ORNL/TM–2001/134

TAFV Alternative Fuels and Vehicles Choice Model Documentation

July 2001

David L. Greene
Corporate Fellow

ORNL/TM–2001/134

TAFV ALTERNATIVE FUELS AND VEHICLES CHOICE MODEL DOCUMENTATION

David L. Greene

Center for Transportation Analysis
Oak Ridge National Laboratory

July 2001

Prepared by the
OAK RIDGE NATIONAL LABORATORY
Oak Ridge, Tennessee 37831
managed by
UT-BATTELLE, LLC
for the
U. S. DEPARTMENT OF ENERGY
under contract DE-AC05-00OR22725

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENT

The author thanks his colleagues Paul Leiby and Jonathan Rubin for helpful comments on an earlier draft of the manuscript, and thanks David Rodgers, Tom White, Barry McNutt and the U.S. Department of Energy for support of this research. Any errors herein are the sole responsibility of the author. This work is dedicated to Michael Greene.

ABSTRACT

A model for predicting choice of alternative fuel and among alternative vehicle technologies for light-duty motor vehicles is derived. The nested multinomial logit (NML) mathematical framework is used. Calibration of the model is based on information in the existing literature and deduction based on assuming a small number of key parameters, such as the value of time and discount rates. A spreadsheet model has been developed for calibration and preliminary testing of the model.

1. INTRODUCTION

This memorandum documents a revised method for forecasting market shares of alternative fuel and advanced technology vehicles for the Transitional Alternative Fuels and Vehicles (TAFV) Model (Leiby and Rubin, 1997; 2000). The revision adds hybrid and fuel cell vehicle technologies and creates a separate technology set for gaseous bi-fuel vehicles. The model's coefficients are derived from basic assumptions and input data, rather than adopted from statistical estimates appearing in the literature. The purpose of the change is to insure that the valuations of attributes implied by the model are transparent, plausible and defensible.

The nesting structure of the vehicle technology choice model and the variables that drive consumer choice are explained in Section 2. The mathematics of the nested multinomial logit (NMNL) model are explained in Section 3. The general approach to estimating coefficients for variables is explained in Section 4. Specific methods used to estimate each of the model's coefficients are set forth in Section 5. Section 6 presents the results of calibrating the model using base year 1995 data, and then discusses the implied attribute values. A spreadsheet model constructed for calibrating coefficients and testing the implications for vehicle technology market shares is described in Section 7.

2. MODEL STRUCTURE

Sales shares are predicted by a NMNL function of relevant vehicle and fuel attributes, fuel and vehicle prices, and other factors such as fuel availability and make and model diversity. There are three levels of nesting, illustrated in Figure 1. The first (lowest) level nesting predicts the probability of choice of *fuel type* for multi-fuel vehicles, given that a bifuel or flex-fuel vehicle has been chosen. The purpose of this level is to determine the expected fuel-related characteristics of vehicles capable of using more than one fuel. The second level nesting represents the choices among alternative *vehicle technologies* within sets of technologies with similar characteristics, conditional on the choice of a particular technology set. The third level choice is among the *technology sets*.

Choices among vehicle technologies are made based on fuel and vehicle characteristics. Fuel characteristics include price, availability, and driving range using the fuel in question (given vehicle fuel economy and tank size). Vehicle characteristics include price, acceleration performance, capacity, the costs of maintenance and battery replacement, the cost of fuel per vehicle mile, refueling options, and make and model diversity. For flexible and bi-fuel vehicles, acceleration is a function of the fuel type chosen. The variables included are listed in Table 1. An argument can be made that other variables should be considered. For example, hybrid vehicles tend to be quieter and their higher voltage electrical systems may offer a variety of benefits.

Table 1. List of Variables Used in the Alternative Fuels and Vehicles Model

Variable	Name	Units
Vehicle Purchase Price	PSPR	1990 $
Fuel Cost per Mile	FLCOST	cents per mile
Range	VRNG	1/miles
Battery Replacement Cost	BRC	1990 $
Acceleration, 0-60 mph	ACCL	seconds
Home Refueling for Evs	HFUEL	dummy
Maintenance Cost	MAINT	annual 1990 $
Luggage Space	LUGG	ratio to gasoline vehicle
Fuel Availability Coefficient 1	BETAFA	multiplier for exp (k*fraction)
Fuel Availability Coefficient 2	BETAFA2	multiplier (k) for fraction of stations offering fuel
Make/Model Availability	MMAVAIL	in (fraction of total gasoline makes and models)
Vehicle Technology Nest Generalized Cost Coefficient	TSGC	1990 $
Fuel Choice Generalized Cost	MFGC	1990 cents/mile

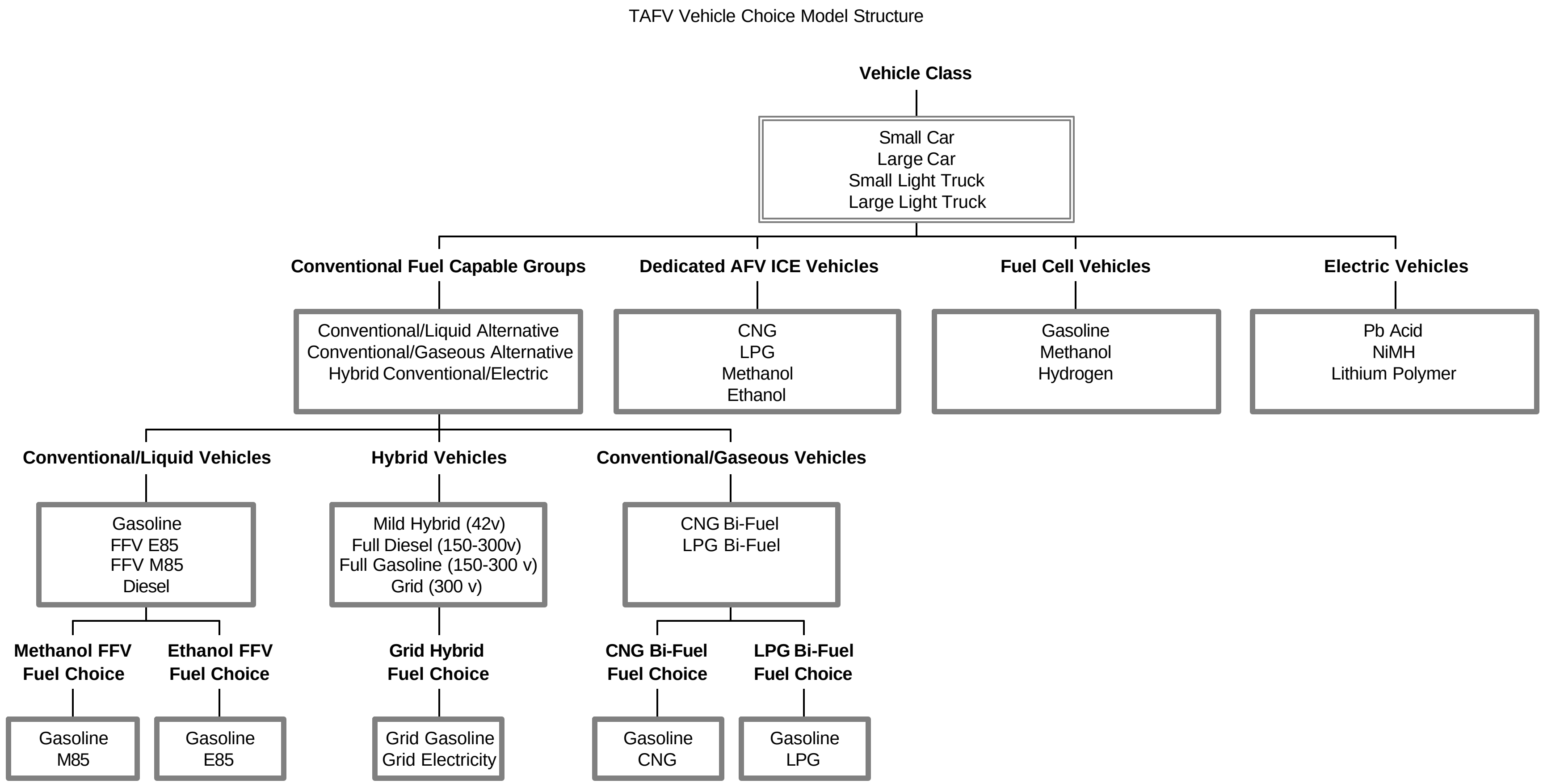

Figure 1. Alternative Fuels and Vehicles Model Nested Choice Structure

The following nested set structure has been implemented in the new NEMS AFVM module:

I. Conventional Liquid Fuel Capable Vehicles

1. Conventional gasoline vehicle
2. Flexible-fuel gasoline/E85
   a. Expected use of gasoline v. ethanol
3. Flexible-fuel gasoline/M85
   b. Expected use of gasoline v. methanol
4. Conventional diesel vehicle (TDI)

II. Conventional Gaseous Fuel Capable Vehicles

5. Bi-fuel CNG vehicle
   Expected use of CNG v. Gasoline
6. Bi-fuel LPG vehicle
   Expected use of LPG v. Gasoline

III. Hybrid Vehicles

7. Mild hybrid gasoline
8. Full hybrid gasoline
9. Full hybrid diesel
10. Grid-connected hybrid gasoline

IV. Dedicated Alternative Fuel ICE Vehicles

11. Dedicated CNG
12. Dedicated LPG
13. Dedicated methanol
14. Dedicated ethanol

V. Fuel Cell Vehicles

15. Fuel cell vehicles reforming gasoline
16. Fuel cell vehicles reforming methanol
17. Hydrogen fuel cell vehicles

VI. Battery electric vehicles

18. Battery powered EV

An advantage of using a nested logit structure is that it allows for differences in the price sensitivities of choices among different technology sets and thereby circumvents the independence of irrelevant alternatives property of the un-nested logit model. The NMNL structure is often misinterpreted as implying that consumers actually do make their choices in the order of nesting (first decide on technology set, then vehicle technology, then fuel type). In fact, this is not necessarily implied by the nested structure. What is implied is that there is a structure to the price sensitivities of the choice decisions. Price sensitivity within a nest is the same for all alternatives in the nest. Price slopes may differ across nests at the same level, however. The price sensitivity of choices in a lower nest must be greater than in a higher nest. In theory, nests contain alternatives that are similar with respect to their unobserved attributes (attributes not explicitly included in the model). At the lowest level of nesting, alternatives are assumed to be most similar (fewest important unobserved attributes). Choices among very similar alternatives will be most price sensitive, because the alternatives are close substitutes. This theoretical requirement turns out to be helpful in calibrating an NMNL model.

In the remainder of this memorandum, the mathematical structure of the NMNL model is presented, followed by an explanation of how the model can be calibrated based on fundamental assumptions about economic behavior and evidence from published studies. Each variable and the derivation of its coefficient is then reviewed, in turn.

3. MATHEMATICS OF THE NMNL MODEL

In the MNL model, the utility of a choice alternative is a function of its attributes and other variables. Denote these variables by x_{ijk} to indicate the i^{th} variable for the j^{th} AFV technology type, in the k^{th} technology set, and let the weight (or marginal utility) for the i^{th} variable be μ_{ik}. A simple functional form for the utility, u_{jk}, of the j^{th} alternative in set k is the sum of weighted variables.[1]

$$u_{jk} = m_{Pk} \sum_{i=1}^{I} a_{ik} x_{ijk} = m_{Pk} c_{jk} \tag{1}$$

The weight μ_{Pk} is the coefficient for vehicle price, P, in technology set k, and $\alpha_{ik} = \mu_{ik} / \mu_{Pk}$. Normalizing by dividing by μ_{Pk} implies that the α-weight for vehicle price equals 1, and that every other variable's weight represents the (negative) value of one unit of that attribute, in dollars. The sum c_{jk} therefore represents a "generalized cost" for alternative j which, when multiplied by the price weight (or slope) gives the utility of AFV technology j , since μ_{Pk} has units of utils per dollar.

