Factors Associated with Aggregate Car Scrappage Rate in the United States: 1966–1992

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Vehicle scrappage or survival models provide estimates of the fraction of vehicles of each model year that survive to each later year. Earlier studies have suggested that many socioeconomic factors are associated with vehicle scrappage decisions, such as vehicle age, new vehicle price, household income, unemployment rate, used vehicle price, vehicle maintenance and repair cost, and interest rate for new car loans. However, most of the vehicle scrappage models used so far have been quite simple, using either vehicle age or new car price as determinants. The objectives of the research presented were to (*a*) develop a statistical vehicle scrappage model capable of describing the association between vehicle scrappage rate and a number of potential determinants such as those just suggested, (*b*) use the developed model to identify socioeconomic factors that may be associated with aggregate car scrappage rate in the United States using historical data and infer a car scrappage model for prediction purposes, and (*c*) illustrate how the suggested scrappage model can be used to predict car scrappage and survival rates.

The proportion of older cars in the U.S. car fleet has increased significantly in the past 18 years. This can be seen from Figure 1, which shows that the percentage of cars 15 years or older in the registered car fleet rose from about 2.3 percent during 1962–1974 to about 11 percent in 1992 (*1*). This aging car fleet has raised considerable concerns as to whether federally mandated legislation on, for example, the use of alternative fuel vehicles and new car fuel economy and emission standards could meet the desired goals of reducing motor fuel consumption and improving air quality, and whether other programs aimed at accelerating vehicle scrappage would be necessary to help achieve such goals (*2*).

Because of the long life span of cars and trucks (about 10 to 15 years), vehicle stock turnover is a slow process. The vehicles purchased now and in recent past will have long-term effects on vehicle stock composition and, therefore, on motor fuel consumption and vehicle emissions (*3–5*). To address properly the aforementioned concerns, one must be able to make a good prediction of vehicle stock compositions.

For many years, vehicle stock dynamic models have been developed for making such predictions. These models have also been included as a major submodel in many energy and environmental analysis models designed to analyze the impact of various regulatory policies on fuel consumption and air quality. Some examples are the alternative motor fuel use (AMFU) model (*6*), the ideas model (*7*), and DRI/McGraw-Hill's transportation model (*2*). The vehicle stock dynamic model usually includes a new vehicle sales model and a vehicle scrappage (or survival) model. Depending on applications, these models may be disaggregated by the type of vehicle or fuel.

The vehicle scrappage model provides estimates on the fraction of vehicles of each model year that survive to each later year. Earlier studies have suggested that many socioeconomic factors are associated with vehicle scrappage decisions, for example, vehicle age, new vehicle price, household income, unemployment rate (or job security), used vehicle price, vehicle maintenance and repair cost, and interest rate for new car loans (*4,8,9*). However, most of the vehicle scrappage models used so far have been quite simple. For example, many have adopted the age-specific scrappage model that uses vehicle age as the only determinant, and Greene's AMFU model uses two determinants: vehicle age and new car price (*6*).

The first objective of the research presented in this paper was to develop a statistical vehicle scrappage model capable of describing the association between vehicle scrappage rate (or probability) and a number of potential determinants such as those socioeconomic factors just suggested. The second objective was to use the developed model to identify socioeconomic factors that may be associated with the aggregate car scrappage rate in the United States using historical data and infer a car scrappage model for prediction purposes. The third objective was to illustrate how the developed scrappage model can be used to estimate and predict aggregate car scrappage and survival rates for future years using predicted values of the identified socioeconomic factors.

STATISTICAL MODEL

Suppose that $N_{t,m}$ vehicles of model year m are in operation at the beginning of calendar year t. Typically, model year m vehicles are introduced in the fall of year $m - 1$. Thus, model year m vehicles are in operation in years $t = m - 1, m, m + 1, m + 2, \ldots$; conversely, in year t vehicles of model years $m = t + 1, t, t - 1, t - 2, t - 3, \ldots$ are in operation. Let $Z_{t,m,i}$, where $i = 1, 2, \ldots, N_{t,m}$, be an indicator variable of 1 or 0 indicating that the ith vehicle of model year m is either scrapped (= 1) or survived (= 0) during year t. Further, assume that the scrappage decision is made independently for each individual vehicle in each year, that is, variables $Z_{t,m,i}$ are independent for all t, m, and i. The probability that the ith vehicle of model year m will be scrapped in year t is postulated to be associated with a set of k socioeconomic and vehicle age variables $x_{t,m,j}$, $j = 1, 2, \ldots k$, by a modified logit model as follows:

$$P(Z_{t,m,i} = 1) = q_{t,m}(\theta)$$

$$= \frac{1}{\alpha + \exp\left(\beta + \sum_{j=1}^{k} x_{t,m,j}\gamma_j\right)} \qquad i = 1, 2, 3, \ldots N_{t,m} \qquad (1)$$

