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A dynamic empirical analysis of household vehicle ownership and utilization

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In this article we develop a dynamic model of household vehicle ownership and utilization behavior by using data that were generated before, during, and after the 1979 energy crisis. The principal empirical findings are that households have maintained a distinct preference for American over foreign cars, but also have strong brand loyalties. The results suggest that notwithstanding recent financial trends, U.S. firms must continue to make technological improvements in their vehicles and must combat the brand loyalty that has developed for foreign vehicles if the domestic automobile industry is to be viable at the present scale of operations.

1. Introduction

■ Historically, automobile sales in the United States have been characterized by a cyclical pattern that strongly affects domestic automobile manufacturers' profitability. The most recent downward cycle, which began with the oil supply disruptions in the Summer of 1979, has been argued to be the most severe and influential cycle in American automobile history. For a period of three years following the 1979 energy shock, domestic automobile sales were dangerously depressed to such a point that Chrysler narrowly escaped bankruptcy, and General Motors and Ford reported record losses. As a result of this financial crisis, labor contract concessions were negotiated, production technologies made greater use of robotics, and billions of dollars were invested by domestic manufacturers to develop product lines that would be more competitive with foreign offerings.

The most recent automobile sales figures indicate that the costly downward sales cycle of the early 1980s has ended. New automobile sales have rebounded from a dismal level in 1982 to profitable levels in 1983 and 1984. But in the wake of the recent expiration of voluntary export restrictions,[1] which were negotiated in 1981, the stability of the industry's financial recovery is being questioned.

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[1] The Japanese government has recently placed a limit on the number of new Japanese cars that can be sold in the United States under a voluntary restraint agreement. This quantity, however, exceeds the limit that existed under the old voluntary export restrictions.

The purpose of this article is to analyze the determinants of households' demand for automobiles to help assess the future financial prospects of the industry.[2] In particular, the following questions need to be addressed. Have consumers' valuation of the tradeoff between vehicle attributes, such as operating and capital costs, changed over time? How responsive, in terms of vehicle purchases, would consumers be to changes in vehicle attributes? Perhaps most importantly, to what extent are consumers' brand preferences toward particular vehicle makes (e.g., foreign versus American manufactured cars) and their brand loyalties based on past ownership experience important in their vehicle selections? Given the inherent problem of consumer inertia in durable goods markets and the degree of import penetration that has occurred in the U.S. automobile industry, an understanding of the sources of consumers' disinclination to change is crucial in assessing the financial future of this industry.

Previous research on the demand for automobiles, while abundant, has not addressed these issues because it has not adequately accounted for the dynamic aspects of vehicle ownership. In addition, such research has not accounted for the relationship between households' decisions as to the quantity of vehicles to own, the types of vehicles to own (make, model, and vintage), and the extent to which a vehicle is used.[3]

We derive and estimate a dynamic model of automobile demand that accounts for households' choices of vehicle quantity, vehicle type, and vehicle utilization. The resulting equations are estimated with data that capture single-vehicle households' and two-vehicle households' purchasing and utilization behavior before, during, and after the June, 1979, energy shock. The vehicle-type choice model forms the heart of the analysis and will illuminate the important influences in vehicle selection and indicate whether these influences have changed over time. Particular attention will be devoted to quantifying the importance of brand preference and brand loyalty in vehicle choice. The vehicle utilization model will provide insight into the determinants of households' use of their vehicle(s) under energy crisis and noncrisis conditions. Finally, the quantity choice model will explain the key determinants of the size of a household's vehicle portfolio. Special attention will be given to the influence that a household's satisfaction with its current vehicle holdings has on portfolio size.

The organization of the article is as follows. In Section 2 we derive an estimable dynamic model of household vehicle quantity, type choice, and utilization. Econometric procedures are discussed in Section 3, and our data base is described in Section 4. In Sections 5 and 6 we report and analyze estimation results for single-vehicle and two-vehicle households respectively. Finally, Section 7 contains concluding observations.

2. A dynamic econometric model of vehicle ownership

■ Dynamic considerations in the household's vehicle ownership problem arise from the evolution of household tastes over time.[4] Taste changes depend on a number of factors. In particular, on the basis of past choices, households can become familiar with a specific

[2] For an analysis of the costs, technology, and productivity of the U.S. automobile industry, see Friedlaender, Winston, and Wang (1983).

[3] Previous research concerned with household vehicle demand has concentrated exclusively on: (1) the quantity of vehicles to own (Burns, Golob, and Nicolaidis, 1976; Lerman and Ben-Akiva, 1976; Golob and Burns, 1978; Train, 1980); (2) vehicle-type choice (Lave and Train, 1979; Manski and Sherman, 1980; Berkovec and Rust, 1981; Hockerman, Prashker, and Ben-Akiva, 1983); or (3) vehicle utilization (Mannering, 1983).

With regard to dynamics, previous work (e.g., Manski and Sherman, 1980; Train and Lohrer, 1982) has addressed this issue by including transaction dummy variables in their demand models without attempting, as will be done here, to provide a theoretical basis for the specification of a dynamic model.

[4] Dynamic considerations also arise from the fact that automobiles are durable goods. Namely, it is important to distinguish between the demand for a stock of durable goods (i.e., the quantity and type of automobiles) at some point in time or during some period of time and the demand for the flow of services that the stock renders (i.e., vehicle-miles travelled or utilization).

vehicle or make of vehicle, thereby developing habits that form a basis for taste changes. Other bases of taste formation include advertising and information collected from contact with other vehicle owners.[5] We incorporate taste changes in this analysis by assuming that such changes are determined solely by past decisions. Specifically, we assume that taste changes are determined by past use of specific vehicles operated by the household.

Operationally, taste changes are introduced through a state variable S_{it}, which we assume summarizes all past utilization relevant to a given vehicle i at time t. Using this approach, we obtain a short-run estimable dynamic utilization equation, which incorporates the influence of past automobile ownership behavior. The dynamic utilization equation that is initially specified, but which cannot be estimated, suggests the existence of an implied Hamiltonian, as could be formulated for an intertemporal utility maximization problem. Using the estimable utilization equation, we apply Roy's identity to recover the corresponding short-run indirect utility function. Finally, we use the indirect utility function to specify a dynamic discrete choice model of vehicle quantity and vehicle type.[6]

□ **The dynamic utilization equation.** Our short-run stochastic dynamic utilization equation for a given household[7] is specified in a simple linear form as:

$$x_{it} = \tau_i + \beta_i(I_t - C_{it}) + \alpha_i S_{it} + \omega_i \psi_{it} + Z'_{it}\theta + \eta_t, \tag{1}$$

where (using discrete time) x_{it} is the accumulated utilization of vehicle i over the discrete time interval, I_t is the interval household income, C_{it} is the interval cost of operating vehicle i, S_{it} is the accumulated value of the state variable over the time interval, ψ_{it} is a corresponding costate variable (interpreted as the implicit value attached to a marginal unit of S_{it}), Z_{it} is a vector of household and vehicle characteristics,[8] η_t is a disturbance term, τ_i, β_i, α_i, ω_i are parameters, and θ is a parameter vector. Recall that the state variable is intended to "summarize" the past utilization of vehicle i—that is, it can be interpreted as the stock of utilization experiences. Since the state variable and corresponding costate variable are not observable, they must be converted to measurable variables if the utilization equation is to be estimable.

To convert the state variable, consider the accounting relationship (at any time t) for variable S_i:

$$\frac{dS_i}{dt} = \dot{S}_{it} = J_{it} - \delta_i S_{it}, \tag{2}$$

where J_{it} is the addition to the state variable over a given time interval resulting from vehicle choices, and δ_i is an assumed constant rate of depreciation of S_{it}. It is assumed that old experience with vehicle i is less reliable than recent experience. In this analysis, J_{it} is defined to be a linear function of the utilization of vehicle i and of the utilization of vehicles of the same make, the well-known notion of brand loyalty. Thus J_{it} can be defined as:

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[5] In principle, taste changes evolve from both learning and the formation of habits.