For the j^{th} vehicle technology in the k^{th} technology set, the simple MNL model gives the probability that the j^{th} technology will be chosen (or equivalently the expected market share), conditional on a consumers' decision to buy a technology in the k^{th} set, as the following function of the utilities of all technologies in the class.

$$s_{j|k} = \frac{e^{u_j}}{\sum_{l=1}^{n_k} e^{u_l}} \tag{2}$$

In equation (2), *l* indexes all of the choice alternatives in technology set k and n_k is the number of AFV technologies in class k. This probability is conditional on the consumer choosing set k. The next step is to determine the choice probabilities for each of the k technology sets.

In the nested MNL (NMNL) model, the technology set shares may depend on set level variables, but they also depend on the level of utility expected from the individual technology choices in the set. The average utility level within set k is given by the following function of the individual technology utilities.

$$\overline{c_k} = \frac{1}{m_{Pk}} ln\left(\sum_{j=1}^{n_k} e^{u_j} \right) \tag{3}$$

[1]Some variables, for example range and fuel availability, actually affect utility in a non-linear manner. However, as long as utility can be represented as a weighted sum of such non-linear functions, equation (1) is appropriate.

This term is referred to as an average generalized cost, since the logarithm of the sum of exponentiated utilities is divided by the price slope (multiplying the generalized cost by the price slope yields a utility, as shown in equation (1) above).

Now the utility of the k[th] technology set can be computed using the AFV technology generalized costs from equation (3), set-specific attributes (y_{ik}) and weights (μ_i), including the set price (or generalized cost) slope, μ_P .

$$s_k = \frac{e^{m_P (C_k + \overline{c_k})}}{\sum_{l=1}^{N} e^{m_P (C_l + \overline{c_l})}} \quad ; \qquad C_k = \sum_{i=1}^{I} a_i y_{ik} \tag{4}$$

Note that the set-level price slope (μ_P) is the weight for the generalized cost variable c-bar, but is not, in general, equal to μ_{Pk} . Indeed, MNL theory requires that $|\mu_P| < |\mu_{Pk}|$ for every k. The μ_{Pk} need not, in general, be equal. It may also be that there are no new variables at the set level. There need not even be constant terms for each technology set. In this case, the sole purpose of the nesting would be to allow a different price elasticity for technology set choice than for the AFV technology choices.

For flexible-fuel vehicles and for gaseous fuel bi-fuel vehicles, the full set of vehicle characteristics cannot be determined without first deciding on which fuels the vehicles will use. For example, the range of a bi-fuel CNG vehicle will be different using CNG than using gasoline, and similarly for an FFV using M85 versus gasoline. Fortunately, the NMNL model provides a solution to this problem. By nesting a conditional fuel choice decision within the conditional vehicle choice decision, a generalized (or expected) cost for the fuel type choice can be passed forward to the vehicle choice level. While this nested fuel choice decision cannot be used to predict the fuel choices for vehicles on the road, it does represent the expected value of the fuel choice at the time of vehicle purchase. At least three variables must be included in the fuel choice nest: (1) fuel cost per mile (p_f), (2) range (r), and (3) fuel availability (x_a). The utility of choice of fuel type f, for vehicle technology type j in technology set k, is given by the following.

$$u_{fjk} = {}_{pjk} p_f + m_{rjk} \frac{1}{r} + m_{ajk} \left(Ae^{bx} \right) \tag{5}$$

In equation (5), range is represented by its inverse, since the time cost of refueling can be shown to decrease with the inverse of range. This is proven in Section 5. Fuel availability is represented by an exponentially declining function of the percent of stations offering the fuel, based on an empirical study by Greene (1998). The logsum term passed forward to the choice of multi-fuel vehicle technology is computed analogously to equation (3).

$$\overline{c_{jk}} = \frac{1}{m_{Pjk}} \ln \left(\sum_{f=1}^{2} e^{u_{fjk}} \right) \tag{6}$$

The summation assumes no vehicle will be able to use more than two fuel types, although any number could be included. The fuel choice price slope , μ_{Pjk}, must be greater (in absolute value) than the vehicle technology choice price slope, μ_{Pk}, which, in turn, must be greater (in absolute value) than the technology set choice slope μ_P. Of course, when this generalized cost is passed forward to the vehicle technology choice level, the relevant fuel attributes (fuel cost, range and availability) are replaced by the generalized cost variable, which is then multiplied by the vehicle technology price slope, μ_{pk} , in computing the utility of the j^{th} vehicle technology type.

4. METHOD OF CALIBRATING COEFFICIENTS

The NMNL model is well suited to the deductive estimation of coefficients. Shares of alternative fuel vehicles (AFVs) depend on a measure of the expected utility, U_j , of each vehicle technology, j. Utility is represented by a weighted sum of relevant vehicle attributes, x_{ij} . The coefficients, μ_i , are therefore the marginal utilities of each attribute. One of the attributes is the retail price, P_j , of the vehicle type. The weight for price is therefore the marginal utility of $1 of cost, present value, or the negative of $1 of income. Thus, if we can deduce the marginal, present value, V_i , of a 1-unit change in a certain characteristic i, we can calculate its marginal utility coefficient, μ_i , by multiplying by the negative of the coefficient of vehicle price, μ_P .

The price slope of the utility function is, therefore, a pivotal parameter, since it is used in estimating every other coefficient in the utility function. It is convenient to calculate a logit price slope parameter from an elasticity. For example, suppose that the price elasticity of carline choice within the subcompact class is known to be -4. In the logit model, the elasticity of the share of alternative j with respect to variable i is β_{ij} is equal to the product of the variable slope coefficient, μ_{ij}, the value of the variable, and one minus the market share. In the case of price, the formula for the price slope as a function of the price elasticity is as follows.

$$m_P = \frac{b_{Pj}}{P_j(1 - s_j)} \tag{7}$$

Other coefficients in the utility function (with the exception of calibration constants) are estimated by computing a dollar value per unit of the attribute, and then multiplying that dollar value by the negative of the purchase price coefficient.

$$m_x = -m_P \left(\frac{\$}{unit} \right)_x \tag{8}$$

This method is derived from the relationship between the marginal utilities of attributes and the marginal utility of the purchase price (which is the marginal utility of one present value dollar). Using the linear utility function shown in equation (1), its partial derivative with respect to a variable x, is the coefficient, or slope, of x. Note that if x appears in the utility function in a non-linear form, as in equation (5), then its partial derivative will be more complex. Taking the ratio of marginal utilities and noting that the ∂u terms will cancel, we obtain the result in equation (9), below.

$$\frac{\P u}{\P x} = m_x \qquad \frac{\P u}{\P P} = -m_P \qquad \Rightarrow \qquad \frac{\P P}{\P x}(-m_P) = m_x \tag{9}$$

The derivative of P with respect to x is value of one unit of x in present value (purchase price) dollars. Thus, the coefficient of x is the negative of the price coefficient, times the dollar value of one unit of x, as shown in equation (11). Therefore, by choosing plausible dollar values for each attribute, and by deriving the price slope from a plausible price elasticity, one can insure that the NMNL model will always make plausible predictions.

5. DEDUCTIVE ESTIMATION OF AFV MODEL COEFFICIENTS

The approach used to estimate coefficients for the AFV model is to derive (or deduce) them from basic economic assumptions, or to use consensus estimates of the marginal values of attributes based on the existing, published literature. Most AFV discrete choice models have inferred their coefficient estimates by applying statistical techniques to stated preference survey data (e.g., Bunch et al., 1993). Predictions based on these surveys generally do not corresponded well with historical AFV market shares. While stated preference surveys can be very valuable in eliciting consumers' preferences for new commodities for which there is no historical record of revealed preference, they suffer from several well-known shortcomings. Most significant among these are the tendency for respondents to underestimate their true sensitivity to market prices, and the inability of respondents to consistently make trade-offs among a large number of attributes. The former leads to much lower price elasticities than obtained using revealed preference data. The latter may result in inconsistent valuation of attributes. Since neither of these properties is acceptable in a model used for policy analysis or technology forecasting, an alternative approach is used here.

Calibrating coefficients using basic economic assumptions and a consensus of estimates from the published literature allows AFV model coefficients to be made more consistent with other assumptions of the TAFV Module, thereby imposing logical consistency in factors such as implied discount rates and annual vehicle usage rates.

Purchase Price Elasticity. The most important coefficient in a vehicle choice model is the marginal utility of purchase price. In effect, the price coefficient serves as a scaling factor for all other variables in the model. In a multinomial logit model, the price elasticity of market share, β_p , is not constant, but depends on the current market share, s, and on the price level, P as follows: $\beta_p = \mu P(1\text{-}s)$. Thus, price elasticity will approach a maximum of μP as s nears 0 and approach 0 as s nears 1. For this reason, price elasticities of different models should be compared at constant price and market share.

In theory, the demand for types of vehicles should be much more price elastic than the demand for vehicles as a whole. Empirical evidence supports economic theory on this point. The overall price elasticity of demand for automobiles is generally agreed to be in the vicinity of -1.0 (see, e.g., Kleit, 1990; McCarthy, 1996). A survey of a dozen econometric studies of vehicle make and model choice produced a much larger consensus price elasticity estimate of -2.8 at 50 percent market share (Greene, 1994). Lave and Train's (1979) seminal study of automobile choice implies a price elasticity of make and model choice of -3 at 50 percent share. Recent studies have confirmed that choices among makes and models of cars are highly price elastic. Bordley (1993) concluded that while own price elasticities of demand for car classes (e.g., compact, midsize, luxury) ranged from -1.7 to -3.4, average elasticities for makes and models within segments ranged from -2.4 to -4.7. Berry et al. (1995) estimated own price elasticities of 1990 carlines ranging from -3.1 to -6.7. These latter estimates apply at the market shares of individual carlines which are much smaller than 50 percent.

A key question is whether choice among AFVs is more or less elastic than choice among carlines. In theory, this depends on the extent to which consumers consider the alternative fuel technologies to be close or distant substitutes. Choices among close substitutes should be highly price elastic. Greene's (1986) revealed preference study suggests that when the choice is between gasoline and diesel engines for an otherwise identical carline, the choice is more elastic, about -10 (at 50 percent market share). Greene's (1998) stated preference study of the value of fuel availability implied a price elasticity of about

-50 for vehicles described as otherwise identical, except for the ability of an engine to use a different fuel. This would seem to be an upper bound on the price elasticity for choices among alternative fuel technologies. On the other hand, the choice between very different AFVs, such as a flex-fuel gasoline-alcohol vehicle and a battery-electric vehicle, should be less price elastic because of significant other design differences between the vehicles.

At present, the TAFV model represents only one vehicle class, a typical passenger car. In the future, four vehicle classes will be represented: (1) small car, (2) large car, (3) small light truck, and (4) large light truck. Alternative fuel and advanced technology choices will be made within each of the four vehicle classes. The NMNL model has been constructed so that there may be different coefficients for each class of vehicle. For illustrative purposes, we will use values for a large passenger car in this section. Assuming a price elasticity of -8.0 at a 50 percent market share and a purchase price of $19,500 implies a price coefficient of -0.00082. The coefficient values presented for illustration below depend on this price coefficient and the specific characteristics of intermediate-size cars.

