Distributional Effects of Alternative Vehicle Pollution Control Policies

Extended Working Paper
to accompany the shorter version forthcoming in

Journal of Public Economics

by

Sarah E. West*

Department of Economics
Macalester College

JEL Classification Nos.: H22, H23, Q28

Key Words: vehicle pollution policies, distributional effects

Abstract

Previous work shows that policies that subsidize new vehicles and tax size, miles, or gasoline efficiently reduce pollution. Less is known about their distributional effects. This paper examines distributional effects by estimating the joint demand for vehicles and miles, using the Consumer Expenditure Survey. Greater price responsiveness among low-income households enhances progressivity of gas or miles taxes across lower incomes, and mitigates regressivity across upper incomes. Taxes on engine size or subsidies to new vehicles are significantly more regressive than gas or miles taxes.

---

* Sarah E. West, Department of Economics, Macalester College, 1600 Grand Ave., St. Paul, MN 55105.
Phone: (651) 696-6482; Fax: (651) 696-6746; e-mail: wests@macalester.edu

American households drove an average of 18,161 miles in 1990 and 20,895 miles in 1995 (ORNL, (1998)). In November 1998, sales of minivans, sport utility vehicles, and pickup trucks captured 51% of the U.S. market for vehicles, surpassing sales of autos for the first time (Warner, (1998)). These developments frustrate efforts to reduce automobile pollution: eleven metropolitan areas remain listed in the extreme or severe categories of ozone non-attainment areas.[1] A tax per unit of emissions would induce all of the cheapest forms of vehicle pollution abatement: households would drive fewer miles and buy vehicles with higher fuel efficiencies and lower emissions per mile. The technology, however, is not yet available to measure each vehicle's emissions in a reliable and cost effective manner. Since an emissions tax is not yet available, researchers seek feasible alternative market incentives that would induce the same efficient responses.

Older or larger vehicles emit more hydrocarbons, carbon monoxide, and oxides of nitrogen per mile (Fullerton and West, 2000).[2] Thus, alternative policies can approximate the effects of emissions taxes by explicitly or implicitly taxing miles, taxing engine size, or subsidizing vehicle newness. For example, gasoline taxes or tolls tax miles.[3] Gas-guzzler taxes apply to vehicles with low fuel efficiencies, and effectively tax engine size. Corporate average fuel economy (CAFE) standards implicitly tax large cars, and subsidize small cars (Goldberg, 1998). Accelerated vehicle retirement programs induce households to scrap old vehicles and to purchase newer ones, effectively subsidizing vehicle newness (Alberini, Harrington, and McConnell, 1996).

---

[1] This was as of May, 2002. For updates on attainment status, see http://www.epa.gov/oar/oaqps/greenbk.

[2] Newer vehicles are subject to more stringent emissions standards than are older vehicles. Until 1994, standards for light-duty trucks (including minivans and sport utility vehicles) were less stringent than for cars. Many new SUVs and trucks are so large that they fall into the heavy-duty category, and so they also face lower standards. In addition, pollution-control equipment deteriorates with time. So even cars that face stringent off-the-assembly-line standards emit more as they age. This is compounded for larger cars with lower fuel efficiencies; cars that burn more gas per mile and have broken pollution control equipment emit more per mile than smaller cars with equipment in the same condition (Harrington (1997)).

[3] A referee points out that other externalities from driving, namely congestion and accidents, are larger on a per mile basis than pollution and that a tax on miles is more effective at reducing these externalities (see Parry and Small (2002)). Households respond to a miles tax exclusively by reducing miles; when faced with a gasoline tax, they avoid some miles reduction by improving their vehicles' fuel efficiency. This means that the economic costs of reducing congestion and accidents by a given amount are larger under a gasoline tax than under a mileage tax. On the other hand, since carbon emissions are proportional to fuel use, a gas tax acts very much like an ideal emissions tax for carbon emissions. This makes a gas tax a particularly attractive policy for carbon reduction in the transport sector since abatement equipment, available for local air pollutants such as ozone, is not available for carbon.