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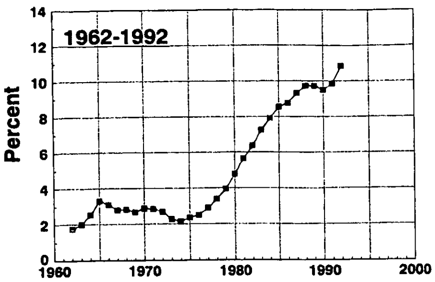

FIGURE 1 Percentage of cars in operation 15 years or older, 1962–1992.

where α (≥ 1), β, and γ_j, $j = 1, 2, \ldots, k$, are unknown parameters to be estimated from the data; and $\theta = (\alpha, \beta, \gamma_1, \gamma_2, \ldots, \gamma_k)^T$ is a column parameter vector. Note that in a conventional logit model, α is set equal to 1, and that in this paper superscript T is used to denote the transpose of a vector or matrix. Given the covariates $x_{t,m,j}$, $j = 1, 2, \ldots k$, the model assumes that $Z_{t,m,i}$ is a Bernoulli random variable with probability $q_{t,m}(\theta)$ of being equal to 1 and with probability $[1 - q_{t,m}(\theta)]$ of being equal to 0. The mean and variance of $Z_{t,m,i}$, which are conditional on the covariates and are denoted by $E(Z_{t,m,i})$ and $\text{var}(Z_{t,m,i})$, are $q_{t,m}(\theta)$ and $q_{t,m}(\theta)[1 - q_{t,m}(\theta)]$, respectively. The covariates $x_{t,m,j}$ could be specific to model year or to year. The former varies only by model year m (e.g., new car price), whereas the latter varies only by year t (e.g., unemployment rate). These two types of covariates will be denoted by $x_{m,j}$ and $x_{t,j}$, respectively, instead of $x_{t,m,j}$. Note that when appropriate, higher-order and interactive terms of covariates can be included in Equation 1 without difficulty.

Equation 1 can be rewritten as

$$Z_{t,m,i} = q_{t,m}(\theta) + u_{t,m,i} \qquad i = 1, 2, \ldots, N_{t,m} \tag{2}$$

where $u_{t,m,i}$, $i = 1, 2, \ldots, N_{t,m}$, are independent random variables for all t, m, and i and have zero mean and variance of $q_{t,m}(\theta)[1 - q_{t,m}(\theta)]$. Summing $Z_{t,m,i}$ over individual vehicles gives

$$\sum_{i=1}^{N_{t,m}} Z_{t,m,i} = N_{t,m} q_{t,m}(\theta) + \sum_{i=1}^{N_{t,m}} u_{t,m,i} \tag{3}$$

or

$$\frac{1}{N_{t,m}}\left(\sum_{i=1}^{N_{t,m}} Z_{t,m,i}\right) = q_{t,m}(\theta) + \frac{1}{N_{t,m}}\left(\sum_{i=1}^{N_{t,m}} u_{t,m,i}\right) \tag{4}$$

Letting

$$Y_{t,m} = \frac{1}{N_{t,m}}\left(\sum_{i=1}^{N_{t,m}} Z_{t,m,i}\right)$$

and

$$e_{t,m} = \frac{1}{N_{t,m}}\left(\sum_{i=1}^{N_{t,m}} u_{t,m,i}\right) \tag{5}$$

gives

$$Y_{t,m} = q_{t,m}(\theta) + e_{t,m} \tag{6}$$

where $q_{t,m}(\theta)$ is expressed in Equation 1. Variable $Y_{t,m}$ on the left side of Equation 6 represents the proportion of model year m vehicles scrapped in year t, the observation of which will be denoted as $y_{t,m}$ and typically is calculated as $(N_{t,m} - N_{t+1,m})/N_{t,m}$. Model residuals $e_{t,m}$ are independent random variables with zero mean and nonconstant variance of $q_{t,m}(\theta)[1 - q_{t,m}(\theta)]/N_{t,m}$.

The modified logit model presented in Equation 6 is quite general. Most of the vehicle scrappage models used in previous studies can be regarded as special cases of this general model. For example, the logit model of Parks (*9*) is when the parameter α in $q_{t,m}(\theta)$ is set equal to 1, and the age-specific logistic model of Greene and Chen (*3*) is when vehicle age is included as the only covariate in the model [also see the work by Feeney and Cardebring (*10*)].