Fuel Cost per Mile. Like maintenance costs, fuel costs can be viewed as a stream of payments extending over the vehicle's lifetime. Thus, the fuel cost coefficient can be related to the coefficient of vehicle price through a discounting of future fuel costs. A dollar of discounted present value of future fuel costs should have the same effect on technology choice as a dollar of vehicle price. The present value of fuel costs depends on future fuel prices, P_t, fuel economy, the consumer's discount rate r, and the number of miles the vehicle will be driven in future years, M_t. More precisely, the present value of future fuel costs is given by equation (10).

$$V_F = \sum_{t=1}^{L} \frac{M_t P_t}{MPG_t (1+r)^t} = \frac{-P_t}{MPG} \sum_{t=1}^{L} \frac{M_t}{(1+r)^t} \qquad (10)$$

Assuming that fuel economy (MPG) will remain roughly constant over a vehicle's lifetime and that consumers use the current fuel price as the value for future fuel prices, the present value of fuel costs equals the current fuel cost per mile times discounted future vehicle miles of travel. Thus, the coefficient for fuel cost per mile is equal to discounted miles times the retail price coefficient, b. Assuming a new vehicle is driven 15,640 miles initially, with usage declining at 4 percent per year, a 14-year vehicle life and an annual discount rate of 12 percent, yields 85,500 lifetime discounted miles. Multiplying by b = -0.00082, and dividing by 100 to convert to cents gives fuel cost (in cents) per mile of -0.702. Note that the value of this coefficient does not depend on the current price of fuel, or on the fuel economy of the vehicle in question, since these are accounted for in the fuel cost per mile variable itself.

Maintenance Cost. Maintenance costs are represented by an annual dollar expenditure for each vehicle type. Economically rational consumers would respond equally to a dollar increase in the present value of maintenance costs and a dollar increase in the retail price of a vehicle. Thus, the coefficient for annual maintenance expenditures should equal the coefficient for retail price, multiplied by the ratio of the present value of maintenance costs, V_m , to annual maintenance costs, m. If we assume that annual maintenance costs are constant over a vehicle's life, an assumption which should probably be reconsidered, then the present value ratio will be the sum of the discounting factors over the vehicle's lifetime, L.

$$\frac{V_m}{m} = \frac{\sum_{t=1}^{L} m \frac{1}{(1+r)^t}}{m} = \sum_{t=1}^{L} \frac{1}{(1+r)^t} \tag{11}$$

Given the discounting assumptions used above, equation (11) is equal to 5.468. Thus, the coefficient of maintenance cost should be -0.00082 x 5.468 = -0.00449. Note that the value of this coefficient is not dependent on other vehicle attributes, but only on the discount rate and retail price coefficient.

Battery Replacement Cost. Like maintenance, battery replacement is a future cost of vehicle ownership. Represented as present value, it would have the same effect on utility, and thus the same coefficient as purchase price. Therefore, the coefficient of battery replacement costs is the ratio of the present value of those costs to their future value, multiplied by the coefficient of purchase price. Let battery replacement be required after y years, at a cost of C_b . Then the coefficient of battery replacement costs, μ_b , is given by equation (12).

Battery replacement timing and cost are heavily dependent on battery technology. Assuming replacement after six years gives a present cost to future cost ration of 0.506, assuming a 12 percent annual discount rate. Multiplying by -0.00082 produces a coefficient estimate of -0.00042.

$$m_b = m_P \frac{\left(\frac{C_b}{(1+r)^y}\right)}{C_b} = \frac{m_P}{(1+r)^y} \tag{12}$$

The Value of Range. If one assumes that the value of increased range is the present value of avoided refueling time, then the proper representation of range and an estimate of its coefficient can be readily deduced.

Range, R, is defined as the typical (not maximum) distance a vehicle travels between refuelings. If the typical driver uses 80 percent of a tank full before refueling, then range is tank size (S, in gallons), times 0.8, times average on-road miles per gallon, times test-cycle MPG, times the ratio of on-road to test-cycle fuel economy, 0.85.

Total refueling cost per year, is equal to the miles driven per year, M, divided by range (which gives the number of refuelings), multiplied by the time required per refueling, H (in hours), and by the value of time, w (in $/hour). The present value of refueling cost will be the discounted sum of costs over the vehicle's lifetime. However, if we assume that range is constant over a vehicle's life, then the value of range is equal to a constant divided by R.

$$V_R = \sum_{i=1}^{L} \frac{wHM_i}{R(1+r)^i} = \frac{1}{R} \sum_{i=1}^{L} \frac{wHM_i}{(1+r)^i} = K\frac{1}{R} \tag{13}$$

If the discounting were computed continuously by integration, the result would be the same. Also, even if the value of time and the amount of time for refueling were to change over time, the value (or cost) of refueling would still equal a constant divided by R, so long as R remains constant over time. This is likely, because vehicle fuel economy deteriorates very little with vehicle age (see, e.g., Murrell, 1980).

The present value of range will be a function of both fuel economy and vehicle tank size. The average EPA MPG of a new intermediate passenger car sold in the United States in 1998 was 25.5 MPG, with a tank size of 17.6 gallons. This gives a nominal range of 449 miles, but after discounting MPG by 15 percent for in-use fuel economy performance and discounting the tank size by 20 percent to account for maintaining a reserve at refueling, a more practical range of 305 miles is estimated. Additional assumptions about vehicle use and lifetime, and discount rate result in a total value for K (representing the value of a 1-unit change in 1/R) of $285,041. This would be, in theory, the value of increasing range from 1 mile to never having to refuel over the life of the car. Of course, half of that value would accrue in increasing range from 1 to 2 miles. The coefficient of 1/range is equal to K times the coefficient of vehicle retail price. If we take the price coefficient to be b = -0.00082, then the coefficient of the inverse of range is -233.9.

The value of range for multi-fuel capable vehicles is handled by nesting the fuel choice decision within the vehicle technology choice decision. The logsum term carried forward from the fuel choice decision represents an expected value for the two fuels characteristics, and takes into account the added value of having a choice of fuels. However, battery-powered electric vehicles and grid-connected hybrid vehicles present special problems. If the range of a grid-connected hybrid on electricity alone versus its range on gasoline are used to represent the ranges for those fuels, electricity is likely never to be chosen. On the other hand, cost minimizing behavior might dictate that the vehicle be charged whenever a convenient charging source were available and the vehicle were parked for an extended period of time. Methods for estimating the value of home-base refueling of grid-connectable electric vehicles are presented in the following section.

Value of Home-Based Recharging. The value of home-based recharging should be related to the cost of refueling, in general. Since we have defined the value of range to be the present value of the cost of refueling as a function of range, we can use the value of range to estimate the value of avoiding commercial refueling by recharging at home. To the extent that home recharging is faster or more convenient, it should reduce the overall cost of refueling. In other words, the value of home-based recharging is the value of not having to refuel away from home, minus the cost of home recharging. A particularly simple approach is to assume that the time cost of home refueling is a certain fraction of that of conventional, retail station refueling, and that a given percent of refueling is done at home.

Electric vehicles that can be charged from the grid may be recharged while operating in the field or at their home base. How much of a vehicles services (vehicle miles) will be provided by each (or by gasoline in the case of the grid-connected hybrid) will depend not only on average daily use, but also on how travel varies from day to day. The two modes of recharging have very different implications for the cost of refueling, and therefore the value of increased range. To the extent that recharging in the field detracts from operating time, time spent recharging should have a substantial opportunity cost. To the extent that recharging at the home base can be scheduled during slack periods, it should have essentially zero time cost. Simplifying assumptions must be made in order to derive workable yet plausible methods of estimating the value of range and the value of the opportunity to recharge at home.

Battery-Powered Electric Vehicles. Recharging of battery electric vehicles may take place at the vehicle's home base during slack periods or on the road. For the two modes of recharging, the time required, H, and the value of time, w, spent recharging may differ. We assume that a constant fraction, f, of the energy services of the vehicle will be produced using home recharging. The total cost of recharging is given in equation (14).

$$V_R^* = \frac{1}{R}\sum_{t=1}^{L}\frac{w_h H_h f M_t + wH(1-f)M_t}{(1+r)^t} \tag{14}$$

The total benefit of home recharging is the total cost of recharging on the road minus V_R^* . Let Z represent discounted lifetime vehicle miles.

$$Z = \sum_{t=1}^{L}\frac{M_t}{(1+r)^t} \tag{15}$$

The savings (negative costs) from home recharging, V^*-V, is given by equation (16).

$$\begin{aligned} V_R^* - V_R &= \frac{Z}{R}\left[w_h H_h f + wH(1-f) - wH\right] \\ &= Zf\left[w_h H_h - wH\right]\frac{1}{R} = K^*\frac{1}{R} \end{aligned} \tag{16}$$

Thus, home recharging for battery-powered electric vehicles can be represented either by introducing the variable 1/R a second time with the coefficient K^* , or equivalently by using the coefficient ($K+K^*$) for the inverse range variable. The former method is used.

Assuming that home base recharging is done during slack periods, the value of time would be zero. However, some time would still be required to connect and disconnect the recharging equipment. Time spent in connecting and disconnecting should probably be valued at the same rate as other refueling time (for lack of evidence to the contrary). In this case, $w_h = w$, but H_h is defined to be only the connect/disconnect time, not the entire time required for recharging.

Assuming 85,512 discounted lifetime miles for a large car, that home recharging supplies 80 percent of the energy for a battery-powered electric vehicle, a value of time of $20 per hour, and that connecting and disconnecting requires 1 minute versus 10 minutes for external recharging, then K=$205,229 and the coefficient of 1/R is K*(-0.00082)=168.4 .

Grid-Connected Hybrid Vehicles. Grid-connected hybrid-electric vehicles have the added complication of being able to recharge themselves while operating. Depending on how recharging algorithms are designed and how vehicles are driven, there may be substantial or very limited opportunity to recharge vehicles from the grid. The key issue is at what state of charge the grid-connected hybrid would automatically recharge its batteries. For example, if the system is designed never to allow the batteries to fall below a 20 percent charge, and if self-recharging is set to cut off at 95 percent charge, the maximum capacity available to be recharged from the grid would be 75 percent.

The NMNL model as formulated here presumes that all vehicle purchasers are identical, except for a random utility factor. The random utility component is drawn from the same distribution for each individual, but its realization is different. Such a formulation may or may not adequately capture the differences in vehicle utilization patterns that could define a niche market for grid-connected vehicles.

For grid connected hybrids, the key recharging parameters are the states of charge at which self-recharging will start and cut off. It is assumed that the midpoint between these two values will be available for home-base recharging. If the points are 20 percent and 95 percent, as in the example above, the midpoint would be a 57.5 percent state of charge, and 37.5 percent of the battery capacity would be assumed to be available for home-base recharging. The next step is to determine what range (in miles) the vehicle could achieve on a 37.5 percent charge. Of course, it is unlikely that the grid hybrid would be operated solely under battery power for the entire range, nonetheless, if the efficiency of electric energy use is approximately constant regardless of how it is used, then it is reasonable to assume that the entire charge could be translated into travel at battery-only operating efficiency. The vehicle services a 37.5 percent charge could supply are then just the total energy storage capacity of the battery pack, times 0.375, times the vehicle's fuel economy (in miles per unit of electrical energy).

