
[e]Year 1971.
[f]Year 1977.

Table 3. Equations for one-year-old used-car price.

Class	Intercept		New-Car List Price		R^2
	C	SE	C	SE	
1	225.941	270.622	0.650	0.039	0.93
2	506.117	217.476	0.673	0.032	0.96
3	259.668	50.083	0.670	0.018	0.98
4	-43.050	93.082	0.757	0.025	0.98
5	-198.972	14.0185	0.737	0.032	0.96
6	-1115.798	152.819	1.100	0.046	0.96

Notes: C = coefficient and SE = standard error.
Number of observations = 22.

our model we deal explicitly only with passenger cars and light trucks. These together account for well over 90 percent of all use. Heavy trucks, however, use nontrivial amounts of gasoline--on the order of 6.5 percent of total highway use (14, Tables 6.1, 7.2B, 8.1A, and 6.1). This must be borne in mind when one interprets model forecasts.

Since the fuel-efficiency data are the key to the model, they merit some description. The methods used in producing these data are the same procedures embodied in the fuel-efficiency submodel (Figure 1). To obtain the estimates used in this analysis, detailed statistics on state vehicle fleet compositions by vehicle make, model, and vintage were combined with city and highway fuel-economy estimates of the Environmental Protection Agency (EPA) to obtain sales-weighted fleet efficiency measures for each state. By using engineering procedures developed by Rose (15), these values were adjusted for the following factors to obtain estimates of realized fuel efficiency for each state: (a) the average U.S. discrepancy between EPA test and on-the-road fuel economy, (b) state monthly temperature distributions, (c) state trip-length distributions, (d) vehicle travel distribution for state urban versus rural roads, and (e) relations between vehicle use, vehicle age, and vehicle age distributions.

Due to the pooled time-series, cross-sectional nature of the data, a variance-components form of the generalized least-squares model was used in estimating the demand equation (12,13).

FUNCTIONAL FORM

Rather than assume a particular functional form, the Box-Cox transformation procedure was used to determine the "optimal" functional form [as discussed, for example, by Zarembka (16)]. In this procedure, both the dependent and independent variables are altered by the transformation

$$X' = (XK_{-1})/K \qquad K \neq 0$$

$$X' = \log(X) \qquad K = 0 \tag{12}$$

Although the maximum likelihood value of K was at 0.15, the approximate confidence interval for K easily included 0.0 (i.e., the double logarithmic transformation). The double log form of the model was therefore accepted.

REGIONAL ELASTICITIES

The error-components model can be construed as implying that intercept terms (the scalar constants in the double log form) vary across states. Perhaps of greater interest is the possibility that slope parameters differ significantly across states and regions. Particular attention has been given to the possibility that gasoline price elasticities vary by state and region (17-20). In general, the conclusions have varied according to the regionalization used and the method of estimation. Greene (21) has suggested that regional gasoline price data may not be of sufficient quality to permit the estimation of regional price elasticities. Income elasticities are also of interest, since substantial income growth in the future is likely to shift regional patterns of consumption. This issue has apparently not been addressed elsewhere.

To test the existence of differing price and income elasticities for the 10 federal regions, all other slope coefficients were assumed constant across states and nine new variables representing the product of the logarithm of price (or income) and a set of regional dummies (d_i) were introduced. The exponent (or elasticity) of price (income) is thus

$$\beta_p = \beta_{10p} + \sum_{i=1}^{9} d_i \beta_{ip} \tag{13}$$

so that each region will have a different elasticity. The results, based on (asymptotic) F-statistics, indicated that both price (F = 2.45) and income (F = 7.66) elasticities vary significantly across regions. An examination of income elasticities reveals that the range of income elasticities is a mere 0.34-0.40 (see Table 4). For this reason, regional income elasticities were not incorporated in the model equations.

Regional short-run price-elasticity estimates, on

Percentage Population in SMSA		Population Density		Unemployment		Residual Variance (df)	
C	SE	C	SE	C	SE	C	SE
0.237	0.071	0.050	0.030	-0.105	0.045	0.136	542
0.088	0.046	-	-	-0.088	0.033	0.073	543
0.138	0.053	-	-	-0.193	0.034		
-	-	0.055	0.013	-0.157	0.026	0.052	542
-	-	-	-	-0.236	0.034	0.060	542
-0.132	0.047	-0.264	0.018	-0.245	0.032	0.051	541

the other hand, exhibit a larger quantitative variability. The estimates range from a high of +0.02 (which is statistically not different from zero) to a low of -0.20. Three of the 10 regions have elasticity estimates greater than -0.10 (see Table 5). The explanation for the geographic variation of these regional estimates is not obvious. However, at least five factors probably contribute to the pattern: (a) inadequate state-level price data (21); (b) spatial choice constraints limiting the ability to reduce travel in more sparsely settled states; (c) through traffic (in general, smaller states astride major Interstate routes would be most affected); (d) commercial gasoline use, which appears to have considerable geographic variability (22); and, finally, (e) the well-known fact that adding dummy variables to an equation contributes multicollinearity (the problem is not severe in this case, but it is undesirable).