Even though vehicle age is the only factor considered in the age-specific logistic model, the model has been found to explain the vehicle scrappage rate pattern quite well (*3,10*). The model has the following form:

$$Y_{t,m} = q_{t,m}(\theta) + e_{t,m} = \frac{1}{\alpha + \exp(\beta + \gamma \cdot \text{AGE}_{t,m})} + e_{t,m} \tag{7}$$

where α (≥ 1), β, and γ (<0) are model parameters, and $\text{AGE}_{t,m}$ is the average age of model year m vehicles in operation during calendar year t. The parameters of this model are easy to interpret. For example, $1/\alpha$ is the asymptotic scrappage rate (i.e., rate of scrappage for vehicles of infinite age), β determines the scrappage rate of vehicles at age 0, and γ is the shape parameter that determines the increase in vehicle scrappage rate as vehicle age increases. Figure 2 shows some example vehicle scrappage rate–age relationships from the logistic model when $\alpha = 4$, $\beta = 6$, and $\gamma = -0.8$, -0.6, and -0.4. As γ increases from -0.8 to -0.4, vehicle scrappage rates decrease at all vehicle ages. Feeney and Cardebring have pointed out (*10*) that as vehicles age, observed scrappage rates tend to increase to a maximum and then either decline or stabilize. This favors the choice of the logistic type of models over other sigmoidal growth models such as the Gompertz and Weibull models. Work by Ratkowsky (*11*) is a good source for the statistical properties of many sigmoidal growth models.

The specific model considered in this paper is a variation of the age-specific logistic model in Equation 7, in which parameter γ is assumed to depend on a set of covariates and, therefore, is allowed

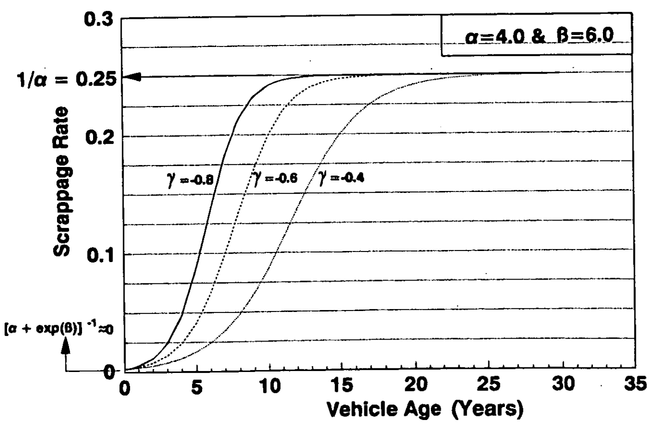

FIGURE 2 Example scrappage rate–vehicle age relationships using logistic models.

to vary over the year and model year. The model has the following form:

$$Y_{t,m} = q_{t,m}(\theta) + e_{t,m}$$
$$= \frac{1}{\alpha + \exp[\beta + (\gamma_1 + \gamma_2 x_{t,m,2} + \gamma_3 x_{t,m,3} + \ldots + \gamma_k x_{t,m,k})\cdot \mathrm{AGE}_{t,m}]} + e_{t,m} \quad (8)$$

where $\gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_k$ are parameters associated with covariates $[\mathrm{AGE}_{t,m}]$, $[x_{t,m,2}\ \mathrm{AGE}_{t,m}]$, $[x_{t,m,3}\ \mathrm{AGE}_{t,m}]$, . . . , $[x_{t,m,k}\ \mathrm{AGE}_{t,m}]$. The model can be seen to be a special model of the modified logit model in Equation 6 where only vehicle age and interactive terms of vehicle age and other covariates are included. This particular model implies that the effect of socioeconomic variables x's on vehicle scrapping decisions is dependent on the age of vehicles. Other variations of Equation 7 are, of course, possible. For example, in this study two other variations of the model were also contemplated: (*a*) to allow β and γ to be dependent on some covariates, and (*b*) to allow α and γ to be dependent on some covariates. Using the data collected in this study, both variations were found to achieve no improvements over the simpler model of Equation 8 in terms of the adjusted R^2, the adjusted coefficient of determination. Note that the adjusted R^2 was computed as follows.

$$\text{Adjusted } R^2 = 1 - \frac{\frac{1}{\text{nobs} - k - 2}\sum_t \sum_m [y_{t,m} - q_{t,m}(\hat{\theta})]^2}{\frac{1}{\text{nobs} - 1}\sum_t \sum_m [y_{t,m} - \bar{y}]^2} \quad (9)$$

where

nobs = total number of observed scrappage rates,
$\hat{\theta}$ = estimated parameter vector, and
$\bar{y}$ = average of all y's available for modeling.