The next step is to determine the fraction of total annual travel the energy supplied by home recharging could produce. This requires a knowledge of the daily travel distribution, since it is assumed that recharging occurs at the home base, at the most once per day. The daily travel distribution is specified by three parameters: (1) the fraction of days on which no travel occurs (zero-mile days), (2) the average daily travel for days on which travel does occur, and (3) the standard deviation of daily travel (using only non-zero travel days). It is assumed that the distribution of travel on non-zero travel days follows a lognormal distribution. The parameters of the lognormal distribution can be computed from its mean (μ) and standard deviation (σ), as can the parameters of the associated normal distribution (let the expected value of the normal distribution be represented by ζ and the variance by ω^2). The formulas below are derived from Johnson, Kotz and Balakrishnan (vol. 1, Ch. 3, 1994).

$$w = \left[\ln\left(\frac{s^2}{m^2}+1\right)\right]^{\frac{1}{2}} \tag{17}$$

$$z = \ln(m) - \frac{1}{2}w^2$$

With these parameters, the estimated daily range available from home recharging, X, can be transformed into a standard normal variate, x, by taking the logarithm, subtracting ζ , and dividing by ω.

$$x = \frac{\ln(X) - z}{s} \tag{18}$$

The fraction of daily travel that could be satisfied by this range, f, can the be calculated by looking up the cumulative normal probability density corresponding to x.

The present value of savings, PVS, derived from home recharging under the above assumptions can be readily calculated. It is the difference between the time costs of refueling with gasoline for the fraction of miles that can be achieved with home refueling and the time costs of home refueling. Let the time required for home recharging be H_e , and the range achievable with a home recharge be R_e . The savings due to home recharging are as shown in equation (19).

$$PVS = f\frac{Z}{R}wH - f\frac{Z}{R_e}wH_e = fZw\left(\frac{H}{R} - \frac{H_e}{R_e}\right) \tag{19}$$

Since it is assumed here that the value of time is the same ($w_n = w$), only the active time required to connect and disconnect the home recharging is counted (for example, one minute as opposed to 10 minutes for refueling with gasoline at a retail filling station). Note that if the range using gasoline is sufficiently large relative to the range on electricity from home recharging, the savings from home recharging could actually be negative.

Assuming that a large passenger car travels 15,640 miles in its first year of operation, and that it has non-zero mileage on 80 percent of the days in a year, then its average miles per day is 53.6. Further assuming that the standard deviation of the lognormal distribution is twice its mean (107.2), then the expected value and standard deviation of the corresponding normal distribution are 3.176 and 1.269, respectively. A grid-connected hybrid with lower and upper charging points of 20 percent and 95 percent of capacity would be able to charge, on average, 37.5 percent of its energy storage capacity at the home base. Given a battery pack size of 45 gallons, and taking into account the relative energy density and fuel economy of battery-powered electric transportation, the grid-hybrid could achieve a range of 36.4 miles on the average home-based recharge. Taking the log of 36.4, and looking up the corresponding cumulative probability for a normal distribution with mean=3.176 and standard deviation = 1.269, produces the result that 63 percent of the vehicle's mileage could be powered by grid electricity. Given this value for f, and the same other parameters as for battery-electric vehicles, the present value of home recharging savings for a large passenger car is only \$95, which produces a coefficient of 0.0777 for the home refueling dummy variable. It may seem surprising that the value of home recharging is so small, given that it could conceivably replace enough energy to supply 63 percent of the vehicle's energy services. The explanation lies in the frequency of home recharging required to achieve this benefit: 8 out of 10 days. Although connecting and disconnecting for recharging requires only one minute, it must be done every day. This erases most of its advantage relative to refueling with gasoline, which is required only every week or so.

Acceleration Performance. Estimates for the value of performance based on consumer survey data vary widely. Greene and Liu (1988) settled on a value of \$450 (1990 \$) per 10 percent increase in horsepower to weight ratio. Greene (1994) chose \$25 per 1 percent increase, arguing that the marginal utility of performance should decrease with increasing performance. McConville and Cooke (1996) found that consumers' valuation of performance seemed to correlate with the log of the acceleration force. Donndenlinger and Cooke (1997) report an estimate of \$270 (1997\$) for a 10 percent reduction in acceleration time from 0-60 mpg. This would be \$225 in 1990 \$. The NEMS model variable is 0-30 mph acceleration time, however, we assume an equivalent value for a 10 percent reduction. Given that a typical 0-30 mph acceleration time is about 3.5 seconds, \$225-\$250/0.35 seconds, gives a range of value of \$643-\$714 per second. We will use \$700/second, which translates into a coefficient of -0.35.

The coefficient for 0-60 mpg acceleration time (in seconds) is derived from estimates of the value of horsepower. Given a value per horsepower, the increase in horsepower is then translated into a reduction in acceleration time, using the following relationship between the ratio of horsepower to weight and 0-60 acceleration time, derived from data on U.S. passenger cars provided by the U.S. EPA (Heavenrich and Hellman, 1999, table 2).

$$t_{0-60} = 0.997\left(\frac{hp}{lb.}\right)^{-0.776} \tag{20}$$

Using equation (20), the change in horsepower to weight resulting from a 10 hp increase for a typical 174 hp, 3,422 lb. large U.S. passenger car would be -0.43 seconds. Using a value of \$12.50 per horsepower, results in an estimated value of $294 per 1 second reduction in acceleration time. Multiplying this by the coefficient of price gives a coefficient estimate of -0.2408. Given that the average acceleration time for a 1999 model year U.S. passenger car is 10.5 seconds, this estimate is very close to Donndenlinger and Cooke's (1997) estimate of $270 per 10 percent reduction in 0-60 time, discussed below.

Luggage Space. The coefficient of luggage space is calculated from an assumed average value per cubic foot, A, and an average luggage volume, v. The value of luggage space per cubic foot is estimated based on other studies. Multiplying the value per cubic foot times the average size (in cubic feet) gives the total present value of luggage space. Since luggage space is represented as a ratio to the luggage space of a conventional vehicle, a change of one unit in the ratio is equal in value to the present value of luggage space for a conventional vehicle. Thus, the coefficient of the luggage space ratio is the present value (average value per cubic foot, times average volume), multiplied by the price coefficient.

$$m_L = m_P\left(Av\right) \tag{21}$$

Several estimates of the value of luggage space can be found in the literature. It is important to keep in mind that the estimates derived from econometric estimates of discrete choice models represent marginal utilities, which are likely to be lower than the average utility in which we are interested. Greene (1994) cited three studies that had reported values for luggage space ranging from $92 to $670 (1990 $) per cubic foot. Greene discounted these estimates, noting that Greene and Liu had found a range of estimates for interior volume of $32 to $192 per cubic foot. They argued that luggage space should be valued at less than passenger space and chose a value of $31. Donndenlinger and Cooke (1997) take issue with Greene's reasoning, arguing that the marginal values of interior room and luggage room should be the same when competition between the two spaces is optimally balanced. They suggest a best estimate of $150 (1990 $). This argument assumes that the production functions for luggage space and interior volume are the same because, if the cost of producing luggage space differed from that of producing interior volume, then there is no reason why the marginal costs should be equal in the optimal design. Optimal design requires that the marginal cost of producing another unit of luggage space equal its marginal utility to the consumer, and the same for interior space. We think it is likely that the cost function for producing luggage space differs from that for interior space and suspect that the marginal utilities differ as well. However, given that the preponderance of the empirical evidence is much closer to Donndenlinger and Cooke's estimate of $150, we will use their value, which translates into a coefficient of 1.72 for the ratio variable for large cars.

Fuel Availability. Lack of availability of fuel is probably the most salient feature of alternative fuel vehicles, at least until they achieve market success and develop a widespread fuel retailing network. There are few empirical studies of the value of fuel availability. Surveys of diesel vehicle owners suggested that at station densities of 10 percent to 20 percent, fuel availability went from a major concern to a minor one (Sperling and Kitamura, 1986; Sperling and Kurani, 1987). Stated preference surveys conducted in California suggest very high values for fuel availability, in the tens of thousands of dollars per vehicle for full versus negligible fuel availability (Brownstone et al., 1995). A recent nationwide stated preference survey, focused exclusively on fuel availability and alternative fuel choice concluded that an increase from 1 percent to 100 percent availability was worth $1,000 to $3,500 to motorists, depending on the context of the choice and functional form used to represent value as a function of percent of stations offering the fuel (Greene, 1998). However, Greene (1998) acknowledged that his analysis was not accurate close to zero, and that he was unable to statistically distinguish between functional forms implying very different values at zero availability. We use here a value of $7,500 for full versus 0 percent fuel availability. The function takes on values of $2,750 at about 5 percent availability and $1,000 at 10 percent, reasonably consistent with Greene's recent study. This is implemented as an exponential function of the fraction of stations, s, offering the fuel, as shown in equation (6).

$$V_A = Ce^{bs} \tag{22}$$

Assuming a value of availability of -\$7,500 at 0 percent and -\$1,000 at 10 percent, and converting to utils by multiplying by the coefficient of purchase price, one can solve for C = -6.154 and b = -20.149. The resulting cost of fuel availability function is shown in Figure 2.

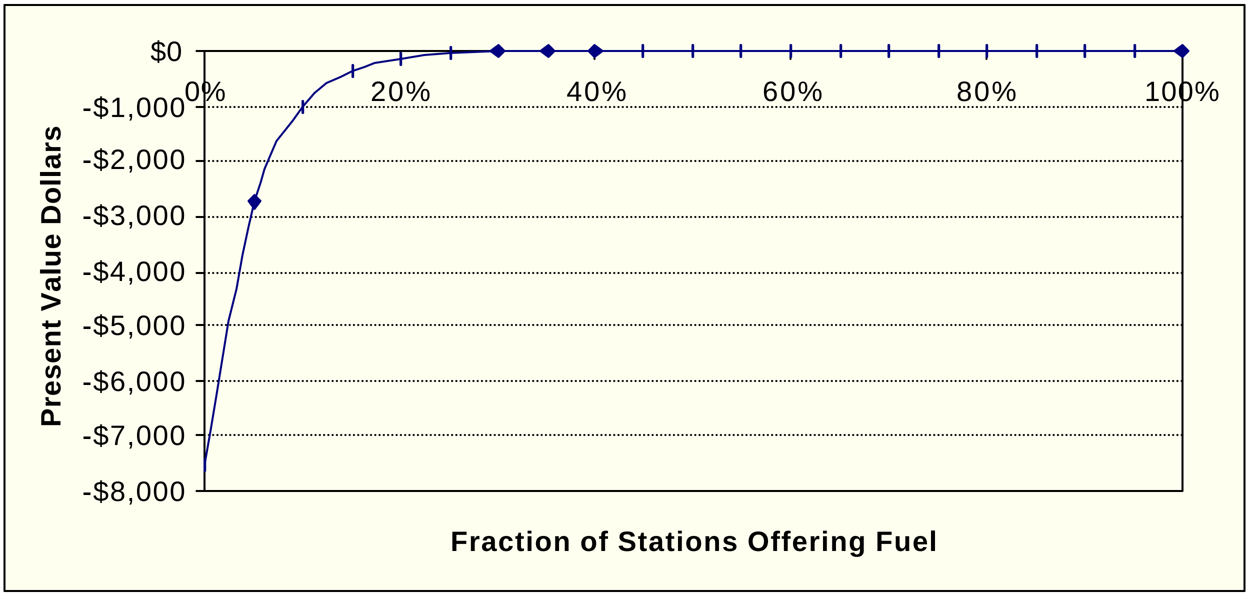

Figure 2. Cost of Fuel Availability

Make and Model Availability. Diversity of choice itself has value to consumers. If a vehicle technology is offered on many different makes and models, it will attain a greater market share than if it is available on only one, all else equal. In the theory of the MNL model, this is because each make and model offers some attributes not included in our variable list (e.g., a particular style, optional feature, mechanical reliability), whose values vary from consumer to consumer. If a vehicle technology is available on only one make and model, it is unlikely that that particular make and model will be any given consumer's favorite (in terms of unobserved attributes). As the number of makes and models offering the option increases, the chances that it will be available on each consumer's "favorite" make and model, increases.