[6] The dynamic vehicle ownership problem can be posed alternatively as a household maximizing its intertemporal utility function with respect to its choice of vehicle quantity, type, and usage, subject to its intertemporal budget constraint. There are, however, several limitations to this approach. These include the highly restrictive conditions that must be imposed on preferences to derive a long-run utility function in the context of habit formation (Pollak, 1976), the high likelihood that the assumption of consistent planning (Strotz, 1956) will not be valid in our context (see Section 5), and the realization that households may behave myopically in terms of their automobile ownership decisions (i.e., households do not take full account of the impact of their present consumption of automobiles on future tastes).

[7] To avoid additional subscripting, we simply note here that the stochastic utilization equations and corresponding indirect utility functions (see below in the text) vary across individual households.

[8] It should be noted that Z could also include, in principle, the prices of modes that are substitutes or complements to auto (e.g., bus, rail, or air, depending on trip purpose). Unfortunately, the construction of a meaningful price variable for a particular mode would be rather difficult in our context. On the other hand, some empirical evidence, based on disaggregate mode choice studies, suggests that automobile cross price elasticities are quite small (Winston, 1985).

$$J_{it} = ax_{it} + cx'_{it}, \tag{3}$$

where x'_{it} is the accumulated utilization over the discrete time interval of a vehicle (not including vehicle i) that is the same make (i.e., manufacturer) as vehicle i. For example, if x_{it} represents utilization of a Ford Mustang, then x'_{it} represents utilization of all Fords that are not Mustangs (e.g., Thunderbirds, Escorts).

Attention can now be given to converting the state and costate variables from equation (1), which are not measurable, into measurable explanatory variables. Since this is done using a straightforward but somewhat tedious differencing procedure, application of the method is relegated to an appendix that is available from the authors upon request. The resulting utilization equation can be written as:

$$x_{it} = A_{i0} + A_{i1}x_{it-1} + A_{i2}x_{it-2} + A_{i3}x'_{it-1} + A_{i4}x'_{it-2} + A_{i5}\lambda_{it} + A_{i6}\lambda_{it-1} + A_{i7}\lambda_{it-2} + Z'_{it}\theta + \nu_t, \tag{4}$$

where the A_i's are parameters, $\lambda_{it} = I_t - C_{it}$,[9] ν_t is the resulting disturbance term,[10] and all other variables are as defined previously.[11]

□ **Derivation of the indirect utility function and a discrete choice model of vehicle quantity and vehicle type.** Given the short-run dynamic utilization equation specified above, it is possible to derive the corresponding short-run dynamic indirect utility function implied by Roy's identity.[12] That is,

$$\frac{\partial V_{it}}{\partial I_t} x_{it} + \frac{\partial V_{it}}{\partial p_{it}} = 0, \tag{5}$$

where V_{it} is the short-run dynamic indirect utility function and p_{it} is the unit price of vehicle utilization. Define the operating cost of vehicle ownership as:

$$C_{it} = \pi r_{it} p_{it}, \tag{6}$$

where r_{it} is the typical vehicle utilization of vehicle i in period t and π is a parameter to be estimated.[13] Thus, using equations (4), (5), and (6), it can be shown (see, for example, Hausman (1981)) that the indirect utility function is of the form:

[9] Our specification of income minus vehicle operating costs enables our indirect utility function, which is derived from the utilization equation, to satisfy the condition that demand for discrete alternatives (i.e., vehicles) is given by Roy's identity (McFadden, 1981). As pointed out by McFadden, the utility structure that satisfies this condition yields choice probabilities that are independent of current income, and thus requires the assumption that indirect utility is additively separable in income. In terms of our analysis, this implies that within a given household vehicle ownership level, the marginal rate of substitution between, for example, operating and capital costs is independent of the level of household income. Given the limited range of income over each vehicle ownership level, this assumption is not implausible.

Correlates of income that serve as proxies for tastes, however, may enter the choice probabilities. In our empirical work this justifies our inclusion of household income in the discrete choice models. The implication of this interpretation of income is that "income" elasticities actually capture households' responses to changes in tastes as manifested by changes in income.

[10] It is assumed that as a result of the transformation this error term is not serially correlated. That is, ν_t was derived from an error term, η_t, that was serially correlated. Unfortunately, this assumption must be made to ensure empirical tractability (see Section 3).

[11] It should be noted that the transformation led to the specification of lagged values of the explanatory variables contained in Z. These are not included here, however, as we found in our subsequent empirical work that the parameters of such variables were small and statistically insignificant.

[12] The application of Roy's identity assumes that more utilization is preferred to less utilization. As discussed in Dubin (1982), Roy's identity will also continue to hold under certain conditions when this assumption is not met.

[13] For estimation purposes, typical vehicle utilization, r_{it}, is used in the construction of vehicle operating costs instead of true vehicle utilization. As will be shown, typical utilization is calculated from aggregate average utilizations and is hence exogenous in our model. If true utilization were used, the complexities caused by the endogeneity of this variable would make empirical estimation exceedingly difficult.

$$V_{it} = [A_{i0} - \pi_i r_{it} + A_{i1}x_{it-1} + A_{i2}x_{it-2} + A_{i3}x'_{it-1} + A_{i4}x'_{it-2} + A_{i5}\lambda_{it} + A_{i6}\lambda_{it-1} + A_{i7}\lambda_{it-2} + Z'_{it}\theta + v_t]e^{-A_{i5}P_{it}} + \epsilon_{it}, \quad (7)$$

where ϵ_{it} is an additional disturbance term.[14]

Given this specification of indirect utility, it is straightforward to derive a discrete choice model of vehicle quantity and vehicle type. First, the joint utility from type choice and quantity choice can be expressed in terms of a random indirect utility function as (suppressing time subscripts):

$$V_{ni_n} = \bar{V}_{ni_n} + \epsilon_{ni_n}, \quad (8)$$

where V_{ni_n} is the utility of selecting n vehicles of type i_n (make, model, and vintage of each of the n vehicles),[15] $\bar{V}_{ni_n}$ denotes the systematic (or mean) component of utility and ϵ_{ni_n} denotes the stochastic component. Assuming an additive mean indirect utility function yields

$$\bar{V}_{ni_n} = \bar{V}_n + \zeta \bar{V}_{i_n|n}, \quad (9)$$

where the mean indirect utility function is decomposed into the mean utility from vehicle quantity, $\bar{V}_n$, and the mean utility from vehicle type conditioned on vehicle quantity, $\bar{V}_{i_n|n}$, and ζ is a parameter.

We can now write the joint probability of choosing vehicle type i and quantity n as:

$$P_{ni_n} = P_n \cdot P_{i_n|n}, \quad (10)$$

where P_{ni_n} is the joint probability of selecting n vehicles of type i_n (make, model, and vintage of each of the n vehicles), P_n is the marginal probability of n vehicles' being selected, and $P_{i_n|n}$ is the probability of a vehicle type's being selected conditional on n. As shown by McFadden (1979), these probabilities can be written explicitly as:

$$P_n = \frac{e^{[\bar{V}_n + \zeta L_n]}}{\sum_{n'} e^{[\bar{V}_{n'} + \zeta L_{n'}]}} \quad (11)$$

$$P_{i_n|n} = \frac{e^{\bar{V}_{i_n|n}}}{\sum_{i'_n} e^{\bar{V}_{i'_n|n}}}, \quad (12)$$

$$L_n = \log [\sum_{i_n} \exp(\bar{V}_{i_n|n})], \quad (13)$$

where L_n is the inclusive value (log sum) interpreted as the expected value of the maximum utility obtained from the choice over all vehicle types.[16] It reflects the importance of vehicle ownership satisfaction to consumers in determining the quantity of vehicles to own.

To summarize, equations (11), (12), and (4) represent an estimable dynamic model of household choice of vehicle quantity, type, and utilization, respectively. The only remaining point to note about the model is that in the case of those households which choose to own two vehicles, the specification of the indirect utility function for the type-choice decision[17]

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[14] The presence of this term is consistent with the use of Roy's identity to recover the stochastic indirect utility function.

[15] In the case of multivehicle ownership, i_n refers to a portfolio of vehicle types. For example, in the case of a two-vehicle choice, i_n could refer to a portfolio consisting of a 1974 Ford Pinto and a 1977 Chevrolet Caprice.

[16] The estimated log sum coefficient can be interpreted as measuring the degree of correlation of error terms within a level choice. A coefficient value of one indicates that the error terms are independent, and hence the choice probabilities reduce to a simple multinomial logit form (i.e., a joint model of level and type). Conversely, a coefficient value of zero indicates perfect correlation of error terms, which in turn implies that for each level of ownership the household will select the vehicle type providing the highest utility with probability one. To be consistent with utility maximization, it is necessary for the log sum coefficient to have a value between zero and one (McFadden, 1981).