For comparison, the conventional logit model that restricts the parameter α in Equation 8 to be equal to 1 was also tested.

From Equation 8, the direct elasticity of car scrappage rate $q_{t,m}(\theta)$ with respect to car age $\mathrm{AGE}_{t,m}$ can be shown to be $E_{t,m}(\mathrm{AGE}_{t,m}) = [\alpha\, q_{t,m}(\theta) - 1]\,\gamma\,(\mathrm{AGE}_{t,m})$, where $\gamma = \gamma_1 + \gamma_2 x_{t,m,2} + \gamma_3 x_{t,m,3} + \ldots + \gamma_k x_{t,m,k}$. In addition, for $\alpha \geq 1$ and $\gamma < 0$ (as required in Equation 8), it can be shown that $E_{t,m}(\mathrm{AGE}_{t,m}) = 0$ when $\mathrm{AGE}_{t,m} = 0$, and that $E_{t,m}(\mathrm{AGE}_{t,m})$ approaches 0 when $\mathrm{AGE}_{t,m}$ approaches ∞. Furthermore, the scrapping elasticity with respect to $x_{t,m,j}$, $j = 1, 2, \ldots, k$ can be shown to be $E_{t,m}(x_{t,m,j}) = [\alpha\, q_{t,m}(\theta) - 1]\gamma_j(\mathrm{AGE}_{t,m})(x_{t,m,j})$.

PARAMETER ESTIMATION

To estimate the parameters of a nonlinear regression model that has a nonconstant variance error component, such as Equation 6, the following iterative reweighted least squares (IRLS) method can be used:

1. Give initial estimates of the parameters $\hat{\theta}^o = (\hat{\alpha}^o, \hat{\beta}^o, \hat{\gamma}_1^o, \hat{\gamma}_2^o, \ldots, \hat{\gamma}_k^o)^T$.
2. Compute weights as the reciprocal of the estimated residual variances:

$$w_{t,m} = \frac{N_{t,m}}{q_{t,m}(\hat{\theta}^o)[1 - q_{t,m}(\hat{\theta}^o)]} \quad (10)$$

where $q_{t,m}(\hat{\theta}^o)$ is the scrappage rate evaluated at $\hat{\theta}^o$.

3. Reestimate the model parameters θ by minimizing the following weighted sum of squares with respect to θ:

$$\sum_t \sum_m w_{t,m}[y_{t,m} - q_{t,m}(\theta)]^2 \quad (11)$$

where the sums are performed over all appropriate t and m. Let the new estimates be $\hat{\theta} = (\hat{\alpha}, \hat{\beta}, \hat{\gamma}_1, \hat{\gamma}_2, \ldots, \hat{\gamma}_k)^T$.

4. If the absolute change of each parameter is less than a small positive number ϵ (e.g., 0.00001), then stop and let the final estimates be $\hat{\theta}$. That is, stop the iterative procedure when $|(\hat{\alpha} - \hat{\alpha}^o)/\hat{\alpha}^o| < \epsilon$, $|(\hat{\beta} - \hat{\beta}^o)/\hat{\beta}^o| < \epsilon$, and $|(\hat{\gamma}_j - \hat{\gamma}_j^o)/\hat{\gamma}_j^o| < \epsilon$ for all j's. Otherwise, let $\hat{\theta}^o = \hat{\theta}$ and go to Step 2.

Standard error estimates of the components of $\hat{\theta}$ are computed by taking the square roots of the diagonal elements of an estimate of the asymptotic variance-covariance matrix of $\hat{\theta}$. The estimate of the matrix is given by

$$\left[\sum_t \sum_m \frac{\left[\frac{\partial \hat{q}_{t,m}}{\partial \theta}\right]\left[\frac{\partial \hat{q}_{t,m}}{\partial \theta}\right]^T}{\hat{\sigma}^2_{t,m}}\right]^{-1} \quad (12)$$

where

$$\hat{\sigma}^2_{t,m} = \frac{q_{t,m}(\hat{\theta})[1 - q_{t,m}(\hat{\theta})]}{N_{t,m}}$$

and

$$\left[\frac{\partial \hat{q}_{t,m}}{\partial \theta}\right] = \left[\frac{\partial q_{t,m}(\theta)}{\partial \alpha}, \frac{\partial q_{t,m}(\theta)}{\partial \beta}, \frac{\partial q_{t,m}(\theta)}{\partial \gamma_1}, \ldots, \frac{\partial q_{t,m}(\theta)}{\partial \gamma_k}\right]^T_{\theta=\hat{\theta}} \quad (13)$$

See work by Beal and Sheiner (*12*) for details of the IRLS method and the asymptotic variance-covariance matrix.