Let n_j be the number of makes and models offering technology j, and N be the total number of makes and models of conventional technology vehicles. The value of diversity of choice is given by the logarithm of the ratio (n_j /N). Assume a simple MNL model (not nested), in which the market share of vehicle technology j is given by the usual formula. (Although K has been used previously to index technology sets, it is used for convenience in equations 23–25 as a dummy index to sum over technologies within a set.)

$$s_j = \frac{e^{U_j}}{\sum_{k=1}^{K} e^{U_k}} \tag{23}$$

Now suppose that each vehicle technology j, is offered on n_j makes and models, and further that the expected utility of each make and model is the same, namely U_j . The share of technology j will be the sum of the shares of the makes and models offering it. Using this fact, and noting that multiplying both the numerator and denominator of the logit equation by a constant (in this case we choose the constant to be $e^{-\ln(N)}$, where N is the number of makes and models of gasoline vehicles), we derive the desired result. The added utility of additional make and model choices is exactly $\ln(n_j /N)$. Note that this derivation assumes equal expected utility for the makes and models. While this does not necessarily imply that they are identical, it does imply that they would achieve equal market shares.

$$s_j = \frac{n_j e^{U_j}}{\sum_{k=1}^{K} n_k e^{U_k}} = \frac{e^{U_j + \ln(n_j) - \ln(N)}}{\sum_{k=1}^{K} n_k e^{U_k + \ln(n_k) - \ln(N)}} = \frac{e^{U_j + \ln(n_j / N)}}{\sum_{k=1}^{K} n_k e^{U_k + \ln(n_k / N)}} \tag{24}$$

The same result can be obtained for the NMNL model, when we assume that the make and model choices are nested within the vehicle technology choices. The NMNL formula for the market share of technology j is the following.

$$s_j = \frac{e^{m_p(U_j + \frac{1}{m_{pk}} ln\left(\sum_{k=1}^{n_j} e^{U_k}\right))}}{\sum_{i=1}^{I} e^{m_p(U_i + \frac{1}{m_{pk}} ln\left(\sum_{k=1}^{n_k} e^{U_k}\right))}} = \frac{e^{m_p(U_j + \frac{1}{m_{pk}} ln\left(n_j e^{U_k}\right))}}{\sum_{i=1}^{I} e^{m_p(U_i + \frac{1}{m_{pk}} ln\left(n_i e^{U_k}\right))}} = \frac{e^{m_p(U_j + \frac{1}{m_{pk}}(U_k + ln\left(n_j / N\right)))}}{\sum_{i=1}^{I} e^{m_p(U_i + \frac{1}{m_{pk}}(U_k + ln\left(n_i / N\right)))}} \tag{25}$$

If all makes and models have the same expected utility, then the coefficient of the log of the ratio (call it γ) would be 1, as shown in equations (25) and (26). In reality, certain vehicles appear to be more likely to be consumers' favorites (have higher than average expected utilities), then the coefficient would be less than 1. Leiby and Rubin (1998) suggest a value of 0.37, based on the distribution of car sales among makes and models in the United States. The cost of lack of diversity can be computed by dividing by the coefficient of vehicle price.

$$V_{diversity} = \frac{}{m_{Pk}} \log_e\left(\frac{n_j}{N}\right) \tag{26}$$

A curve illustrating the cost of lack of diversity for $\gamma = 0.67$ is shown in Figure 3. Diversity turns out to be an extremely important factor in the attractiveness of alternative fuel vehicles. Even if 40 percent of all makes and models offer a particular technology, the cost of lack of diversity is substantial, almost \$500.

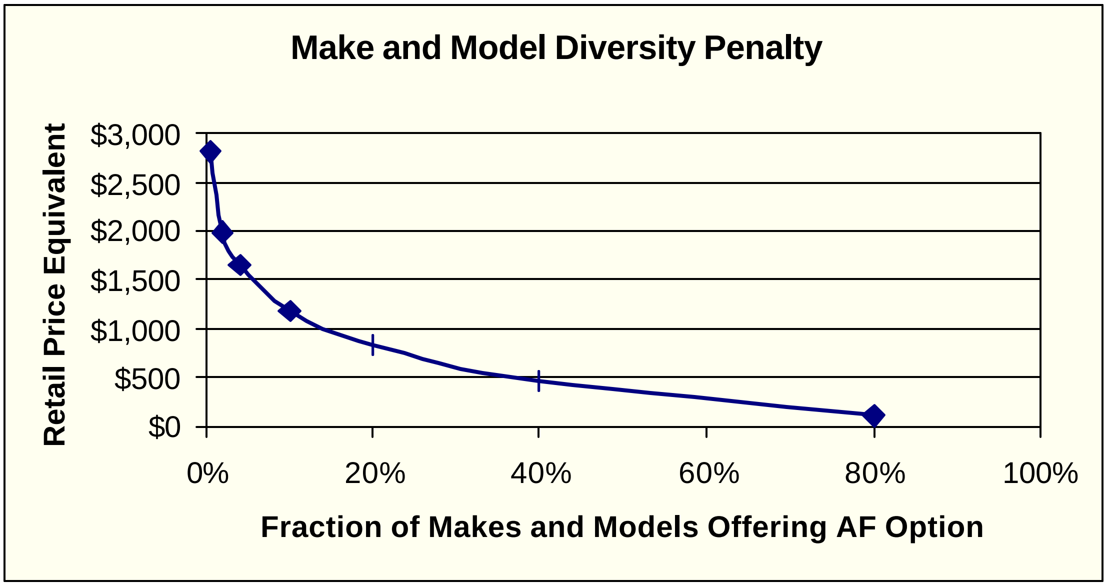

Figure 3. Value of Diversity in Choice Among Makes and Models

6. CALIBRATION OF NEMS AFV MODEL COEFFICIENTS

6.1 PRICE ELASTICITIES

Because of their role in calculating all other coefficients, and because they thereby determine the overall sensitivity of choices to changes in utility, price slopes are the most critical parameters of the NMNL model. Three price slopes must be determined: (1) a fuel-type choice price slope for flexible and bi-fuel vehicles, (2) the alternative fuel technology price slope, and (3) the technology set price slope. Theory requires that the price slopes (which are negative) have the following relationship $\mu_1, < \mu_2 < \mu_3$. That is, sensitivity to price should decrease as one goes from choice of fuel type for the same vehicle, to choice between technology sets (e.g., conventional fuel engines versus battery electric vehicles). Theory also indicates that the price elasticity of choice among technology sets should be less elastic than the overall price elasticity of demand for automobiles. There is a broad consensus in the econometric literature that the price elasticity of demand for automobiles is approximately -1.0 (e.g., Kleit, 1990; McCarthy, 1996; Bordley, 1994).

Because of the relative scarcity of alternative fuel vehicles, there are almost no revealed preference (based on actual market behavior) econometric estimates of the price elasticity of choices among classes of alternative fuel technologies. Greene's (1986) analysis of the choice between gasoline and diesel engines for the same model line of vehicles is an exception. Using carline monthly sales data for 1979-1983, Greene estimated price slopes in the vicinity of -0.002 (for price in 1983 dollars), implying price elasticities of diesel market share in the vicinity of -10 (Greene, 1994).

Several stated preference (based on survey responses) studies of choice of alternative fuel vehicles in California have been published since 1990. Stated preference studies tend to produce lower estimates of price sensitivity than revealed preference studies, perhaps because respondents pay greater attention to other attributes when money does not actually change hands. In a similarly structured national survey, Tompkins et al. (1998) estimated price slopes ranging from -0.000056 for large cars to -0.000107 for small cars. With car prices at about $14,000, this indicates a range of elasticities at a 50 percent market share from -0.4 to -0.75, lower even than the price elasticity of demand for automobiles.

Analyses of choices among makes and models of vehicles can provide useful reference points. In theory, when technologies are similar, the choice of technology type for a given make and model should be somewhat more price sensitive than choices among makes and models. If one assumes that alternative fuel technologies are made available as alternatives to gasoline engines on a particular make and model, then make and model choice elasticities should be a lower bound on AF technology choice elasticity. An example of very similar technologies would be the choice between an FFV and conventional gasoline engine for a particular brand of minivan. Less similar technologies would be the choice between gasoline and CNG bi-fuel vehicles. Even in this case, the vehicles can always be operated on gasoline, in which case the differences would be limited to the effects of the additional CNG storage tank.

Three U.S. studies have estimated detailed own and cross price elasticities for makes and models of vehicles. Using make and model data for 1968-75, Irvine (1993) estimated own price elasticities ranging from -4.59 to -16.99, with a mean of -10.42. With data on 2217 carlines from 1971 to 1990, Berry et al. (1995) estimates a complete set of own and cross price elasticities. Elasticities for a sample of 1990 cars ranged from -6.5 to -3.1, with price sensitivity generally decreasing as purchase price increased. In a similarly comprehensive analysis using a different method and data for 1986, Bordley (1994) found an average own price elasticity for product lines of -5. The average elasticity Bordley found for seven broad market segments (e.g., subcompact, sport, etc.) was -2.

Choice of fuel for a fuel-flexible or bi-fuel vehicle should be still more sensitive to price. Studies of choice among gasoline grades suggest that the choice of fuels for multi-fuel capable vehicles will be very price elastic. Greene (1989) estimated price elasticities at 50 percent market share of -15 to -20 for choice among gasoline grades. Phillips and Schutte (1988) estimated price elasticities of -35 to -40 for the choice between full and self-service gasoline. Both studies were based on revealed preference data. Estimates of choice among alternative fuels for bi-fuel and flex-fuel vehicles based on stated preference data have, once again, produced much lower elasticities. Results from Bunch et al. (1993) and Golob et al. (1992) suggest that price elasticity would be about -3.

The nested MNL model requires that choices within lower nests be more price-sensitive than choices among higher nests. Intuitively, this reflects the grouping of alternatives into increasingly similar sets as one moves from technology sets to types within a set to choices among fuels for the same vehicle. At all levels, it is important to remember that the model, as it has been structured, assumes that choices among technologies apply to a given make and model of vehicle. That is, the consumer is not assumed to be choosing among, for example, an SUV electric vehicle, a two-seater hybrid, full-size gaseous, and intermediate FFV, but rather among, for example, a Ford Taurus version of each. Thus the vehicles will be similar or identical with respect to most attributes not explicitly represented in the choice model (style, comfort, etc.).

Given that choices among technology *types* apply to the same carline, it is assumed that these choices will be at least as price-sensitive as choices among carlines. This implies that the price elasticity of the choice among technology types (at 50 percent market share) should be at least -5 and probably closer to -10. Plausible choices are elasticities of -8 for large cars and trucks and -10 for smaller cars and trucks. For large cars, this implies a price slope of -0.00082, assuming a price of $19,498 and a 50 percent market share. Choices among technology *sets* should be less sensitive to price on the grounds that unobserved attributes differ more among choices involving e.g., gaseous fuels versus battery power. An assumed elasticity of -4 implies a price slope of -0.00041, half as price-responsive as the technology type choice. Fuel choice should be most price-sensitive of all. Assuming a cost-per-mile elasticity of -15 at 50 percent market share implies a cost-per-mile (in cents) slope of -5.93. Converting this to an equivalent slope for present value miles (85,512) implies a price (in $) slope of -0.00693. These assumed price slopes satisfy the theoretical requirement of increasing price sensitivity as one goes from technology sets (-0.00041) to technology types (-0.00082) to fuel types (-0.00693).