[17] This specification incorporates the implicit aggregation restriction that the lagged utilization of each vehicle in the portfolio has the same effect on utility. This restriction turned out to be justified statistically in our subsequent estimations.

and the specification of the utilization equation refer to the combination of vehicles or total utilization that corresponds to a given vehicle portfolio. It should be noted that only 7.8% of all households own three or more vehicles so that our omission of these households from the analysis is not particularly important.

3. Econometric issues

■ We have derived a discrete/continuous model of vehicle quantity (discrete), type (discrete), and utilization choice (continuous). One important econometric issue concerns the statistical correlation between vehicle-specific attributes and additive error terms in the dynamic utilization equations. We expect some correlation between unobserved variables affecting vehicle-type choice and utilization. For example, the unobserved effects that tend to increase usage (e.g., pleasure of driving) will adversely affect the probability of selecting an old, decrepit vehicle from which little driving pleasure can be derived. Such correlation implies that ordinary least squares will lead to biased and inconsistent estimates of the utilization equations, because vehicle-specific attributes, which are included as explanatory variables, will be correlated with the disturbances. To alleviate this problem we follow an approach taken by Dubin and McFadden (1984) and express the utilization equation as conditional on the choice of vehicle type *i*. This is done by interacting the explanatory variables with dummy variables that take on a value of one for the chosen vehicle and 0 for nonchosen vehicles in the entire choice set. Consistent estimates are then obtained by replacing the dummies by estimated probabilities from the discrete-type choice model.

A second issue concerns the estimation of a number of parameters in the type-choice models (A_0, π_t, A_5, A_6, A_7, and ν_t), whose presence can be traced to the indirect utility function (see equation (7)). These terms will vary across alternatives because they are multiplied by $e^{-A_5 p_{it}}$. Allowing these terms to vary across alternatives would make estimation difficult, if not impossible, because for example, ν_t, the utilization equation disturbance, is not known. To resolve this problem and to retain a logit structure, we write the total error term as:

$$\xi_{it} = \nu_t e^{-A_5 p_{it}} + \epsilon_{it}. \tag{14}$$

Applying a Taylor series expansion around the mean operating price $\bar{p}_t$ yields

$$\xi_{it} = \nu_t e^{-A_5 \bar{p}_t}\left[1 + (p_{it} - \bar{p}_t) + \frac{(p_{it} - \bar{p}_t)^2}{2!} + \ldots + \frac{(p_{it} - \bar{p}_t)^{N-1}}{(N-1)!} + \ldots\right] + \epsilon_{it}. \tag{15}$$

If higher-order terms are not assumed to contribute significantly,[18] the error term becomes:

$$\xi_{it} = \nu_t e^{-A_5 \bar{p}_t} + \epsilon_{it}. \tag{16}$$

Therefore, since $e^{-A_5 \bar{p}_t}$ does not vary across alternatives, the term $\nu_t e^{-A_5 \bar{p}_t}$ can be eliminated[19] from the specification.[20] Similarly, the terms A_0, πr_t, $A_5 I_t$, $A_6 I_{t-1}$, and $A_7 I_{t-2}$ can also be

[18] This assumption is reasonable to the extent that there is relatively small variation in operating prices (i.e., price per gallon/vehicle miles per gallon).

[19] As indicated previously, we are forced to assume that the remaining error term is serially independent. Theoretical work on serial correlation in the context of discrete choice models has been undertaken by Heckman (1981), but his analysis is based on a simple binary probit model. Extensions of this work to a multinomial logit structure such as the one proposed here are likely to be exceedingly difficult. In addition, the treatment of serial correlation in the presence of a lagged endogenous variable in a dynamic discrete choice context requires an approximation of initial conditions, which in our case is an impossible data requirement.

[20] Because a number of terms in the type-choice model are still multiplied by $e^{-A_5 \bar{p}_t}$, estimation was achieved by a grid-search procedure. In particular, it was found that the log likelihood at convergence was relatively insensitive to values of $-A_5$. For example, values of $-A_5$ in the range of -3.0 to $+13.0$ did not result in significant differences in the log likelihood at convergence or in parameter estimates. Thus, for all the estimations carried out here, $-A_5$ was set equal to $-.1$. This is a theoretically plausible value, because it is a price coefficient. It is also statistically within the range of admissible values that maximize the log likelihood.

eliminated.[21] It will be recalled from the argument given in Section 2 that income can still be incorporated in the specification. (See footnote 9.)

A final point relates to the estimation of the discrete-type choice model. In this analysis the type of vehicle is defined by make (e.g., Ford), model (e.g., Mustang), and vintage (e.g., 1967). Theoretically, with this definition the household has thousands of choices available. If every one were included in a given estimation, the computational burden would be excessive. Fortunately, the assumption that the disturbances of the discrete choice model are jointly distributed with a generalized extreme value distribution permits consistent estimation using a subsample of the available choice set.[22] For this analysis the household's choice set included ten alternative vehicle types (by make, model, and vintage). Any vehicles a household owned in the preceding period were included among the ten alternatives.[23]

4. Data description

■ The basic data source for this research is a household sample obtained by combining two surveys: (1) the National Interim Energy Consumption Survey and (2) the Household Transportation Panel. Both of these surveys were designed by the Energy Information Administration of the U.S. Department of Energy. To provide data on energy consumption in the residential sector, the National Interim Energy Consumption Survey (NIECS) was conducted, and information on 3,842 households was obtained during November and December, 1978. This survey collected a wide range of household socioeconomic data including: household income; number of household members along with their age, sex, employment status, and education level; geographic location of the household; and type of residence. In addition, vehicle information gathered included the make (e.g., Pontiac), model (e.g., Firebird), vintage and engine size of vehicles owned at the time of the survey and of those vehicles owned during the past year (i.e., back to November and December, 1977). Also, information was collected on the extent to which these vehicles were used (in miles) during the 1977–1978 period.

To provide additional information on residential energy consumption, the Energy Information Administration initiated a follow-up survey, the Household Transportation Panel. This panel consisted of previously surveyed NIECS households that had at least one automotive vehicle. The eligible NIECS sample households were divided into six groups, and monthly information was collected on vehicles owned, fuel consumed, and miles driven (from actual odometer readings). The panel was initiated in June, 1979, and one group was

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[21] Note that the current and lagged operating cost variables associated with A_5, A_6, and A_7 are not eliminated because they vary across alternatives. But initial estimations yielded highly insignificant and small parameter estimates for the lagged operating cost variables. Thus, the only lagged variables in our final specification are utilization variables, and our specification is thereby brought in line with the habit formation work of Pollak and Wales (1969) and Pollak (1970).

[22] McFadden (1978) has shown that, predicated on the assumption that the multinomial logit model is correct, this sampling procedure results in consistent estimates of multinomial logit parameters. We tested for possible violations of the independence of irrelevant alternatives property associated with the logit model. Specifically, we applied the Small and Hsiao (forthcoming) specification test for both the one-vehicle and two-vehicle household type-choice models by using subsamples of the ten alternative choice sets (see text below): (1) selected at random, (2) consisting of domestic vehicles only, and (3) consisting of only large cars (curb weight of 3,500 pounds or more). On the basis of the Small-Hsiao procedure, we found for all the specification tests carried out that the null hypothesis of a multinomial logit structure could not be rejected at reasonable confidence levels.

[23] This procedure is consistent with procedures used in previous vehicle-type choice models (Manski and Sherman, 1980; Berkovec and Rust, 1981). To test for the robustness of the sample strategy, we estimated models with choice sets of eight, twenty, and thirty alternative vehicle types and found virtually no change in parameter values. Finally, it should be noted that regardless of the number of alternatives chosen for estimation, it is still necessary (as in most discrete-choice estimation) to constrain parameters that were previously subscripted by i to be constant across alternatives. This restriction is required for the subsampling estimation procedure described in the text.

brought into the sample each month for a two-month reporting period. Starting in December, 1979, these groups were returned to the sample, one each month, for another two-month reporting period.