In this paper, for comparison purposes the ordinary least squares (OLS) method was also used to estimate model parameters in Equation 8. The OLS method assumes that model residuals $e_{t,m}$ have zero mean and constant variance.

DATA AND DATA SOURCES

Car registration data compiled by the R.L. Polk & Company and published in *Vehicle Facts and Figures* (*1*) were used to compute car scrappage rates. Polk's registration data represent a snapshot of the number of cars in operation on July 1 of each year. Typically, the data are tabulated for the latest 16 model years, and earlier model years are grouped under one category. Registration data for the latest 16 model years from 1965 to 1992 were used in this study. The same data source has been used in earlier scrappage rate studies: Greene and Chen (*3*) used data from 1966 to 1977, Hu (*13*) used data from 1970 to 1982, and Feeney and Cardebring (*10*) used data from 1971 to 1983. Note that 1980 registration data were not used in this study because some passenger vans (1.2 percent of the passenger car fleet) were reclassified from passenger cars to trucks in that year.

To compute the "observed" average car scrappage rate for each calendar year using Polk's July 1 registration data, the following formula was used:

$$y_{t,m} = \frac{1}{2}\left(\frac{N^*_{t-1,m} - N^*_{t,m}}{N^*_{t-1,m}} + \frac{N^*_{t,m} - N^*_{t+1,m}}{N^*_{t,m}}\right) \quad (14)$$

where $N^*_{t,m}$ is the number of model year m cars in operation on July 1 of year t.

To estimate the average age of model year m cars in year t, denoted by $AGE_{t,m}$, two observations were made from Polk's registration data: (*a*) about 65 percent of model year m cars are sold by July 1 of year m (*10*), and (*b*) model year m cars are typically introduced in the fall of year $m - 1$. Similar to the linear interpolation approach used by Feeney and Cardebring (*10*), average car ages were approximated in this paper as follows:

$$AGE_{t,m} \approx t - m + 0.25 \tag{15}$$

where $t = m + 1, m + 2, \ldots$. Note that Feeney and Cardebring used 0.225 in Equation 15 instead of 0.25.

In addition to car age, $AGE_{t,m}$, other covariates considered for use in Equation 8 include one variable specific to model year and six variables specific to year:

$x_{m,2} = NCPI_m$ = new car price index for all urban consumers (1982–1984 = 100) (*1*);

$x_{t,3} = DI/HH_t$ = real disposable income per capita ($1,000, 1988) × number of persons per household (*14*) (Note that this is intended to be an estimate of real disposable household income);

$x_{t,4} = UNEMP_t$ = unemployment rate (%) (*14*);

$x_{t,5} = UCPI/MRCI_t$ = used car price index for all urban consumers (1982–1984 = 100) (*1*) divided by total maintenance and repair cost index for all urban consumers (1982–1984 = 100) (*14*);

$x_{t,6} = NCLOAN_t$ = annual rate of new car loans (%)—most common rate by commercial banks (*14*); and

$x_{t,7} = ACC/REG_t$ = number of motor vehicle accidents—from the Insurance Information Institute (*14*), divided by the total number of cars in operation (*1*).

The expected relationship between each variable and the car scrappage rate is as follows:

- $NCPI_m$: higher new car price is expected to be associated with lower scrappage rates at all ages in later years (6,9).
- DI/HH_t: The role of disposable household income on car scrappage rate is not clear from previous studies. Parks (*9*) indicated that

> Real disposable personal income per family did not appear significant in any of the equations. . . . A rise in income would . . . be associated with a shift in demand from old to new, [which] would lead to a fall in the relative price of older cars and an increase in the scrapping of older cars. This effect could be offset, however, to the extent that rising income produced a demand for multiple car ownership.

Recent data on vehicle ownership, however, appear to favor the theory of multiple car ownership as household income increases. For example, data from the decennial census indicated that the share of households owning two vehicles increased from 19 percent in 1960 to 37 percent in 1990, and during the same period the share of households owning three or more vehicles increased from 3 to 18 percent (*15*). As will be presented in the next section, the results from this study also support the multiple car ownership theory. (Note that during the same period the average size of households dropped from about 3.33 to 2.63 persons.)