Using the above elasticities, equation (7) and the base year prices of each vehicle class, price slopes can be computed for fuel type choice, vehicle technology choice (by size class), and technology set choice. The calculations for vehicle technology choice are shown in Table 2.

6.2 ANALYSIS OF IMPLIED ATTRIBUTE VALUES

The reasonableness of coefficient estimates can be checked by calculating the values they imply for a one-unit change in the variable in question. This is done for the coefficients for the large car class in Table 3. The value of a one-unit change in a particular variable is obtained by dividing the variable's coefficient by the coefficient of vehicle price, then multiplying by -1. Thus, the value of a one unit change in price is exactly $1.

Table 2. Estimate of Price Slopes Using Assumed Elasticities

	Small Cars	Large Cars	Small Light Trucks	Large Light Trucks
Average Price	$15,285	$19,498	$17,175	$17,766
Elasticity	-10	-8	-10	-8
Market Share	50.0%	50.0%	50.0%	50.0%
Price Slope	**-0.0013**	**-0.00082**	**-0.00093**	**-0.00113**

In assessing the values implied by coefficients, it is important to consider carefully what a one-unit change in a variable means. In the case of fuel costs measured in cents per mile, a one-unit change is one cent per mile. A change from three cents per mile to four, would therefore be worth $855, present value to a consumer. Consider that a consumer driving 15,000 miles per year would save $150 per year for each one cent change in fuel cost per mile.

Table 3. Value (1990$) of a One-Unit Change in Vehicle Characteristics for a Small Car

Variable	**Name**	**Units**	**Value (Small Car)**	**Small Car**
Constant				
Vehicle Purchase Price	PSPR	1990 $	-$1.00	-0.00131
Fuel Cost per Mile	FLCOST	cents per mile	-$855.12	-1.11893
Range	VRNG	1/miles	-$285,040.52	-37297539
Battery Replacement Cost	BRC	1990 $	-$0.51	-0.0007
Acceleration, 0-60 mph	ACCL	seconds	-$217.67	-0.28482
Home Refueling for Evs	HFUEL	1/miles	$205,229.17	268.54228
Annual Maintenance Cost	MAINT	annual 1990 $	-$5.47	-0.00715
Luggage Space	LUGG	ratio to conv.	$1,800.00	2.3553
Fuel Availability Coefficient 1	BETAFA	exp(k*fraction)	-$7,500.00	-9.81375
Fuel Availability Coefficient 2	BETAFA2	fraction	n.a.	-20.14903
Make/Model Availability	MMAVAIL	ln(fraction)	$509.49	0.66667
Vehicle Technology Nest Generalized Cost	TSGC	1990 $	n.a.	-0.0007
Fuel Choice Net Generalized Cost	MFGC	1990 cents/mile	n.a.	-7.19542

A one unit change in the inverse of range, on the other hand, is an enormous quantity, representing the difference between a car with a range of only one mile and a car with an infinite range (1/1 versus 0). Such a comparison is not particularly meaningful. Consider instead a change in range from 400 to 500 miles, or in terms of 1/range, from .0025 to .0020, or .0005. This would be worth $285,040 (0.0005) = $142, a relatively modest sum. In fact, this may seem too low, but it follows directly from the following assumptions: refueling time of 10 minutes, value of time of $20/hr., 15,640 annual miles driven declining at 4 percent/yr., discount rate of 12 percent, and assumed vehicle lifetime of 14 years. It can be argued that refueling has a nuisance value and should be valued at more than the average value of travel time, but unfortunately we have no information upon which to evaluate this possibility.

A dollar of battery replacement cost should be worth less than a dollar of vehicle price, since the replacement will take place several years in the future. We assume that advanced lead-acid batteries will last six years. Given the discount rate of 12 percent, one dollar of expenditure six years from now is worth about $0.51 in the present. For modern nickel-metal-hydride batteries a lifetime of 10 years or approximately 120,000 to 130,000 miles is more appropriate. This would reduce the present value of a dollar of battery replacement cost.

Zero-to-sixty miles per hour acceleration time is valued at over $200 per second, based on an assumed value of $125 per 10 horsepower.

Home refueling for electric vehicles is range dependent. Assuming that each home refueling event takes 1 minute, time is valued at $20 per hour, and that 80 percent of refueling is done at home, the ability to recharge conveniently at a home base eliminates about 70 percent of the cost of the EV's limited range.

Each dollar of annual maintenance cost is valued at just over $5, based on the discounted present value of the full stream of annual maintenance costs over the vehicle's lifetime. No attempt is made here to accurately reflect patterns of maintenance cost over time. Manufacturers may offer a number of initial years of free maintenance in order to encourage customers to purchase new, unfamiliar technologies, such as hybrid vehicles. A possibly useful enhancement to the model might therefore be to allow patterns of maintenance costs over time to be explicitly represented.

Luggage space is expressed as a ratio to a conventional vehicle's luggage space. Thus the value of $1,800 applies to the total luggage space of a typical conventional vehicle. This is based on an average (not marginal) value of $150 per cubic foot, and a 12 cubic foot luggage compartment for small cars, 14 for large cars and light trucks. Pick-ups are assigned a nominal luggage capacity of 14 cubic feet.

Fuel availability, measured as the fraction of stations offering a fuel, has a value of $7,500 per unit. Thus, the difference between 100 percent availability and 0 percent availability is $7,500, close to the cost of retrofitting an engine. Just as important as the total value of fuel availability is the shape of the curve (see, Figure 3) which indicates that the cost of availability drops below $500 before 20 percent of stations offer a fuel.

Diversity of choice is measured by the logarithm of the ratio of the number of makes and models offering the alternative fuel technology to the total number of conventional makes and models. The value of diversity of choice is just over $500 per unit. In going from a ratio of 1.0 to 0.5 (available on 100 percent of makes and models to 50 percent), the logarithm decreases from 0 to -0.69, an implied cost of $350 per car. But costs increase rapidly as market share decreases. The implied costs per car for availability on only 1 percent of makes and models versus 50 percent is almost $2,000.

7. SPREADSHEET MODEL DESCRIPTION

A TAFV.ChoiceMNL.xls spreadsheet workbook has been constructed in Excel™ for three purposes: (1) calculating model coefficients based on available evidence on attribute values and the modeler's judgment, (2) calibrating the NMNL choice model to a base year set of market shares, and (3) testing the sensitivity of the resulting model to input variables.

The spreadsheet produces two tables of coefficients: one contains variable coefficients for each of four vehicle classes and another contains calibration constants by vehicle technology type, separately for passenger cars and light trucks.

The workbook is comprised of 12 sheets: 4 individual sheets, and two sets of 4 vehicle class-specific sheets. The first sheet "Coefficients", performs all the calculations necessary for calculating NMNL variable coefficients, and contains the tables of coefficients and calibration constants. The second sheet, "LDV Shares Summary" combines predicted vehicle technology shares for each of the twelve vehicle types to produce a table of summary shares for passenger cars, light trucks, and all light-duty vehicles combined. LDV Shares Summary is also where calibration constants are calculated. A third individual sheet, "M&M Availability" is where base year data on numbers of makes and models of alternative fuel vehicles, by vehicle technology type and size class are entered. The fourth individual sheet, "Fuel Characteristics" contains information on alternative fuels that is common to all vehicle technology types and size classes.

The next four sheets contain NMNL model calculations for each of the four vehicle classes. Little data must be entered in any of these spreadsheets. The final four sheets contain additional data on vehicle technologies, and translate those data into values for variables in the NMNL model.

Each sheet and its functions are discussed in turn below.

7.1 COEFFICIENTS

Coefficients are displayed and can be separately computed for each of the four vehicle classes, shown in Table 4.

Table 4. Vehicle Class Groupings for Coefficient Estimation

Vehicle Group	NHTSA Classes
Small Cars	2-seaters, minicompact, subcompact, compact
Large Cars	intermediate, large
Small light trucks	compact SUV, compact pick-up, compact van
Large light trucks	large SUV, large pick-up, large van

.

The spreadsheet permits different assumptions to be made about factors such as annual miles of use, in-use MPG, and vehicle lifetime, for each vehicle group.

The values of the coefficients for every variable of the NMNL model are found in the Coefficients by Vehicle Class table in the range G9..K21. Constant terms for calibrating the model to a set of base year technology type shares are found in the Calibration Coefficients by Technology Type table, and the actual coefficient values are in the range X9..Y24. Above them, in cell W5 is a zero/one indicator variable that turns the calibration constants on or off. If the cell is set to zero, all of the calibration constants are zero. If it is one, they are the values calculated in the LDV Shares Summary spreadsheet (see below). No values other than zero or one should be put in this cell.

Key assumptions and base year data must be entered in the *Coefficients* sheet. Beginning at row 25, data describing the usage and ownership patterns of each vehicle group must be entered in the 1995 Base Vehicle Use and Ownership Assumptions table. Among these, only the discount rate and price of gasoline do not vary across vehicle groups. Annual miles of travel, the rate of decrease in annual travel with vehicle age, vehicle lifetime, and the ratio of in-use to EPA test MPG must be entered for each vehicle type.

Immediately to the right, beginning in column F, vehicle characteristics data must be entered for each of the four vehicle classes in the table labeled "Price Slopes and Selected Vehicle Characteristics by Class." Data that must be entered are annual sales by class, purchase price, horsepower, weight, MPG, tank size and annual maintenance cost. The sales are used to calculate weighted averages of these variables for each of the five groups.

Price elasticity. Immediately below the vehicle characteristics table, an assumed purchase price elasticity and the market share at which it applies must be entered for each of the five groups. These inputs plus the calculated group average prices are used to calculate the purchase price slopes for each group.

Vehicle range. Beginning at cell A60, the coefficient for the inverse of vehicle range is calculated. Key assumptions that must be entered are the average value of time in dollars per hour, and the average time required per refueling, in minutes. Also entered is the typical tank level at which vehicles are refueled, in terms of percent *empty*. This latter number is not used to compute the value of range, since it determines the range achieved, not its value.

Fuel availability. Calculation of the value of fuel availability begins at cell A109. An exponential curve is fitted to two, user-supplied points. While any points on the fuel availability cost curve can be supplied, it is recommended that the total cost at 0 percent availability (the origin) and 10 percent or 20 percent availability be supplied. The general consensus of studies in the literature conclude that fuel availability becomes a minor consideration when the percent of stations which offer the fuel moves above the range of 10 percent to 20 percent. An embedded graph illustrates the shape of the resulting curve.

Home charging. The value of home charging for electric vehicles is calculated beginning in cell A137. The user must supply: (1) the amount of time required to set up and disconnect home charging (presumably this will be less than refueling at a commercial outlet), and (2) the percent of charging that will be done at home, on average. The value of home refueling is then calculated as the avoided cost of service station refueling, net of the time cost of home recharging. For grid-connected hybrid vehicles additional data must be supplied: (1) upper and lower charging points, (2) percent of days that the vehicle is used, and (3) the ratio of the standard deviation of the log normal distribution of miles to its mean.

Maintenance. Beginning at cell A150, annual maintenance costs are used to calculate the present value of maintenance costs. Discounting assumptions are taken from the Base Vehicle Ownership and Usage Assumptions in rows 25 to 56.

Battery replacement. The coefficient for battery replacement costs is computed next in rows 160 through 169. The user must enter the number of years a new battery pack can be expected to last. The value of the battery pack is used to calculate its present value for illustrative purposes.

Make and model diversity. The value of make and model diversity is computed in rows 175 to 190 for illustration purposes. The user must input the coefficient itself; all the spreadsheet does is draw a graph illustrating the implications of the chosen coefficient for the dollar cost of limited availability.