Several papers find that these kinds of alternative market-based instruments can be quite efficient relative to a first-best emissions tax.[4] Less is known, however, about the distributional effects of these policies. It can probably be safely assumed that wealthier households buy newer vehicles, but it is not so clear whether they buy smaller or larger vehicles. Nor is it clear which households spend more as a proportion of their income on gasoline, after they respond to a tax. Since distributional concerns are often central to vehicle pollution policy discussions, the incidence of these policies warrants examination. To determine the incidence of a miles or gas tax, a size tax, and a newness subsidy, I estimate a model of discrete vehicle choice, including vintage and size choice, and the continuous choice of vehicle-miles-traveled *(VMT)*.

Many studies find that because gasoline and miles have income elasticities of less than one, taxes on them would be regressive (see for example Kayser (2000), Sipes and Mendelsohn (2001), Walls et al. (1994)).[5] Most of these studies measure income as annual income and only consider households that own automobiles. Sevigny (1998) considers distributional effects using annual income and cars owners only, and finds a miles tax to be quite regressive. Poterba (1991) measures income as consumption expenditures, includes households that do not own vehicles, and finds that low-income households spend less of their budget on gas than middle-income households.[6] A gas tax is thus less regressive than other analyses suggest. Walls and Hanson (1999) use annual income and a measure of lifetime income to consider the distributional effects of vehicle pollution control policies, including a miles tax. Results using annual income show all policies to be regressive across all income groups, while results using lifetime income are similar to Poterba's results (1991).[7]

---

[4] See De Borger (2001), Devarajan and Eskeland (1996), Fullerton and West (2000), Innes (1996), Kohn (1996), and Plaut (1998).

[5] See also Dahl (1986), Dahl and Sterner (1991), and Espey (1996) for reviews of gas demand literature.

[6] He also finds that middle-income households spend more of their budget on gas than upper-income households.

[7] These studies and mine are exercises in absolute tax incidence analysis, wherein environmental taxes are considered in isolation. Metcalf (1999) conducts a differential tax incidence analysis, and finds increases in environmental taxes can have a "negligible impact on the income distribution when funds are rebated to households through reductions in payroll and personal income tax" (p. 655). Also, I focus on the cost side of vehicle pollution policies; I do not consider the distribution of health benefits from improved pollution (see Baumol and Oates (1988) and Brooks and Sethi (1997) for discussion of the distribution of benefits).

These studies provide evidence on the distributional effects of taxes on gasoline or miles holding household behavior constant, or assuming that all households have the same degree of price responsiveness. Yet poor households, because they have smaller budgets or if they are more willing to use mass transit, may be more responsive to prices than the wealthy. On the other hand, if poor people have fewer transportation options, they may be less price-responsive. To allow for the possibility that poor and wealthy households behave differently in response to increases in driving costs, I estimate price elasticities by decile and simulate changes in miles.

The joint nature of the demands for vehicles and miles complicates estimation of these demands. The choices of vehicle and VMT are related because characteristics that influence a household to purchase a certain vehicle may also influence that household's choice of miles. For example, a person that lives far from work may gain more enjoyment from commuting in a large, comfortable vehicle. Residence location also makes it likely that this person will drive more miles. The two choices are also related through the effect that vintage and engine size have on fuel efficiency. Since the demand for VMT depends on the price per mile, and thus fuel efficiency, the household's choice of vehicle affects their demand for miles, and vice versa. To reliably estimate the demand for miles, one must construct a model of the *joint* choice of vehicles and miles.

An appropriate framework for modeling this joint choice is found in Dubin and McFadden (1984).[8] They derive models to estimate the joint demand for durables and energy use. In this case the automobile is the durable good, and miles-driven is the service provided by the automobile through gasoline use. Five studies use the Dubin and McFadden framework to estimate the joint demand for vehicles and miles.[9] None of these studies, however, uses recent data from the United States. Recent data may yield very different results than older data, given the increases in commute distances and the surge in popularity of sport utility vehicles. All use traditional

---

[8] Some studies estimate the discrete choice of vehicle, but not the demand for miles (Berkovec (1985), Berkovec and Rust (1985), McCarthy (1996)). While some studies of the demand for miles include indicator variables for vehicle choice in equations that estimate miles demand, they do not explicitly model the joint nature of the choice (Archibald and Gillingham (1981), Sevigny (1998), and Walls et al. (1994)).