For the purposes of the current study, the Household Transportation Panel Groups first entering in June, July, and August, 1979 (and returning to the panel in December 1979, and January and February, 1980, respectively) were selected and linked with their corresponding NIECS information. The combination of these two surveys provides vehicle ownership information for the same households from the Fall of 1977 to the Spring of 1980.

With the linkage of the two surveys completed, the resulting data were organized into five discrete time intervals of a six-month duration.[24] Thus, we have household vehicle holdings as of December, 1977, with corresponding utilization accumulated over the January, 1978, to June, 1978, period, holdings as of June, 1978, with corresponding utilization from July, 1978, to December, 1978, and so on for December, 1978, June, 1979, and December, 1979. We were forced, however, to begin our empirical analysis with the vehicle holdings as of December, 1978, because this was the first time period for which we could incorporate one *and* two time-period utilization lags. Consequently, in our estimations, three time periods were used: Period 1 is type choice as of December, 1978, with utilization from January, 1979, to June, 1979; Period 2 is type choice as of June, 1979, with utilization from July, 1979, to December, 1979; Period 3 is type choice as of December, 1979, with utilization from January, 1980, to June, 1980. These periods respectively capture household purchasing and utilization behavior before, during, and after the June, 1979, energy shock.

Finally, to supplement the cross sectional time series household data, a vehicle attribute file was constructed that provided additional vehicle information. This file provided detailed vehicle characteristics of over 2,000 different makes, models, and vintages of motor vehicles. These characteristics included vehicle weight, front and rear seat shoulder room, luggage space, horsepower, fuel efficiency, engine displacement, and the "Red Book" vehicle values for each of the time periods.

5. Estimation results: single-vehicle households

■ Using the data base described in Section 4, we estimated models of type choice, utilization, and quantity choice for single-vehicle and two-vehicle households. Models were estimated for distinct and combined time periods in our sample,[25] with the time periods as defined above.

□ **Type-choice models.** The estimation results for the type-choice models for single-vehicle households are presented in Table 1. The model specification included the characteristics of a given vehicle such as its operating cost and capital cost, age, shoulder room, luggage space, and engine technology,[26] and indicator variables that reflected the make of a given

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[24] The choice of six-month time intervals implies that households evaluate their vehicle holdings and determine vehicle utilization every six months. In reality, this evaluation is undertaken in a continuous manner; but because of data availability, we are forced to work in discrete time.

It should also be noted that the choice of time interval places no restrictive assumptions on the length of time households choose to own (hold) particular vehicles. In fact, mean holding periods can be calculated from our type choice specifications for any specific vehicle type (make, model, and vintage). Unfortunately, such calculations have not been undertaken in this work because of excessive computational costs.

[25] When we combined time periods to estimate the discrete and continuous models, we did not account for the fact that there may be two or three observations from the same household. As pointed out by Chamberlain (1980), it can be difficult to account for household-specific effects in the context of discrete choice models. Since there exists the possibility of omitted variable bias if this effect is not taken into account, one must view the results of our combined time period estimations with some caution.

[26] Engine technology was the only performance variable that yielded reasonable estimation results. It is defined as horsepower divided by engine displacement. Exploration of automotive road tests indicated that this variable is highly correlated with the performance-related attributes of engine torque and cornering power (measured by lateral

vehicle. The indicator variables can be interpreted as capturing the degree of household preference for particular vehicle makes. The make associated with the indicator variable with the highest positive coefficient yields the greatest utility, *all else equal,* to households. Further, the specification incorporated household characteristics such as income and family size, and household experiences or familiarity with a given vehicle as reflected in past vehicle usage, which was incorporated through two-period utilization lags.[27] The lagged utilization variables also capture the effects of brand loyalty.

From a methodological perspective, including lagged utilization variables in the model is likely to improve the accuracy of the estimated coefficients for the operating and capital cost variables relative to a model that incorporates only concurrent economic conditions. In the latter type of model, the contemporaneous economic conditions reflect two effects that work in opposite directions: the inertial effect of brand loyalty, which encourages holding the current vehicle, and the effect of manufacturers' introducing more fuel efficient vehicles, which encourages vehicle switching. By including variables that summarize ownership experience, these two effects can be separated, and more accurate estimates obtained.

The expected signs of the parameters are straightforward: the operating and capital cost variables should have a negative effect on type choice, and the remaining vehicle characteristics and the household characteristics should have a positive effect on type choice. As can be seen in the table, the parameter estimates are generally reliable and are of expected sign.

Our estimation results shed considerable light on the extent and importance of households' brand preference and brand loyalty. Brand preference is defined as the tendency to purchase a specific make of vehicle. This tendency may be influenced by the extent of the make's dealer network, repair service, parts availability, and so on. In our specification the extent of brand preference (and thus the strength of the effects noted above) is captured by vehicle-make indicators. The actual estimates are relative to GM's coefficient, which is implicitly normalized to zero. Our empirical findings indicate that households attach significantly less utility to a car (all else equal) if it is made by a foreign producer,[28] while they also attach less utility to a car (all else equal) if it is manufactured by Chrysler or AMC. These results suggest that Ford, and to some extent General Motors, have the greatest potential to benefit from brand preference. At a more general level, the results reveal that single-vehicle households do have an inherent preference for American cars.[29] As suggested above, this preference is most likely due to factors such as parts availability and service. This inherent advantage has been diminished, however, as import restrictions have encouraged foreign firms (e.g., Toyota and Honda) to establish manufacturing subsidiaries in the United States or to license U.S. firms to produce their products. In addition, other foreign firms have future plans to produce automobiles in the U.S. (e.g., Mazda and Nissan).

The effect of brand loyalty is captured by the lagged utilization variables: the process through which brand loyalty is developed consists of the accumulation of information,

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acceleration). This variable was defined only for households that had household heads of 35 years of age or less, because it was hypothesized that the type of performance captured by this variable would be particularly valued by young households. This hypothesis was borne out by subsequent statistical tests.

[27] Earlier "dynamic" vehicle type-choice models have used zero/one dummy variables to account for household experiences with a given vehicle (see, for example, Manski and Sherman (1980) and Berkovec and Rust (1981)). It has been argued that such variables account for the transaction costs incurred when entering the vehicle market. Similarly, our lagged usage variables can be interpreted as capturing transaction costs in the sense that a cost is incurred when vehicle ownership habits are changed.

[28] As is consistent with the national vehicle fleet, the number of vehicles attributable to any given foreign make in our sample (e.g., Jaguar, Honda, and so on) tends to be relatively small. Thus, we are forced, for empirical reasons, to aggregate all foreign makes in the estimation of a brand-preference indicator variable.

[29] Recent market survey data (Power, 1982) indicate that repeat-buying behavior—a consumer purchasing a new car of the same make as the one being replaced—which implicitly includes both brand loyalty and brand preference, continues to favor American-made vehicles.