Fuel cost. No additional data need be input to calculate the coefficient for fuel cost (cell A194) because it can be directly calculated from data in the Base Vehicle Use and Ownership table. Those data are used to compute a discounted lifetime miles of travel. The fuel cost per mile coefficient is equal to the coefficient of vehicle purchase price times the discounted miles divided by 100 (to convert from dollars to cents).

Luggage (cargo) space. Luggage space is measured relative to the luggage space of a conventional gasoline vehicle. Thus, a unit change in luggage space should have the same value as the entire luggage space of a conventional vehicle. The calculation of the luggage space coefficient, beginning in cell A204, requires the user to input the average value per cubic foot and the total cubic feet of space. Of course, pick-up trucks, SUVs and cargo vans have qualitatively different cargo space from passenger cars. This same method will work if one has an estimate of the total quantity and value per cubic foot.

Acceleration time, 0–60 mph. Finally, the coefficient for acceleration is calculated beginning in cell A215. The calculation is based on the marginal value of ten horsepower, which must be input by the user. A typical value is about $125 per ten horsepower. Then, using the vehicle class horsepower and weight which has already been entered in the table of Price Slopes and Selected Vehicle Characteristics by Class, the reduction in 0-60 acceleration time which could be achieved by 10 horsepower is then computed. This value is then divided into the value of ten horsepower to obtain the value of a one-second reduction in acceleration time.

7.2 LDV SHARES SUMMARY

The next worksheet contains a summary of the NMNL spreadsheet model predictions. Base year market shares by vehicle class are shown in the range B8..B22 (taken from the Coefficients worksheet). The Vehicle Technology Type table, in range F9..H25, summarizes the NMNL model's predicted market shares by technology type for passenger cars and light trucks, and light-duty vehicles combined. Below these tables, in rows 28 through 72, the predicted shares are shown by vehicle class.

To the right of the Vehicle Technology Type table is a table of shares to which the model may be calibrated in the base year. In the range J10..K24, the user may enter base year shares for all technology types, except gasoline, for passenger cars and light trucks. The gasoline share is computed as one minus the sum of the other shares, to insure that the shares always sum to exactly one (the user is responsible for insuring that the sum of shares for other technologies is less than one). Calibration constants that insure that the model will fit these base shares can be calculated using the Solver function of Excel. The calibration constants will appear in cells N9 through O24, and are then transferred to the Coefficients worksheet. To the right of the constants in the range Q4..R26, are scaled, squared deviations of the desired shares from the predicted shares, used by the solver to find calibration constants.

To compute the calibration constants, one must first enter the desired shares in range J10..K24. Next, the calibration constants indicator in the coefficients worksheet must be set to 1. The indicator is displayed for information only in cell N9 of the LDV Shares Summary Worksheet, but **must be changed in the Coefficients worksheet** (cell W5). The Solver is then invoked by clicking on Tools in the Menu Bar, and then clicking on Solver. Constants for passenger cars and light trucks must be computed separately. For passenger cars, the Set Target Cell box should contain the address Q27, while the By Changing Cells box should contain N10..N25. For light trucks, the target cell is R27, while the cells to be changed are O10..O25. The Equal to: option must be set to Min. Clicking on the solve button will invoke the solver. In general, determining an adequately precise set of coefficients will require invoking the solver two or three times. This could also be accomplished by changing the solver's default settings to allow more iterations. When restarting the solver for a **new** set of desired shares, it is recommended that the By Changing cells be reinitialized by setting them all to zero.

Care should be exercised in the use of calibration constants, because the constants may strongly affect market shares throughout a forecast. If base year shares are thought to be due to initial conditions that will **not** persist over time, the use of calibration constants should be avoided.

7.3 MAKE AND MODEL AVAILABILITY

The Make and Model Availability worksheet has two functions: (1) it calculates base year availability ratios based on the user's inputs of numbers of makes and models offering advanced technologies by vehicle class (in range C7..U27), and (2) it allows the user to input a default value for the make and model ratio in the case of zero availability (cell B31). When there are no makes and models of a particular technology type available, the ratio to total makes and models will obviously be zero. However, taking the logarithm of zero, as required by the diversity measure, is mathematically undefined and will cause an error. Thus, some very small fraction (such as 0.000001) must be used instead. Base year make and model counts have been taken from the National Highway Traffic Safety Administration's 1999 Corporate Average Fuel Economy Data Base. Counts for 1999 were used instead of 1995 due to the greater number of alternative fuel technologies available in 1999.

The resulting diversity index ratios are shown below in the range D33..U38. These values are used in the shares model worksheets.

7.4 FUEL CHARACTERISTICS

The fuel characteristics worksheet contains data on alternative fuels and vehicles that do not vary by vehicle class. The first table, beginning in A4, contains data on the Btu content and prices of fuels, listed by vehicle technology. These are then converted to prices per energy equivalent of a gallon of gasoline. Numbers of refueling sites for each vehicle technology follows (Alt. Fuels Data Center, 6/19/00, taken from the website at, http://www.afdc.nrel.gov/refuel/state_tot.shtml). The number of gasoline stations, 95,847, was obtained from the County Business Patterns 1994-97, U. S. Bureau of the Census, found at http://www.census.gov/prod/www/abs/cbptotal.html . Diesel was assumed to be available at 25 percent of gasoline refueling stations. Fuel availability is then calculated as the percent of total stations offering each fuel type. Although a single station may offer more than one fuel type, the total number of stations is computed by summing the station counts for gasoline stations and alternative fuel stations of each fuel type (except diesel, which is included in the gasoline total). While this may over-count stations to some extent, it will not result in substantial errors in the estimated frequencies of alternative fuel sites, due to the predominance of gasoline refueling stations.

Beginning in cell A27 is a table of data on the relative performance and cost of alternative fuel technologies, supplied by Energy and Environmental Analysis, Inc. (personal communication, Dan Mezler, EEA, June, 2000). Most data are expressed in terms of a fractional change relative to a conventional gasoline vehicle. These variables include: (1) change in horsepower, (2) range, (3) fuel economy, and (4) weight. Other data are tank size, incremental retail price at low and high volume, maintenance costs, relative luggage space, battery replacement costs and the home recharging dummy variables. Both low-volume and high-volume price increments are provided for each technology, but only the high volume increments are used in the spreadsheet NMNL model. These relative attributes represent average changes for all vehicle types and are not broken down by vehicle class. Since some of these data do vary by vehicle class in the reality, this may be a fruitful area for future improvements to the model.

7.5 SHARES MODEL WORKSHEETS

Four worksheets are used to calculate vehicle technology shares for each of the four vehicle classes. All the worksheets have exactly the same structure. Beginning in cell A4, a table summarizes the predicted shares by fuel and technology type for the vehicle class in question. To the right of this table, in the range M4..M20 are the calibration constants which may or may not have been used to compute the shares. An indicator in cell G18 is 1 if the constants were used, and zero if not.

Market shares are calculated in five sub-tables starting in row 26 and ending in row 149. The first covers Conventional Liquid Fuel Capable Vehicles, which comprise gasoline, diesel and flex-fuel vehicles. All the NMNL vehicle technology tables have the same structure, but the number of alternatives varies. First the variable names and units are listed, followed by the coefficient values taken from the Coefficients worksheet. Then for each alternative, the attribute values (values of the variables) are shown, followed by the product of each attribute value and its respective coefficient. These products are summed in a cell below the column, to give the indirect utility index for that vehicle technology. The exponentiated indirect utility is shown in the cell below that, and beneath the exponentiated utility is the conditional share for the vehicle technology in question.

The conditional share is a vehicle technology’s share of the sales within the technology set to which it belongs (e.g., conventional gasoline vehicle’s share of the conventional liquid fuels set is shown in cell G42). To get its overall market share, the conditional share must be multiplied by the technology set’s market share, which is calculated in column B at the bottom of the table. First, the exponentiated utility indexes for all choices in the technology set are summed (e.g., in cell B41). Next the logarithm of the sum is taken in cell B42. This is then multiplied by the technology set price slope to obtain the utility index for the technology set in cell B43. Finally the technology set share is shown in cell B44.

To the right of this table, beginning in cell R26, is a table for calculating the nested choices of fuels for the FFV vehicles. At present, the Conventional Liquid and Gaseous Fuel Capable Vehicle sets are the only technology sets that have fuel choice nests. These nests determine the expected value (or generalized costs) of the fuel-related characteristics of multi-fuel vehicles. Two parameters must be entered in each of the two fuel choice tables. The assumed price elasticity of fuel choice must be entered in cell S46 and the market share at which that elasticity is assumed to apply must be entered in cell S48.

The variables appearing in the fuel choice nest are fuel cost, range, acceleration and fuel availability. Consequently, these variables do not appear in the vehicle technology choice table for the multi-fuel vehicles, with the exception of fuel cost, which now represents the expected value of all three fuel attributes and not only fuel price divided by MPG.

7.6 AFV CHARACTERISTICS WORKSHEETS

Finally, there are twelve worksheets containing the characteristics of vehicle technologies for each of the twelve vehicle classes. For each of the five technology sets there are two tables. The main table beginning in column A contains the values for each variable in the vehicle technology choice equations. Flex and bi-fuel vehicles have two columns of data, reflecting their different attributes when using different fuels. To the right of this table is a table of relative attribute values, drawn from the fuel characteristics worksheet and used in calculating the attribute values in the main table. The table includes incremental retail price, and relative MPG, range, luggage space, and maintenance costs.

8. REFERENCES

1. Berry, S., J. Levinson and A. Pakes. (1995). "Automobile Prices in Market Equilibrium," *Econometrica*, vol. 64, no. 4, pp. 841-890.

2. Bordley, R.F. (1993). "Estimating Automotive Elasticities From Segment Elasticities and First Choice / Second Choice Data," *The Review of Economics and Statistics*, vol. LXXV, no. 3, pp. 455-462.

3. Bordley, R. (1994). "An Overlapping Choice Set Model of Automotive Price Elasticities," *Transportation Research B*, vol. 28B, no. 6, pp. 401-408.

4. Brownstone, D., D.S. Bunch, T.F. Golob and W. Ren. (1995). "A Transactions Choice Modelfor Forecasting Demand for Alternative Fuel Vehicles," University of California, Irvine.

5. Bunch, D.S., M. Bradley, T.F. Golob, R. Kitamura, and G.P. Occhiuzzo. (1993). "Demand for Clean-Fuel Vehicles in California: a Discrete-Choices Stated Preference Pilot Project," *Transportation Research A*, vol. 27A, no. 3, pp. 237-254.

6. Donndenlinger, J.A. and H.E. Cook. (1997). *Methods for Analyzing the Value of Automobiles*, SAE Technical Paper 970762, Society of Automotive Engineers, Warrendale, PA.

7. Golob, T.F., R. Kitamura, D.S. Bunch, M. Bradley, and J. Golob. (1992). "Clean Vehicles/Fuels Stated Preference Pilot Study: Final Report," Demand Forecasting Office, California Energy Commission, Sacramento, California.

8. Greene, D.L. (1998). "Fuel Availability and Alternative Fuel Vehicles," *Energy Studies Review*, vol.8, no. 3, pp. 215-231.

9. Greene, D.L. (1994). *Alternative Fuels and Vehicles Choice Model*, ORNL/TM-12738, Center for Transportation Analysis, Oak Ridge National Laboratory, Oak Ridge, Tennessee, October.

10. Greene, D.L. (1989). "Motor Fuel Choice: an Econometric Analysis," *Transportation Research A*, vol. 23A, no. 3, pp. 243-254.