In summary, there are good reasons why one should expect short-run price elasticities to vary geographically. However, there appear to be equally good reasons--most importantly, data shortcomings--why the particular estimates presented here should be treated with caution. As a result, we have not included regional price elasticities in the model.

FUEL-EFFICIENCY RESPONSIVENESS

A major objective was to empirically estimate the degree to which improvements in the fuel efficiency of the vehicle fleet, as measured by the estimated state fleet realized fuel economy, would be translated into realized fuel savings. The elasticity of state gasoline demand with respect to the estimated realized efficiencies was therefore econometrically estimated. The results are given in Table 6. Once again, since the equation was estimated in double log form, the coefficients may be interpreted as constant elasticities.

A useful interpretation of the fuel-efficiency (MPG) elasticity is obtained by considering the relation between it and the elasticity of fuel cost per mile:

$$p^{\alpha}\,MPG^{\beta} = (P/MPG)^{\alpha}\,MPG^{\gamma} \tag{14}$$

where $\beta = \gamma - \alpha$. Thus, the estimated elasticity of MPG in Table 6 is, in effect, the fuel-efficiency elasticity minus the gasoline-price elasticity. The point estimate of γ is therefore

$$\gamma = -0.91 + (-0.10) = -1.01 \tag{15}$$

which is about what one would naively expect. In other words, all of the estimated on-the-road fuel-efficiency improvement will be translated into energy savings, but as the vehicle fleet becomes more efficient consumers will face a lower fuel price per mile and travel more. In the context of household production theory, this is interpreted as a change in the travel production function. The estimates suggest that a 10 percent increase in fleet fuel efficiency would result in roughly a 1 percent increase in travel and an overall fuel savings of 9 percent. Assuming that this is accurate, fleet fuel-efficiency improvements should be an extremely effective method of reducing the demand for gasoline. As a caveat, however, one should note that the asymptotic 95 percent confidence interval for the elasticity of fuel efficiency is quite large: $\epsilon_E \doteq -0.91 \pm 0.39$.

SUMMARY

The specification and econometric estimation of a state-level highway gasoline demand model has been described. The model comprises models for new- and used-vehicle demand, vehicle efficiency, and gasoline demand. New-car demand is estimated by state

Table 4. Variance-components estimation of gasoline demand equation with regional income coefficients.

Variable	Estimated Coefficient	t-Statistic	Standard Error
Intercept	6.40	8.13	0.79
Price	-0.13	-3.64	0.04
Income	0.36	12.08	0.03
1	0.01	0.89	0.01
2	-0.02	-1.92	0.01
3	0.02	1.89	0.01
4	0.03	4.11	0.01
5	0.01	0.62	0.01
6	0.03	3.75	0.01
7	0.01	1.07	0.01
8	0.01	1.70	0.01
9	0.01	1.43	0.01
Population under 18	-0.19	-3.79	0.02
Small cars	0.09	7.55	0.01
Large cars	0.05	1.62	0.03
Light trucks	0.03	2.92	0.01
Urbanization	-0.05	-3.08	0.02
Population density	-0.05	-3.31	0.01
Labor force	0.06	5.46	0.01
Fuel efficiency	-1.45	-6.68	0.22

Note: $\sigma_\mu^2 = 0.0083$, $\sigma_\nu^2 = 0.0001$, $\sigma_\gamma^2 = 0.0005$, and df = 530.

Table 5. Variance-components estimation of gasoline demand equation with regional price coefficients.

Variable	Estimated Coefficient	t-Statistic	Standard Error
Intercept	5.19	6.73	0.77
Price	-0.13	2.82	0.04
1	-0.00	-0.11	0.04
2	0.12	2.20	0.05
3	-0.00	-0.06	0.04
4	-0.07	-1.79	0.04
6	-0.06	-1.31	0.04
7	-0.02	-0.50	0.04
8	0.04	1.08	0.04
9	-0.00	-0.10	0.05
10	0.14	-3.04	0.05
Income	0.38	12.28	0.03
Population under 18	-0.19	-3.62	0.05
Small cars	0.08	7.36	0.01
Large cars	0.08	2.70	0.03
Light trucks	0.04	3.44	0.01
Urbanization	-0.05	-3.00	0.02
Population density	-0.07	-5.36	0.01
Labor force	0.07	5.82	0.01
Fuel efficiency	-1.14	-5.41	0.21

Note: $\sigma_\mu^2 = 0.0081$, $\sigma_\nu^2 = 0.0001$, $\sigma_\gamma^2 = 0.0006$, and df = 530.

Table 6. Variance-components estimation of gasoline demand equation.