TABLE 1 Single-Vehicle Household Type-Choice Model Estimates*

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
(Fuel Cost ($/mi.) × Typical Utilization (mi.)) ÷ Income ($/yr.)[a]	−21.17 (11.91)	−23.40 (7.91)	−31.41 (7.85)	−26.20 (6.57)	−25.08 (5.01)
Vehicle Capital Cost ($) ÷ Income ($/yr.)[b]	−2.80 (.535)	−2.32 (.489)	−2.45 (.522)	−2.51 (3.75)	−2.46 (.298)
1 Period Lagged Utilization (mi.) Same Vehicle	.675E-03 (.687E-04)	.777E-03 (.763E-04)	.591E-03 (.709E-04)	.629E-03 (.489E-04)	.668E-03 (.419E-04)
2 Period Lagged Utilization (mi.) Same Vehicle	.211E-03 (.671E-04)	.663E-04 (.621E-04)	.414E-03 (.745E-04)	.312E-03 (.495E-04)	.226E-03 (.390E-04)
1 Period Lagged Utilization (mi.) Same Make Vehicle	.563E-04 (.100E-03)	.338E-03 (.117E-03)	.281E-03 (.13E-03)	.164E-03 (.773E-04)	.200E-03 (.682E-04)
2 Period Lagged Utilization (mi.) Same Make Vehicle	.264E-03 (.641E-04)	.587E-04 (.843E-04)	.549E-04 (.117E-03)	.197E-03 (.677E-04)	.158E-03 (.581E-04)
Front and Rear Shoulder Room (in.) for Households with 2 or Fewer Members	.186E-01 (.619E-02)	.214E-01 (.635E-02)	.250E-01 (.686E-02)	.211E-01 (.454E-02)	.212E-01 (.366E-02)
Front and Rear Shoulder Room (in.) for Households with 3 or More Members	.430E-01 (.125E-01)	.377E-01 (.110E-01)	.516E-01 (.136E-01)	.478E-01 (.925E-02)	.450E-01 (.702E-02)
American Motors Indicator (1 If AMC, 0 Otherwise)	−.257 (.467)	−.072 (.409)	−.901 (.487)	−.550 (.336)	−.378 (.258)
Ford Indicator (1 If Ford, 0 Otherwise)	.555 (.229)	.146 (.218)	.298 (.223)	.442 (.158)	.351 (.127)
Chrysler Indicator (1 If Chrysler, 0 Otherwise)	−.181 (.279)	−.512 (.281)	−.799 (.299)	−.466 (.203)	−.477 (.163)
Foreign Car Indicator (1 If Foreign Car, 0 Otherwise)	−.849 (.356)	−1.25 (.357)	−1.36 (.387)	−1.08 (.260)	−1.12 (.207)
Horsepower ÷ Engine Displacement (CI) for Households with Heads 35 Years Old or Less	1.27 (1.21)	1.92 (1.20)	1.03 (1.46)	1.23 (.942)	1.57 (.735)
Luggage Space (ft^3) for Households with Four or More Members	.381E-02 (.139E-01)	.436E-02 (.101E-01)	.200E-01 (.105E-01)	.132E-01 (.838E-02)	.863E-02 (.650E-02)
New Vehicle Indicator (Vehicle 2 Years Old or Newer)	.554 (.276)	.760 (.270)	.564 (.291)	.525 (.196)	.583 (.157)
Old Vehicle Indicator (Vehicle 8 Years Old or Older)	−.699 (.234)	−.357 (.218)	−.188 (.225)	−.421 (.158)	−.400 (.127)
Log Likelihood at Zero	−794.4	−831.2	−838.1	−1633	−2464
Log Likelihood at Convergence	−316.8	−354.4	−304.3	−630.5	−993.6

TABLE 1 ***(Continued)***

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
χ^2-Statistic (Likelihood-Ratio Test)				18.8	36.2
Number of Observations	345	361	364	709	1,070

* Standard errors in parentheses.

[a] Fuel cost is determined by dividing the prevailing price per gallon by vehicle fuel efficiency. Typical utilization is determined by applying the following equation:

$$\text{typical utilization } (r_i) = 2684 + 457.8 \times \text{number of household members} + .0529 \times \text{income (\$/yr.)}.$$

The parameters in this equation were estimated by ordinary least squares by using average utilizations derived from all available periods in the household sample.

[b] Capital cost is the vehicle's prevailing market value.

through driving and ownership experience, on particular vehicle makes (brands). Lagged utilization variables, however, are not specified by manufacturer because this would unrealistically imply that learning processes differ according to vehicle make. We find very strong brand loyalty effects as the coefficients for all of the lagged utilization variables are significant for the statistically valid combination of periods one and three (see below). This indicates that the development of brand loyalty has also occurred for foreign firms, thus making it difficult for domestic firms to recapture lost market shares from foreign competitors, should this become necessary (e.g., owing to a weakening of the macroeconomy) to ensure adequate financial performance. Perhaps more importantly, Japanese firms have developed a substantial market share that they can expand, given the expiration of the quotas. As a methodological point, since the testable implications of the dynamic taste change model used here concern the importance of the lagged utilization variables, their statistical significance provides support for our theoretical model and facilitates our attempt to distinguish between the effects of brand loyalty and brand preference.

□ **Additional empirical results.** We also find that households' valuations of vehicle operating costs have increased over time, while their valuations of vehicle capital costs have slightly fallen over time. Subject to the qualification that these changes could have been induced to some degree by relative price changes, these results can be interpreted as indicating that households may have actually changed their tastes in terms of their valuation of these attributes. This conclusion is underscored by our estimates of the marginal rate of substitution of operating and capital costs and individual household discount factors.[30] As shown in Table 2, the amount that a household is willing to pay in terms of increased capital costs for a one-cent per mile decrease in operating costs (in constant dollars) has increased significantly over time, while the corresponding discount factors have decreased.[31] These results most likely indicate an increase among households in expected fuel prices or a higher valuation of future reductions in operating expenses.

At a more general level, we tested for structural stability of the type-choice parameters by using likelihood ratio tests. In testing for structural stability, we attempted to determine whether parameter shifts have resulted from sources other than those explicitly controlled

[30] The discount factors presented here implicitly include the discount rate plus expected vehicle depreciation. As such, estimated discount factors in the vicinity of 15–30% are plausible because for such values, annual capital costs including depreciation and present value of operating costs will be equal.

[31] This empirical finding suggests that the assumption of consistent planning (associated with an intertemporal model) is not likely to be met in our context.

TABLE 2 **Marginal Rates of Substitution between Operating and Capital Costs (price willing to pay for 1¢/mi. decrease in operating costs) and Implied Annualized Discount Factors: Single-Vehicle Households***

	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
MRS, Dollars	332.66	453.35	578.80	466.74	456.70
	(195.68)	(178.13)	(186.14)	(134.51)	(103.80)
Discount Factors, Percent	26.4	19.8	15.6	19.2	19.6
	(15.5)	(7.8)	(5.0)	(5.5)	(4.5)

* Standard errors in parentheses.

for in the specification (e.g., changes in expectations, or taste changes that do not emanate from past vehicle ownership experiences). As indicated by the χ^2-statistics for these tests, we can reject the hypothesis of parameter stability over all periods at the 80% level. When we consider only the first and third periods, thereby eliminating the period when the energy shock initially occurred, we find that structural stability can only be rejected at the 71% confidence level and thus identify the influence of the energy shock on parameter stability. We note, as a methodological point, that failure to include the lagged utilization variables in the specification yields results that do *not* allow us to reject the hypothesis of parameter stability at any reasonable confidence level. This is important because, as argued previously, the inclusion of the lagged utilization variables is likely to improve the accuracy of other estimates in the model (e.g., coefficients of operating and capital costs).

Additional information regarding households' type-choice behavior can be obtained by using the parameter estimates to calculate selection probability elasticities with respect to income, capital costs, and operating costs for a representative range of vehicle types and vintages.[32] The elasticities are presented in Table 3 for old and new domestic compact, foreign compact, domestic midsize, and domestic full-size vehicle types. The first point to note about the elasticity estimates is that they are consistent with our previous conclusions regarding changes in households' sensitivity to operating costs and capital costs over time. Specifically, household responsiveness to changes in operating costs has increased steadily over time, while responsiveness to changes in capital costs has decreased slightly over time. In the most recent period the elasticities for operating costs start to approach or, in some cases, exceed the corresponding capital cost elasticities for each vehicle considered.

Taking a closer look at the elasticity estimates, it is interesting to note that the income and capital cost elasticities are much larger for new vehicles as opposed to older vehicles, while the opposite results appear to be true for the operating cost elasticities. In addition, the income and capital cost elasticities are fairly similar for the new (1979) foreign cars and U.S. cars of all sizes, while the operating cost elasticities for the larger new U.S. cars are generally greater than the operating cost elasticities for the new foreign cars. These results indicate, as expected, that operating cost elasticities are larger in instances where there would be a clear benefit from improvement in vehicle operating cost performance.

□ **Utilization model.** The specification of the vehicle utilization equation includes economic aspects of usage (namely operating costs), the driving habits of the households (as measured by past utilization and the constant), household characteristics (including income, age of

[32] The vehicle type-choice specification employed in this study restricts the sum of the operating and capital cost elasticities to equal in absolute value the income elasticity. In our preliminary estimations, we found that such a restriction, which is not implausible, was actually necessary to obtain reasonable estimation results that controlled for income differences among households.