11. Greene, D.L. (1986). "The Market Share of Diesel Cars in the U.S.A., 1979-83," *Energy Economics*, vol. 8, no. 1, pp. 13-21.

12. Greene, D.L. and J.T. Liu. (1988). "Automotive Fuel Economy and Consumers' Surplus," *Transportation Research A*, vol. 22A, no. 3, pp. 203-218.

13. Heavenrich, R. M. and K. H. Hellman. (1999). *Light-Duty Automotive Technology and Fuel Economy Trends Through 1999*, EPA420-R-99-018, Office of Mobile Sources, U.S. Environmental Protection Agency, Ann Arbor, Michigan.

14. Irvine, F.O. (1993). “Demand Equations for Individual New Car Models Estimated Using Transaction Prices with Implications for Regulatory Issues,” *Southern Economic Journal*, vol. 49, no. 3, pp. 764-782.

15. Johnson, N.L., S. Kotz and N. Balakrishnan. (1994). *Continuous Univariate Distributions*, John Wiley and Sons, New York.

16. Kleit, A.N. (1990). “The Effect of Annual Changes in Automobile Fuel Economy Standards,” *Journal of Regulatory Economics*, vol. 2, pp. 151-172.

17. Lave, C.A. and K. Train. (1979). “A Disaggregate Model of Autotype Choice,” *Transportation Research A*, vol. 13A, pp. 1-9.

18. Leiby, P. and J. Rubin. (2000). “The Alternative Fuel Transition,” ISSN 1070-1516, Misc. Report 419, Maine Agricultural and Forest Experiment Station, University of Maine, Orono, Maine, September 17.

19. Leiby, P.N. and J. Rubin. (1997). “Technical Documentation of the Transition Alternative Fuels and Vehicles (TAFV) Model,” Oak Ridge National Laboratory, Oak Ridge, Tennessee, July 17.

20. McCarthy, P.S. (1996). “Market Price and Income Elasticities of New Vehicle Demands,” *The Review of Economics and Statistics*, vol. LXXVII, no. 3, pp. 543-547.

21. McConville, G.P. and H.E. Cook. (1996). *Examining the Trade-Off Between Automobile Acceleration Performance and Fuel Economy*, SAE Technical Paper 960004, Society of Automotive Engineers, Warrendale, Pennsylvania.

22. Murrell, J.D. (1980). *Passenger Car Fuel Economy: EPA and Road*, EPA 460/3-80-010, Environmental Protection Agency, Ann Arbor, Michigan, September.

23. Phillips, O.R. and D.P. Schutte. (1988). “Identifying Profitable Self-Service Markets: A Test in Gasoline Retailing,” *Applied Economics*, vol. 20, February, pp. 263-272.

24. Sperling, D. and R. Kitamura. (1986). “Refueling and New Fuels: An Exploratory Analysis,” *Transportation Research A*, vol. 20A, no. 1, pp. 15-23.

25. Sperling, D. and K.S. Kurani. (1987). *Refueling and the Vehicle Purchase Decision: The Diesel Car Case*, SAE Technical Paper 870644, Society of Automobile Engineers, Warrendale, Pennsylvania.

26. Thompkins, M., D. Bunch, D. Poyer, D. Santini and A. Vyas. (1998). “Determinants of Alternative Fuel Vehicle Choice in the Continental United States,” presented at the *77th Annual Meeting of the Transportation Research Board*, Washington, DC, January.

INTERNAL DISTRIBUTION

1. M.A. Brown
2. G.E. Courville
3. T.R. Curlee
4. S. Das
5. S.C. Davis
6. R.C. DeVault
7. R.L. Graves

8–37. D.L. Greene

38. G.R. Hadder
39. P.S. Hu
40. D.W. Jones
41. R.M. Lee
42. P.N. Leiby
43. R.N. McGill
44. C.I. Moser
45. R.B. Shelton
46. R.E. Ziegler
47. Central Research Library
48. Document Reference Section
49. Laboratory Records
50. Laboratory Records—RC

EXTERNAL DISTRIBUTION

51. L.A. Abron, President, PEER Consultants, P.C., 1460 Gulf Blvd., 11th Floor, Clearwater, FL 34630
52. S.L. Cutter, Director, Hazards Research Lab, Department of Geography, University of South Carolina, Columbia, SC 29208
53. S.G. Hildebrand, Director, Environmental Sciences Division, Oak Ridge National Laboratory, Post Office Box 2008, Oak Ridge, TN 37831-6037
54. P.R. Rittelmann, FAIA, Executive Vice President, Burt Hill Kosar Rittelmann Associates, 400 Morgan Center, Butler, PA 16001-5977
55. S.F. Tierney, The Economic Resource Group, Inc., One Mifflin Place, Cambridge, MA 02138
56. C.M. Walton, Ernest H.Cockrell Centennial Chair in Engineering and Chairman, Department of Civil Engineering, University of Texas at Austin, E. Cockrell, Jr. Hall I, Suite 4210, Austin, TX 78712-1075
57. Fred Abel, U.S. Department of Energy, PO-24, Room 7H-082, 1000 Independence Avenue, S.W., Washington, DC 20585
58. Rich Bechtold, TA Engineering, Inc., Catonsville Professional Center, 405 Frederick Road, Suite 252, Baltimore, MD 21218
59. Steve Bernow, Tellus Institute, 11 Arlington Street, Boston, MA 02116-3411
60. Bill Breed, U.S. Department of Energy, PO-22, Room 7H-063, 1000 Independence Avenue, S.W., Washington, DC 20585
61. Barry Cohen, U.S. Department of Energy, Energy Information Administration, EI-81, Room 2F-095, 1000 Independence Avenue, S.W., Washington, DC 20585
62. John DeCicco, American Council for an Energy-Efficient Economy, 1001 Connecticut Avenue, N.W., Suite 801, Washington, DC 20036
63. Mark A. Delucchi, 3925 Main Street, Fair Oaks, CA 95628
64. Carmen Difiglio, U.S. Department of Energy, PO-62, Room 7H-063, Forrestal Building, 1000 Independence Avenue, S.W., Washington, DC 20585

65. Jeff Dowd, U.S. Department of Energy, PO-22, Room 7H-075, 1000 Independence Avenue, S.W., Washington, DC 20585
66. K.G. Duleep, Energy and Environmental Analysis, Inc., 1655 North Fort Myer Drive, Suite 600, Arlington, VA 22209
67. Ralph Erickson, U.S. Department of Transportation, Federal Highway Administration, 400 Seventh Street, S.W., HPM-10, Room 3306, Washington, DC 20590
68. Lew Fulton, International Energy Agency, 9 Rue de la Federation, Paris 75015, France
69. John Garbak, U.S. Department of Energy, EE-32, Room 5G-023, 1000 Independence Avenue, S.W., Washington, DC 20585
70. Stephen Goguen, U.S. Department of Energy, EE-33, Room 5G-086, 1000 Independence Avenue, S.W., Washington, DC 20585
71. Charles Gray, U.S. Environmental Protection Agency, 2565 Plymouth Road, Mail Code AAATSD, Ann Arbor, MI 48105
72. Kevin Greene, Volpe National Transportation Systems Center, 55 Broadway, Kendall Square, Cambridge, MA 02142-1093
73. Lorna Greening, International Resources Group, 1211 Connecticut Avenue, N.W., Suite 700, Washington, DC 20036
74. Thomas J. Gross, EE-30, U.S. Department of Energy, Room 5G-086, 1000 Independence Avenue, S.W., Washington, DC 20585
75. David Hitchcock, Houston Advanced Research Center, Center for Global Studies, 4800 Research Forest Drive, The Woodlands, TX 77381
76. K. John Holmes, The H John Heinz III Center for Science, Economics and the Environment, 1001 Pennsylvania Avenue, N.W., Suite 735 South, Washington, DC 20004
77. Douglas Howell, Environment & Energy Study Institute, 2021 3rd Avenue, Seattle, WA 98121
78. Damian Kulash, Eno Transportation Foundation, One Farragut Square South, 1634 I Street, N.W., Suite 500, Washington, DC 20006-4003
79. Skip Laitner, U.S. Environmental Protection Agency, Mail Code 6206J, 401 M Street, S.W., Washington, DC 20460
80. Jose Mantilla, Volpe National Transportation Systems Center, 55 Broadway, Kendall Square, Cambridge, MA 02142-1093
81. John D. Maples, EI-84, U.S. Department of Energy, Energy Information Administration, 1000 Independence Avenue, S.W., Washington, DC 20585
82. Jim March, U.S. Department of Transportation, Federal Highway Administration, HPP-12, 400 Seventh Street, S.W., Washington, DC 20590
83. Jason Mark, Union of Concerned Scientists, 2397 Shattuck Avenue, Suite 203, Berkeley, CA 94705
84. Barry McNutt, U.S. Department of Energy, PO-62, Room 7H-921, Forrestal Building, 1000 Independence Avenue, S.W., Washington, DC 20585
85. Tien Nguyen, U.S. Department of Energy, EE-31, Room 1J-105, 1000 Independence Avenue, S.W., Washington, DC 20585
86. Robert Noland, U.S. Environmental Protection Agency, Energy and Transportation Sectors Division, Office of Policy, Planning, and Evaluation, 401 M Street, S.W. (2126), Washington, DC 20460
87. Joan M. Ogden, Princeton University, Energy and Environmental Studies, H113 Engrg Quad, Princeton, NJ 08544
88. Phil Patterson, CE-30, U.S. Department of Energy, Forrestal Building, 1000 Independence Avenue, S.W., Washington, DC 20585

89. Steve Plotkin, Argonne National Laboratory, 955 L'Enfant Plaza, S.W., Suite 6000, Washington, DC 20024
90. Peter Reilly-Roe, Energy Mines and Resources Canada, Transportation Energy Use Division, 580 Booth Street, 12th Floor, Ottawa, Ontario, Canada K1A 0E4
91. David Rodgers, U.S. Department of Energy, EE-34, Room 5G-086, 1000 Independence Avenue, S.W., Washington, DC 20585
92. Mark Ross, University of Michigan, Department of Physics, 2071 Randall Laboratory, Ann Arbor, MI 48109-1120
93. Danilo J. Santini, Argonne National Laboratory, Center for Transportation Research, 9700 South Cass Avenue, ES/362 2B, Argonne, IL 60439-4815
94. Lee Schipper, Internationl Energy Agency, Office of Long-Term Cooperation and Policy Analysis, 2, rue Andre Pascal, 75775 Paris Cedex 16, France
95. Jhih-Shyang Shih, Resources for the Future, 1616 P Street, N.W., Washington, DC 20036
96. Margaret Singh, Argonne National Laboratory, 955 L'Enfant Plaza, S.W., Suite 6000, Washington, DC 20024
97. Dan Sperling, Institute of Transportation Studies, University of California at Davis, One Shields Avenue, Davis, CA 95616-8762
98. Donald R. Trilling, U.S. Department of Transportation, Office of the Secretary, 400 7th Street, S.W., Room 9222, Washington, DC 20590
99. Phil Tseng, U.S. Department of Energy, 1000 Independence Avenue, S.W., Washington, DC 20585
100. Michael Q. Wang, Argonne National Laboratory, 9700 South Cass Avenue, Argonne, IL 60439
101. Tom White, PO-22, Room 2E-088, U.S. Department of Energy, 1000 Independence Avenue, S.W., Washington, DC 20585
102. Mary Beth Zimmerman, U.S. Department of Energy, PO-62, Room 7H-075, 1000 Independence Avenue, S.W., Washington, DC 20585
103. James Zucchetto, Board on Energy and Environmental Systems, National Academy of Sciences, National Academy of Engineering, 2101 Constitution Avenue, N.W., Washington, DC 20418