- $UNEMP_t$: Unfavorable economic conditions give rise to higher unemployment rate and depress new car demand and are, therefore, expected to prolong the retention of old vehicles in the car fleet (*4*).
- $UCPI/MRCI_t$: Walker's study (*8*) indicated that higher ratio of used car price over maintenance and repair cost was associated with a lower scrappage rate.
- $NCLOAN_t$: As indicated in Greene (*4*), three-fourths of all new car purchases were financed. Higher interest rates on new car loans discourage the purchase of new cars and, therefore, slow vehicle retirement rates.
- ACC/REG_t: Vehicle accidents increase total maintenance and repair costs and may shorten a vehicle's life span. Higher values of accident-registration ratios are, therefore, expected to be associated with higher scrappage rates. The original idea was to collect the total number of cars that either were scrapped or required significant repairs (in the economic sense) as a result of being involved in severe crashes. However, because of the lack of such crash data, the total number of motor vehicle accidents (including all minor and major accidents and both car and truck accidents) was used as a surrogate variable.

MODEL RESULTS, ILLUSTRATIONS, AND DISCUSSION

Equation 8 was the main scrappage model considered in this paper. The estimated parameters from the IRLS method and the adjusted R^2 value of the estimated model are given as Model 1 in Table 1. For comparison, the results from three other models (or estimation methods) are also presented in the table:

- Model 2: The age-specific logistic scrappage model in Equation 7 that was also estimated by the IRLS method;
- Model 3: Same as Model 1, but parameters were estimated using the OLS method; and
- Model 4: A logit model estimated by the IRLS method (i.e., same as Model 1) but parameter α was set equal to 1.

Several observations can be made from the estimation results presented in Table 1:

1. All the estimated parameters in Model 1 have expected algebraic signs. Except ACC/REG_t, all other variables have very high asymptotic t-statistics (≥ 3.0). Car age, $AGE_{t,m}$, is the most dominant factor in terms of t-statistics. A high adjusted R^2 value of 0.95 suggests that the model fits the data quite well.
2. Model 2 (the age-specific logistic scrappage model) indicates that car age alone explains about 77 percent of the variance in the observed scrappage rate data.
3. The OLS results from Model 3 are consistent with the IRLS results from Model 1 in terms of the algebraic signs of the estimated parameters. The OLS method, however, renders $NCPI_m$ statistically insignificant and ACC/REG_t significant. This model is not recommended because the variance of the residuals from the model was tested to be nonconstant.
4. All the estimated parameters in Model 4 (the logit model) also have expected algebraic signs and are generally consistent with those from Model 1. The adjusted R^2 value of the estimated model is 0.74, which is even lower than Model 2, indicating that setting parameter α to 1 is overly restricted in the fitting of the observed scrappage rates.

TABLE 1 Estimated Model Parameters and Associated Statistics

Model Parameter, [Expected Sign], & Variable Name	Model 1 Eq. 8 IRLS Method	Model 2 Eq. 7 IRLS Method	Model 3 Eq. 8 OLS Method	Model 4 Eq. 8 w/ α=1, Logit Model IRLS Method
α [+] Constant	3.29163 (26.87)	4.21850 (17.06)	3.21802 (51.34)	1.0
β [+] Constant	5.56929 (75.23)	5.80231 (40.32)	5.54511 (40.47)	4.78940 (77.77)
γ [-] $AGE_{t,m}$		-0.476107 (-19.92)		
γ_1 [-] Constant Associated with $AGE_{t,m}$	-1.29996 (-11.66)		-1.49131 (-13.16)	-0.732487 (-9.76)
γ_2 [+] $NCPI_m$	0.00081693 (3.00)		0.00008022 (0.24)	0.00057406 (2.27)
γ_3 [+] DI/HH_t	0.0134764 (6.05)		0.0214045 (8.88)	0.0065747 (4.08)
γ_4 [+] $UNEMP_t$	0.0090247 (3.70)		0.0117853 (4.94)	0.0043987 (2.24)
γ_5 [+] $UCPI/MRCI_t$	0.255644 (6.91)		0.291888 (8.10)	0.166644 (5.89)
γ_6 [+] $NCLOAN_t$	0.0114301 (6.49)		0.0171277 (9.45)	0.0068181 (4.71)
γ_7 [-] ACC/REG_t	-0.258674 (-0.88)		-0.825293 (-2.84)	-0.269513 (-1.23)
Adjusted R^2	0.95	0.77	0.96	0.74

Notes: (1) Sample size: 293, and (2) values in parentheses are asymptotic t-statistics of the estimated parameters above.