TABLE 3 **Type-Choice Elasticities: Single-Vehicle Households***

Elasticity with Respect to	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Income					
1972 Chevrolet Vega: Compact	.639	.678	.881	.728	.717
1972 Toyota Corolla: Compact	.718	.752	.968	.808	.798
1979 Chevrolet Chevette: Compact	1.817	1.53	1.58	1.64	1.65
1979 Toyota Corolla: Compact	1.99	1.62	1.67	1.73	1.75
1972 Ford Maverick: Midsize	.897	.922	1.17	.991	.976
1979 Ford Granada: Midsize	2.16	1.85	2.01	1.98	1.99
1972 Oldsmobile Cutlass: Full Size	1.16	1.22	1.57	1.31	1.29
1979 Oldsmobile Cutlass: Full Size	2.23	1.90	2.05	2.04	2.05
Capital Costs					
1972 Chevrolet Vega: Compact	−.311	−.216	−.180	−.230	−.235
1972 Toyota Corolla: Compact	−.376	−.271	−.237	−.289	−.295
1979 Chevrolet Chevette: Compact	−1.59	−1.13	−.980	−1.21	−1.23
1979 Toyota Corolla: Compact	−1.70	−1.22	−1.06	−1.30	−1.33
1972 Ford Maverick: Midsize	−.466	−.315	−.253	−.337	−.343
1979 Ford Granada: Midsize	−1.73	−1.24	−1.09	−1.33	−1.35
1972 Oldsmobile Cutlass: Full Size	−.576	−.398	−.331	−.426	−.435
1979 Oldsmobile Cutlass: Full Size	−1.80	−1.29	−1.13	−1.38	−1.41
Operating Costs					
1972 Chevrolet Vega: Compact	−.326	−.459	−.647	−.495	−.479
1972 Toyota Corolla: Compact	−.339	−.478	−.726	−.515	−.499
1979 Chevrolet Chevette: Compact	−.278	−.393	−.598	−.424	−.410
1979 Toyota Corolla: Compact	−.276	−.390	−.595	−.421	−.408
1972 Ford Maverick: Midsize	−.427	−.603	−.913	−.649	−.628
1979 Ford Granada: Midsize	−.423	−.598	−.908	−.644	−.623
1972 Oldsmobile Cutlass: Full Size	−.578	−.815	−1.23	−.877	−.850
1979 Oldsmobile Cutlass: Full Size	−.423	−.598	−.908	−.644	−.623

* Elasticities were calculated by using the formula

$$\partial P_{i_n|n}/\partial k \cdot k/P_{i_n|n},$$

where $P_{i_n|n}$ is the probability of choosing vehicle type i conditional on n vehicles' being selected, and k is an explanatory variable. Estimates were obtained by enumerating through the household sample.

household head, number of workers, urban or nonurban residence), and regional residence.[33] Recall that the endogeneity of vehicle attributes is accounted for by the procedure discussed in Section 3. Although the parameter estimates for the utilization models (see Table 4) are statistically reliable and of plausible sign before, and to some extent after, the energy shock, they appear to be generally unreliable during the shock. In particular, it appears that during the 1979 energy shock consumers placed high value on the driving habits they had formed before the shock. This suggests there was some delay in translating the information on gasoline prices into new consumption patterns, a result that could be expected for a durable good such as automobiles. As is hardly surprising, one can easily reject the hypothesis of parameter stability at reasonable levels of significance when the second period is included in the Chow tests (see the appropriate F-statistics). In contrast, the hypothesis can be rejected

TABLE 4 Single-Vehicle Household Utilization Model Estimates*

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Fuel Cost ($/mi.) × Typical Utilization (mi.)[a]	−9.67 (3.18)	−1.12 (2.91)	−2.36 (1.70)	−4.98 (1.14)	−4.22 (1.12)
Income ($/yr.)	.036 (.018)	.020 (.018)	−.002 (.014)	.013 (.010)	.016 (.009)
1 Period Lagged Utilization (mi.) Same Vehicle	.295 (.028)	.158 (.054)	.363 (.032)	.322 (.020)	.369 (.019)
2 Period Lagged Utilization (mi.) Same Vehicle	.278 (.051)	.554 (.036)	.310 (.041)	.315 (.031)	.447 (.021)
1 Period Lagged Utilization (mi.) Same Make Vehicle	.720 (.268)	.026 (.634)	.416 (.448)	.782 (.260)	.497 (.183)
2 Period Lagged Utilization (mi.) Same Make Vehicle	.386 (.154)	.470 (.142)	.431 (.144)	.341 (.107)	.388 (.083)
Urban Indicator (1 If Urban Location, 0 Otherwise)	−412.7 (371.5)	−418.8 (409.2)	−399.4 (313.1)	−415.4 (242)	−369.9 (212.2)
Northeast Indicator (1 If Northeastern U.S. Location, 0 Otherwise)	−207.7 (359.5)	104.2 (399.1)	30.34 (306.8)	−88.3 (235.6)	−11.55 (207.2)
Age Indicator (1 If Head of Household 50 Years Old or Less, 0 Otherwise)	894.4 (353.9)	1007 (396.7)	458.3 (295.8)	669.1 (228.9)	842.2 (202.7)
Number of Household Workers	413.2 (244.4)	−112.4 (276.1)	56.33 (200.9)	206.6 (156.1)	6.83 (138.1)
Constant	3220 (629.4)	1797 (768)	2077 (540.6)	2636 (344.5)	2366 (322.2)
R-Squared	.512	.648	.644	.572	.600
F-Statistic (Chow Test)				1.46	3.60
Number of Observations	345	361	364	709	1070

* Standard errors in parentheses.

[a] Fuel cost and typical utilization defined as in Table 1.

[33] A number of other vehicle-specific variables, including vehicle age and capital costs, were initially incorporated in the estimation of the utilization equations. The only vehicle-specific variables with parameters of plausible magnitude and reliability were operating costs and lagged utilization.

TABLE 5 Single-Vehicle Household Utilization Elasticities*

Elasticity with Respect to	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Operating Costs, Short Run	−.389 (.128)	−.061 (.146)	−.173 (.125)	−.284 (.065)	−.228 (.060)
Income, Short Run	.100 (.050)	.058 (.052)	−.007 (.050)	.044 (.032)	.049 (.035)
Operating Costs, Long Run	−.911 (.288)	−.212 (.507)	−.257 (.186)	−.446 (.102)	−.279 (.074)
Income, Long Run	.234 (.117)	.201 (.181)	.011 (.074)	.069 (.050)	.060 (.043)

* Standard errors in parentheses.

only at the 80% confidence level when the second period is not included in the Chow tests. This again identifies the influence of the energy shock on parameter stability.

As shown in Table 5, the short-run and long-run elasticities for the operating cost and income variables are not only small in absolute value, but have actually declined in magnitude over time. It is worth noting that particular government policies that lead to increases in operating costs, such as the gas tax passed by Congress in 1982, may have a small effect on vehicle miles travelled and hence on efficient resource allocation.[34] To make a methodological point, we note that although the qualitative policy implications derived from the utilization elasticities do not change when the lagged utilization variables are dropped from the specification, the quantitative implications do change as the utilization elasticities become substantially smaller.

6. Estimation results: two-vehicle households

■ The estimation results for two-vehicle households are generally similar to those obtained for one-vehicle households; and thus we summarize the main findings here and present the estimates themselves in the Appendix. The specification of the type-choice model is similar to the specification of the single-vehicle type-choice model with the major exceptions' being: (a) the operating and capital costs variables refer to a two-vehicle portfolio as opposed to a single vehicle, and (b) the inclusion of an indicator variable that reflects the notion that, owing to vehicle-type specialization, two-vehicle households might prefer a portfolio that consists of a pickup truck and a passenger vehicle to one that consists of two passenger vehicles.

The most striking differences between single-vehicle and two-vehicle household type-choice behavior are reflected in the various elasticity estimates. Generally, the income elasticity estimates and the capital cost elasticity estimates (for new cars) for two-vehicle households are smaller than the corresponding elasticity estimates for single-vehicle households. In addition, the range of income, capital cost, and operating cost elasticity estimates for two-vehicle households is smaller across vehicle types (e.g., old vs. new, domestic vs. foreign). We speculate that higher average household income levels and the flexibility afforded by the ownership of an additional vehicle lead to smaller and to more uniform responses across vehicle types with respect to changes in automobile costs or income. In spite of these differences, the two-vehicle household elasticity estimates lead to the same conclusions as the

[34] This observation should be qualified as the elasticities presented in Table 5 do not account for the possibility that households will adjust vehicle quantities or vehicle types.

single-vehicle elasticity estimates in terms of relative magnitudes and changes over time in households' responsiveness to changes in operating and capital costs.[35]

□ **Utilization model.** The specification of the utilization equation for two-vehicle households differs from that for single-vehicle households in two ways. First, the operating costs variable now refers to the vehicle portfolio. Second, an additional indicator variable, showing which utilization equation pertains to the newer vehicle in the portfolio, has been included in the specification. These changes did not, however, lead to any significant changes from the single-vehicle results with regard to identifying the primary determinants of vehicle utilization. That is, economic considerations do not play a dominant role *vis-à-vis* driving habits and household composition in the determination of vehicle utilization. This conclusion is strengthened by the very small short-run and long-run elasticity estimates for operating costs and income.