Variable	Estimated Coefficient	t-Statistic	Standard Error
Intercept	4.56	6.24	0.73
Price	−0.10	−2.90	0.04
Income	0.40	12.74	0.03
Small cars	0.07	6.62	0.01
Large cars	0.08	2.55	0.03
Light trucks	0.05	4.33	0.01
Population under 18	−0.18	−3.54	0.05
Urbanization	−0.04	−2.54	0.02
Population density	−0.06	−5.28	0.01
Labor force	0.06	5.07	0.01
Fuel efficiency	−0.91	−4.62	0.20

Note: $\hat{\sigma}_\mu^2 = 0.0096$, $\hat{\sigma}_\nu^2 = 0.0001$, $\hat{\sigma}_\gamma^2 = 0.0006$, and df = 539.

for six vehicle classes. Given last year's used-car fleet composition, current used-car stocks by state, class, and vintage are estimated. Based on state fleet composition as well as historical and exogenously supplied information on vehicle fuel efficiencies, the in-use fuel efficiency of each state's vehicle fleet is estimated. Gasoline demand is estimated conditional on state fleet composition and fuel efficiency. The model also provides the ability to introduce new vehicle technologies by class, keep track of their penetration into state vehicle fleets, and estimate their fuel use according to their proportions in state vehicle fleets. The model thereby provides a capability for policy- and technology-sensitive forecasting of gasoline demand at the state level. The modeling system has been implemented on computer systems at the Energy Information Administration of DOE and at Oak Ridge National Laboratory.

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REFERENCES

1. C. Difiglio and D. Kulash. Marketing and Mobility: Report of a Panel of the Interagency Task Force on Motor Vehicle Goals Beyond 1980. Publications Section, Office of the Secretary of Transportation, TAD-443.1, 1976.
2. J.L. Sweeney. The Demand for Gasoline: A Vintage Capital Model. Department of Engineering and Economic Systems, Stanford Univ., Stanford, CA, 1977.
3. R.A. Pollak and M.L. Wachter. The Relevance of the Household Production Function and Its Implications for the Allocation of Time. Journal of Political Economy, Vol. 83, No. 2, 1975, pp. 255-277.
4. D.L. Greene and others. ORNL Highway Gasoline Demand Model Documentation. Oak Ridge National Laboratory, Oak Ridge, TN, Vols. I-VI, 1980.
5. G.C. Chow. Demand for Automobiles in the United States. North Holland Publishing Co., Amsterdam, The Netherlands, 1957.
6. M. Nerlove. A Note on Long-Run Automobile Demand. Journal of Marketing, July 1957, pp. 57-64.
7. F.C. Wykoff. A User Cost Approach to New Automobile Purchases. Review of Economic Studies, Vol. 40, No. 123, 1973.
8. T.R. Johnson. Aggregation and the Demand for New and Used Automobiles. Review of Economic Studies, Vol. 45, No. 140, 1978, pp. 311-328.
9. G.R. Schink and C.J. Loxley. An Analysis of the Automobile Market: Modeling the Long-Run Determinants of the Demand for Automobiles. Transportation Systems Center, U.S. Department of Transportation, Cambridge, MA, Vols. 1-3, 1977.
10. R. Dubin, D.L. Greene, and C. Begovich. Multivariate Classification of Automobiles by Use of an Automobile Characteristics Data Base. TRB, Transportation Research Record 726, 1979, pp. 29-37.
11. R. Parks. Determinants of Scrapping Rates for Postwar Vintage Automobiles. Econometrica, Vol. 45, No. 5, 1977, pp. 1099-1115.
12. G.S. Madalla. Econometrics. McGraw-Hill, New York, 1976.
13. SAS User's Guide 1979 Edition and Supplemental Library User's Guide. SAS Institute, Inc., Raleigh, NC, 1979.
14. J.N. Hooker, A.B. Rose, and D.L. Greene. End Use Energy Consumption Data Base: Transportation Sector. Energy Information Administration, U.S. Department of Energy, Rept. DOW/EIA/CR-7405-01, 1980.
15. A.B. Rose. Energy Intensity and Related Parameters of Selected Transportation Modes: Passenger Movements. Oak Ridge National Laboratory, Oak Ridge, TN, ORNL-5506, 1979.
16. P. Zarembka. Transformation of Variables in Econometrics. In Frontiers in Econometrics (P. Zarembka, ed.), Academic Press, New York, 1974.
17. H.S. Houthakker, P.K. Verleger, Jr., and D.P. Sheehan. Dynamic Demand Analyses for Gasoline and Residential Electricity. American Journal of Agricultural Economics, Vol. 56, No. 2, 1974, pp. 412-418.
18. J. Kraft and M. Rodekohr. Regional Demand for Gasoline: A Temporal Cross-Section Specification. Journal of Regional Science, Vol. 18, No. 1, 1978, pp. 45-55.
19. J.S. Mehta, G.V.L. Narasimham, and P.A.V.B. Swamy. Estimation of a Dynamic Demand Function for Gasoline. Journal of Econometrics, Vol. 7, 1978, pp. 263-279.
20. D.L. Greene. The Spatial Dimension of Gasoline Demand: An Econometric Analysis of State Gasoline Use. Geographical Survey, Vol. 9, No. 2, 1980, pp. 19-28.
21. D.L. Greene. Regional Demand for Gasoline: Comment. Journal of Regional Science, Vol. 20, No. 1, 1980, pp. 103-109.
22. G. Kulp and others. Regional Analyses of Highway Energy Use. Oak Ridge National Laboratory, Oak Ridge, TN, ORNL-5587, 1979.

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