The elasticities of the car scrappage rate with respect to different car ages for cars of the 1970 model year are shown in Figure 3. The greatest elasticity occurred between ages 7 and 9. (Note that all other model years considered in this paper had the same elasticity pattern as that of 1970.) The elasticities of the car scrappage rate with respect to the socioeconomic variables when averaged over the observed period and different car ages are as follows:

- $NCPI_m$: -0.21;
- DI/HH_t: -1.85;
- $UNEMP_t$: -0.24;
- $UCPI/MRCI_t$: -0.91;
- $NCLOAN_t$: -0.58; and
- ACC/REG_t: -0.27.

The average elasticity of -1.85 for DI/HH_t clearly indicates that household income has played an important role in car scrapping decisions. This result is contrary to Parks' finding in 1977 (*9*).

Table 2 presents the average annual growth rate (AAGR) of $NCPI_m$, DI/HH_t, and $UCPI/MRCI_t$ and the annual average of $UNEMP_t$, $NCLOAN_t$, and ACC/REG_t for 1965–1992. To illustrate how Model 1 can be used for estimating and predicting car scrappage and survival rates, it is assumed that these AAGRs and averages during 1965–1992 will persist up to year 2010. Under this assumption, Figure 4 shows the estimated and predicted car scrappage rates by car age for 7 calendar years between 1970 and 2000 with a 5-year time interval. Using the same assumption, Figure 5 shows the estimated and predicted survival rates by car age for five model year cars: 1970, 1975, 1980, 1985, and 1990. The median lifetime is expected to increase from 10.7 years for 1970 model year cars to 13.7 years for 1990 model year cars.

Technology is an important factor that was not considered explicitly in this paper. Over the years, new cars with better safety equipment, fuel efficiency, antipollution devices, built-in durability (due to better materials and structural design), and quality control have been introduced to the new car market. The introduction of these cars can either increase or decrease aggregate car scrappage rates. Demand for safer, more fuel efficient, and cleaner cars would increase the demand for newer cars and would lead to a rise in the scrapping of older cars if car holdings remain the same. On the other hand, higher new car prices as a result of such added safety features

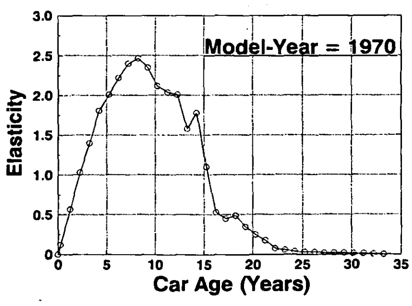

FIGURE 3 Elasticities of scrappage rate with respect to car age: 1970 model year.

TABLE 2 AAGR or Average of Socioeconomic Variables

Variable		1965-75	1975-85	1985-92	1965-92
New Car Price Index	AAGR -	2.43%	5.39%	2.77%	3.57%
Real Disposable Household Income	AAGR -	1.36%	0.26%	1.28%	0.93%
Unemployment Rate	Average -	4.96%	7.63%	6.35%	6.20%
Used Car Price Index/Maintenance & Repair Cost Index	AAGR -	-2.16%	2.70%	-2.81%	-0.48%
Interest Rate of New Car Loans	Average -	9.63%	13.15%	11.23%	11.40%
No. of Accidents/Total Car Registration	Average -	0.27	0.26	0.27	0.27

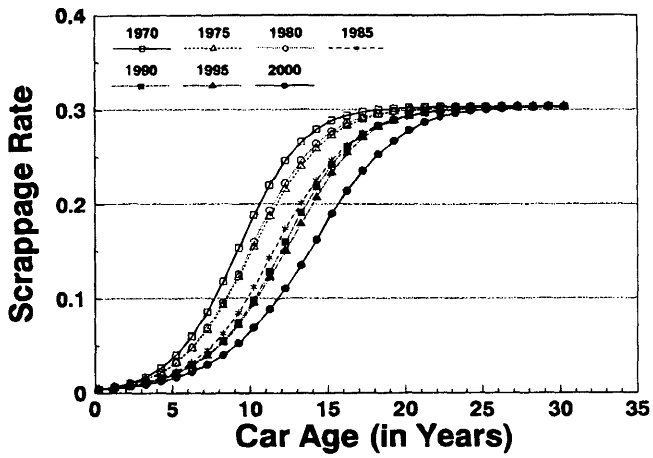

FIGURE 4 Estimated car scrappage rates by vehicle age for several calendar years.

and antipollution devices might reduce new car sales and prolong the retention of older cars. Better built-in durability and quality control reduce repair frequency and cost over the lifetime of a vehicle.