It should be noted that the utilization operating cost elasticities for two-vehicle households are consistently smaller than the utilization operating cost elasticities for one-vehicle households. This finding is expected since two-vehicle households can respond to an increase in operating costs by driving their most fuel efficient vehicle more often as opposed to reducing their vehicle miles travelled.

□ **Level-choice model.** The final model that we estimated was a level- or quantity-choice model. The specification incorporated household characteristics including income, number of household members, number of household workers, urban or nonurban residence, and the expected utility derived from the households' current vehicle portfolio. As can be seen in Table 6, the parameter estimates of this model are very reliable and of expected sign for

TABLE 6 Level Choice Model Parameter Estimates*

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Number of Household Members	.372	.387	.247	.311	.345
(Defined for 2-Vehicle Alt. Only)	(.080)	(.075)	(.071)	(.052)	(.043)
Number of Household Workers	.508	.581	.618	.593	.559
(Defined for 2-Vehicle Alt. Only)	(.141)	(.135)	(.128)	(.093)	(.076)
Income ($/yr.)	.356E-04	.731E-05	.199E-04	.254E-04	.198E-04
(Defined for 2-Vehicle Alt. Only)	(.100E-04)	(.811E-05)	(.758E-05)	(.597E-05)	(.48E-05)
Urban Indicator (1 If Urban Location, 0 Otherwise, Defined for 2-Vehicle Alt. Only)	−.515	−.453	−.565	−.557	−.500
	(.227)	(.214)	(.206)	(.150)	(.122)
Log Sum from Type-Choice Models	.622	.871	.389	.402	.531
	(.074)	(.094)	(.046)	(.034)	(.036)
Choice Indicator (1 If 2-Vehicle Alt., 0 Otherwise)	−2.34	−1.95	−1.86	−2.14	−2.17
	(.327)	(.304)	(.283)	(.212)	(.174)
Log Likelihood at Zero	−473.4	−492.8	−503.2	−976.6	−1469
Log Likelihood at Convergence	−305.6	−331.5	−369.5	−691.6	−1029
χ^2 Statistic (Likelihood Ratio Test)				33.0	44.8
Number of Observations	683	711	726	1409	2120

* Standard errors in parentheses.

[35] One additional difference between the estimation results for single-vehicle and two-vehicle households is that we can reject the hypothesis of parameter stability at higher confidence levels in the case of two-vehicle households. As indicated by the χ^2-statistics, it is possible to reject the hypothesis of parameter stability at the 95% confidence level when all periods are considered, and at the 88% confidence level when the second period is eliminated.

all periods and models. It is particularly interesting to note that the estimated log sum variable (a measure of vehicle ownership satisfaction) is well behaved,[36] in addition to reflecting strongly the importance (particularly during the energy shock) of vehicle ownership satisfaction in determining the quantity of vehicles to own.

Although we can reject the hypothesis of parameter stability for the model when all periods are considered, as well as when the second period is eliminated (again, this is not the case when the lagged utilization variables are omitted), there are no pronounced changes over time in the effects of the variables considered here on quantity choice that appear to merit an economic explanation. Moreover, it is not clear that any particular variable has an exceptionally large impact in influencing the level of households' vehicle holdings.

7. Concluding observations

■ This article has provided a dynamic empirical analysis of household vehicle ownership and utilization decisions by using data that captured households' behavior before, during, and after the June, 1979, energy shock. From a methodological perspective, the dynamic approach taken here has led to the incorporation of important lagged utilization variables in the specification of the type-choice and quantity-choice and utilization models. As indicated throughout the article, the failure to include such variables can have significant implications for the validity of any results. Further, such an omission can prevent one from distinguishing between the important effects of brand loyalty and brand preference.

The substantive empirical results contribute to an assessment of the past and future performance of the domestic industry. The preference indicators suggest that U.S. consumers prefer American to foreign cars if all other things (including vehicle attributes) are the same. Hence the brand preference estimates suggest that the import penetration that contributed significantly to the domestic industry's financial problems during the 1979–1982 period resulted from U.S. firms' producing vehicles that offered substantially inferior attributes relative to foreign vehicles' attributes. Further, the performance of the macroeconomy during this period inhibited sales. The recent financial recovery of the industry can thus be largely attributed to U.S. manufacturers' introduction of product lines that offer improved vehicle attributes, particularly operating costs, and to the improvement in the macroeconomy, which was accompanied by a tax cut.

Our results also suggest, however, that one must exercise caution in assessing the future financial prospects of the domestic industry as a number of factors indicate that the industry is still very vulnerable to foreign competition. In particular, U.S. consumers have begun to develop brand loyalty toward foreign vehicles through vehicle ownership experience that will make it very difficult for the domestic firms to recapture lost market shares from foreign competitors. Further, public policies such as import quotas may have undermined the domestic firms' brand preference advantage as some foreign firms have responded by producing their vehicles in the United States. Finally, the expiration of voluntary export restrictions signals a renewed intensification of Japanese competition. Indeed, the U.S. Department of Commerce has recently estimated that the share of imports in new car sales could rise from 23% in 1984 to as high as 36% by 1988. Taken collectively, these considerations suggest that notwithstanding recent financial trends, it is essential for the U.S. firms to continue to make technological improvements in their vehicles and to counter the brand loyalty that has developed toward foreign vehicles if the domestic automobile industry is to be viable at the present scale of operations.

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[36] The results of our analysis indicate consistency with utility maximization, as all log sum coefficients are between zero and one. It is interesting to note, however, that for the period of the energy shock (Period 2), the log sum coefficient is not statistically significantly different from one. This indicates that the unobserved effects shared by one- and two-vehicle households became much smaller than they were in nonshock periods. As a final point, it should be noted that the standard errors reported in Table 6 are not corrected for the fact that an estimated value of the log sum was used as opposed to the true value. Amemiya (1976) has shown that the use of estimated log sums results in standard errors that are biased downward, although actual parameter estimates are not affected. As such, the standard errors reported in Table 6 should be viewed as a lower bound.

Appendix

■ Tables A1–A5 set out the estimation results for two-vehicle households.