The present work could be extended in several directions:

1. It would be formally straightforward to extend the current framework to study *truck* scrappage decisions.

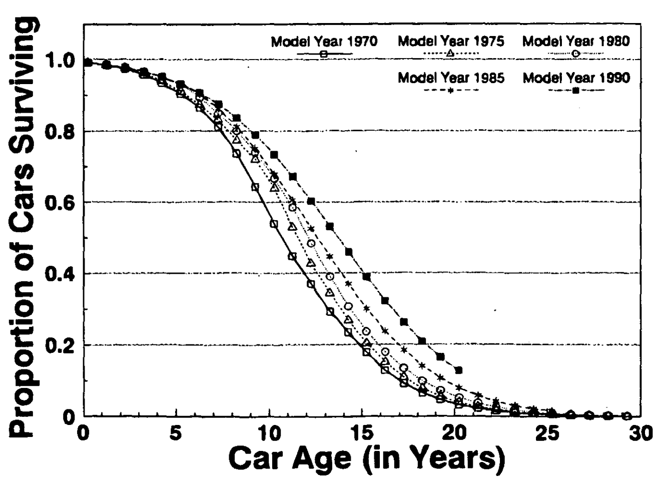

FIGURE 5 Estimated proportions of cars surviving by vehicle age for several model years.

2. Because of the lack of used car price data by model year, the variable was considered exogenous in this study. In reality, used car price may be endogenous and a simultaneous equation model may be more appropriate.

3. The available registration data grouped cars 16 years and older into one category. In this study, these data were not used in estimating model parameters. An estimation procedure should be developed to make the best use of these data that contain useful information on the scrapping rates of older cars.

4. To make long-term predictions of car scrappage rates, the potential for saturation effects in the relationships among income, size of households, and vehicle ownership should be analyzed.

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REFERENCES

1. *Motor Vehicle Facts and Figures.* American Automobile Manufacturers Association, Detroit, Mich., annual.
2. *DRI/McGraw-Hill Transportation Sector Analysis Capabilities.* DRI/McGraw-Hill, Inc., 1993.
3. Greene, D. L., and C. K. Chen. Scrappage and Survival Rates of Passenger Cars and Light Trucks in the U.S., 1966–1977. *Transportation Research*, Part A, Vol. 15A, No. 5, 1981, pp. 383–389.
4. Greene, D. L. *Analysis of Vehicle Stock Dynamics, New Car Fuel Economy, and Automotive Fleet Fuel Economy.* U.S. Department of Energy; Oak Ridge National Laboratory, Oak Ridge, Tenn., 1983.
5. Greene, D. L., and J. T. Liu. *Scrappage, Depreciation, and the Supply of Used Capital Stock: Highway Vehicles in the United States.* Oak Ridge National Laboratory, Oak Ridge, Tenn., 1986.
6. Greene, D. L., and A. Rathi. *Alternative Motor Fuel Use Model: Model Theory and Design and User's Guide.* ORNL/TM-11448. Oak Ridge National Laboratory, Oak Ridge, Tenn., 1991.
7. The AES Corporation. *An Overview of the Ideas Model: A Dynamic Long-Term Policy Simulation Model of U.S. Energy Supply and Demand.* U.S. Department of Energy, 1993.
8. Walker, F. V. Determinants of Auto Scrappage. *Review of Economic Statistics*, Vol. 50, 1968, pp. 503–506.
9. Parks, R. W. Determinants of Scrapping Rates for Postwar Vintage Automobiles. *Econometrica*, Vol. 45, 1977, pp. 1099–1115.
10. Feeney, B. P., and P. Cardebring. Car Longevity in Sweden: A Revised Estimate. *Transportation Research*, Part A, Vol. 22A, No. 6, 1988, pp. 455–465.
11. Ratkowsky, D. A. *Nonlinear Regression Modeling: A Unified Practical Approach.* Marcel Dekker, Inc., New York, 1983.

12. Beal, S. L, and L. B. Sheiner. Heteroscedastic Nonlinear Regression. *Technometrics*, Vol. 30, No. 3, 1988, pp. 327–338.
13. Hu, P. S. *Scrappage and Survival Rates of Passenger Cars and Trucks in 1970–1982.* Office of Vehicle and Engine, U.S. Department of Energy; Oak Ridge National Laboratory, Oak Ridge, Tenn., 1983.
14. *Statistical Abstract of the United States.* Bureau of the Census, U.S. Department of Commerce, annual.
15. *Nationwide Personal Transportation Survey: Special Reports on Trip and Vehicle Attributes.* Draft, 1990 NPTS Report Series. FHWA, U.S. Department of Transportation, 1994.

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