TABLE A1 Type-Choice Model Estimates*

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
(Fuel Cost ($/mi.) of Both Vehicles × Typical Utilization) ÷ Income ($/yr.)[a]	−13.19 (13.32)	−22.45 (12.71)	−20.43 (8.44)	−18.41 (7.15)	−18.71 (6.10)
Capital Cost of Both Vehicles ($) ÷ Income ($/yr.)[b]	−2.12 (.649)	−1.57 (.407)	−1.35 (.469)	−1.61 (.376)	−1.56 (.271)
1-Period Lagged Utilization (mi.) of Same Vehicles in Vehicle Portfolio	.747E-03 (.850E-04)	.681E-03 (.727E-04)	.110E-02 (.749E-04)	.102E-02 (.509E-04)	.934E-03 (.371E-04)
2-Period Lagged Utilization (mi.) of Same Vehicles in Vehicle Portfolio	.257E-03 (.802E-04)	.137E-03 (.578E-04)	.108E-04 (.690E-05)	.115E-04 (.554E-05)	.117E-04 (.515E-05)
1-Period Lagged Utilization (mi.) of Same Make Vehicles in Portfolio	.279E-03 (.909E-04)	.243E-03 (.101E-03)	.539E-03 (.810E-04)	.424E-03 (.610E-04)	.378E-03 (.508E-04)
2-Period Lagged Utilization (mi.) of Same Make Vehicles in Portfolio	.891E-04 (.615E-04)	.341E-04 (.709E-04)	−.933E-04 (.681E-04)	−.147E-04 (.386E-04)	−.183E-04 (.325E-04)
Front and Rear Shoulder Room Summed over Both Vehicles	.772E-02 (.501E-02)	.122E-01 (.463E-02)	.781E-02 (.476E-02)	.825E-02 (.339E-02)	.967E-02 (.271E-02)
Pickup Truck Indicator	.500 (.433)	−.266E-01 (.418)	.543 (.414)	.586 (.294)	.370 (.238)
Number of American Motors Cars in Portfolio	.146 (.506)	−.271 (.380)	−.520 (.465)	−.192 (.340)	−.228 (.252)
Number of Fords in Portfolio	.016 (.244)	.089 (.214)	−.018 (.231)	.026 (.165)	.083 (.129)
Number of Chryslers in Portfolio	−.127 (.284)	−.425 (.242)	−.194 (.263)	−.157 (.189)	−.237 (.147)
Number of Foreign Cars in Portfolio	−.640 (.283)	−.714 (.240)	−.723 (.278)	−.685 (.194)	−.683 (.150)
Number of Vehicles 2 Years Old or Newer in Portfolio	.174 (.337)	.764 (.311)	.817 (.313)	.446 (.225)	.496 (.180)
Number of Vehicles 8 Years Old or Older in Portfolio	−.210 (.219)	−.141 (.185)	−.036 (.197)	−.132 (.143)	−.124 (.111)
Log Likelihood at Zero	−778.3	−805.9	−833.5	−1612	−2418
Log Likelihood at Convergence	−226.1	−291.2	−246.2	−482.7	−784.5
χ^2-Statistic (Likelihood Ratio Test)				20.82	42.0
Number of Observations	338	350	362	700	1,050

* Standard errors in parentheses.

[a] Fuel cost is determined by dividing the prevailing price per gallon by vehicle fuel efficiency. Typical utilization is determined by applying the following equation:

typical utilization of each vehicle = 331 + 151.1 × number of household members + .047 × income ($/yr.).

The parameters in this equation were estimated by ordinary least squares using average utilizations derived from all available periods in the household sample.

[b] Capital cost is the vehicle's prevailing market value.

TABLE A2 **Marginal Rates of Substitution between Operating and Capital Costs (price willing to pay for 1¢/mi. decrease in operating costs) and Implied Annualized Discount Factors***

	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
MRS, Dollars	300.31 (308.01)	693.58 (402.08)	739.66 (357.32)	554.68 (245.43)	580.28 (207.24)
Discount Factors, Percent	32.1 (32.9)	14.0 (8.1)	13.2 (6.4)	17.4 (7.7)	16.7 (6.0)

* Standard errors in parentheses.

TABLE A3 **Type-Choice Elasticities**

Elasticity with Respect to	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Income					
1972 Chevrolet Vega: Compact	.692	.962	.994	.840	.843
1972 Toyota Corolla: Compact	.729	1.00	1.03	.876	.879
1979 Chevrolet Chevette: Compact	1.07	1.22	1.22	1.12	1.11
1979 Toyota Corolla: Compact	1.12	1.26	1.25	1.16	1.15
1972 Ford Maverick: Midsize	.764	1.07	1.11	.936	.940
1979 Ford Granada: Midsize	1.18	1.38	1.39	1.26	1.25
1972 Oldsmobile Cutlass: Full size	.856	1.22	1.28	1.06	1.07
1979 Oldsmobile Cutlass: Full Size	1.20	1.40	1.41	1.28	1.27
Capital Costs					
1972 Chevrolet Vega: Compact	−.407	−.301	−.241	−.298	−.293
1972 Toyota Corolla: Compact	−.438	−.324	−.262	−.322	−.316
1979 Chevrolet Chevette: Compact	−.804	−.601	−.511	−.609	−.594
1979 Toyota Corolla: Compact	−.850	−.638	−.543	−.646	−.630
1972 Ford Maverick: Midsize	−.444	−.329	−.266	−.326	−.320
1979 Ford Granada: Midsize	−.860	−.643	−.548	−.652	−.636
1972 Oldsmobile Cutlass: Full Size	−.483	−.359	−.293	−.357	−.350
1979 Oldsmobile Cutlass: Full Size	−.884	−.662	−.565	−.672	−.655
Operating Costs					
1972 Chevrolet Vega: Compact	−.319	−.692	−.806	−.586	−.590
1972 Toyota Corolla: Compact	−.322	−.703	−.816	−.593	−.598
1979 Chevrolet Chevette: Compact	−.300	−.650	−.758	−.552	−.555

TABLE A3 ***(Continued)***

Elasticity with Respect to	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Operating Costs					
1979 Toyota Corolla:					
Compact	−.297	−.651	−.755	−.549	−.553
1972 Ford Maverick:					
Midsize	−.357	−.775	−.903	−.657	−.661
1979 Ford Granada:					
Midsize	−.354	−.769	−.898	−.653	−.657
1972 Oldsmobile Cutlass:					
Full Size	−.412	−.899	−1.04	−.760	−.765
1979 Oldsmobile Cutlass:					
Full Size	−.352	−.768	−.894	−.650	−.655

TABLE A4 **Utilization Model Parameter Estimates***

Variable	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Fuel Cost ($/mi.) of Both Vehicles × Typical Utilization (mi.)[a]	−.132	−.040	−.923	−.658	−.557
	(1.59)	(1.25)	(.846)	(.518)	(.489)
Income ($/yr.)	.013	.016	.014	.013	.015
	(.011)	(.012)	(.010)	(.007)	(.006)
1-Period Lagged Utilization (mi.) of Same Vehicles in Vehicle Portfolio	.195	.273	.392	.259	.255
	(.020)	(.028)	(.029)	(.016)	(.014)
2-Period Lagged Utilization (mi.) of Same Vehicles in Vehicle Portfolio	.198	.163	.014	.131	.152
	(.026)	(.023)	(.030)	(.019)	(.014)
1-Period Lagged Utilization (mi.) of Same Make Vehicles in Portfolio	.027	.199	.238	.125	.129
	(.095)	(.158)	(.077)	(.063)	(.060)
2-Period Lagged Utilization (mi.) of Same Make Vehicles in Portfolio	.094	.109	.176	.110	.124
	(.062)	(.069)	(.083)	(.052)	(.041)
Urban Indicator (1 If Urban Location, 0 Otherwise)	18.23	−71.77	38.3	12.26	−11.91
	(274.3)	(301.6)	(252.6)	(188.1)	(159.9)
Northeast Indicator (1 If Northeastern U.S. Location, 0 Otherwise)	−214.7	−263.4	−3.40	−145	−186.1
	(321.7)	(339.1)	(283.4)	(215)	(182.4)
Age Indicator (1 If Household Head 50 Years Old or Less, 0 Otherwise)	134.6	195	234.2	173.3	186.3
	(282)	(307.3)	(258.0)	(191.8)	(163.2)
Number of Household Workers	199.3	−59.48	76.48	154.4	91.5
	(175.8)	(185)	(152.2)	(116.3)	(98.7)
New Vehicle Indicator (1 If Newer Vehicle of Pair, 0 Otherwise)	1717	1705	1355	1516	1576
	(253.8)	(275.7)	(233.7)	(174)	(147.9)
Constant	676.1	140.2	249.9	351.2	319.2
	(670.8)	(706.5)	(583.8)	(360)	(319.5)
R-Squared	.453	.439	.493	.459	.448
F-Statistic (Chow Test)				3.67	4.32
Number of Observations	676	700	724	1,400	2,100

* Standard errors in parentheses.

[a] Fuel cost and typical utilization defined as in Table A1.

TABLE A5 Utilization Elasticities*

Elasticity with Respect to	Period 1	Period 2	Period 3	Periods 1 & 3	All Periods
Operating Costs, Short Run	−.102 (.121)	−.004 (.131)	−.127 (.116)	−.071 (.056)	−.059 (.052)
Income, Short Run	.055 (.048)	.069 (.052)	.067 (.047)	.058 (.053)	.065 (.027)
Operating Costs, Long Run	−.168 (.199)	−.007 (.232)	−.214 (.195)	−.116 (.092)	−.099 (.087)
Income, Long Run	.091 (.079)	.122 (.092)	.113 (.079)	.095 (.087)	.110 (.046)

* Standard errors in parentheses.

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