[9] Two use data from the 1970s. Mannering and Winston (1985) develop a dynamic model of vehicle ownership and use, wherein use is the sum of miles driven in all vehicles in the household. Train's (1986) model is not dynamic, but it does examine the number of miles driven in each vehicle in the household. Goldberg (1998) uses data on car purchases from the 1980s to estimate the effects of CAFE standards in the United States. Two studies use foreign data. Using Canadian data from the 1980s, Berkowitz et al. (1990) expand upon previous studies to include travel mode choice. Hensher et al. (1992) use Australian panel data from 1981 to 1985 to estimate a dynamic model of vehicle choice and use.

measures of income and no study determines the effects of household characteristics on the demand for both newness and engine size, attributes that are important for analyzing emission-reduction policies. Finally, none of these studies considers distributional effects of such policies.

This paper fills those gaps. It implements the Dubin and McFadden framework using data from the 1997 U.S. Consumer Expenditure Survey and other sources. Current income includes transitory components, and so I use current total consumption expenditures as a more accurate measure of well-being.[10] I estimate a model of the joint determination of miles driven and vehicle attributes in two stages. The first stage estimates a nested logit of households' choices from among vehicle bundles classified according to the number of vehicles, vintage, and engine size. The second stage estimates the demand for *VMT* and controls for the endogeneity of vehicle choice by implementing a conditional expectation correction method.

As expected, households with higher incomes prefer newer vehicles and newness subsidies would be regressive. The results for engine size are not so straightforward: households with higher incomes that own 1980s-vintage vehicles prefer smaller engine sizes, while those with 1990s vehicles prefer larger engine sizes. Wealthier households that own 1990s vehicles would still spend less on size tax as a proportion of their income, however, and so size taxes would also be regressive.

Since many of the poorest households do not own vehicles, a tax on miles or gasoline is progressive over the bottom half of the income distribution. While these taxes are still regressive over the wealthiest half of the income distribution, the greater degree of price-responsiveness on the part of low-income households enhances the degree of progressivity in the poorest income groups and mitigates the regressivity in the upper income groups. Policy makers are generally averse to increases in gas taxes but more enthusiastic about policies that tax size or subsidize newness. These preferences are not justifiable on distributional grounds. Overall, gas or miles taxes are significantly less regressive than newness subsidies or size taxes.

[10] Slesnick (2001) explains, "An individual's material well-being is a function of the goods consumed rather than the income received," and "When income is temporarily low, because the individual is young or has experienced a transitory reduction in income, consumption levels are preserved either by drawing down [a] savings account or by borrowing. The reverse occurs when income is temporarily high" (p. 4). If one accepts this description of spending behavior, consumption provides a better approximation to welfare than income does, though it is still an approximation. It is problematic, for example, for households that cannot smooth consumption by saving or borrowing.

Section I derives a model of the discrete choice of vehicle bundle and the continuous choice of miles. Section II describes the data, explains the classification of vehicle bundles, details the derivation of variables used in the estimation, and provides summary statistics. Section III presents elasticities and distributional results, and Section IV concludes.

I. Model

This section presents a model of the joint discrete choice of vehicle bundle and the continuous choice of miles. I specify a functional form for conditional indirect utility and solve for the conditional demand-for-miles equation.

Households face the discrete choices of the number of vehicles to own, the vintage, and the engine size of each vehicle. They also face the continuous choice of vehicle-miles-traveled, *VMT.* Households first choose the number of vehicles to own, n . Conditional on having chosen n vehicles, they choose from among different combinations of engine size and vintage. Call this choice of engine size and vintage their choice of bundle, b. A household chooses from among a set of mutually exclusive, exhaustive vehicle bundles. Given number of cars n and bundle b , the consumer has a conditional indirect utility function

$$V_{nb} = f(b, y - r_{nb}, p_{nb}, c_{nb}, h, \varepsilon_{nb}, \eta) \qquad (1)$$

where y is household quarterly total expenditures, r_{nb} is the quarterly[11] life-cycle cost of n vehicles in bundle b , p_{nb} is the cost per mile for the n vehicles in bundle b, c_{nb} is observable attributes of bundle b, h is observed household characteristics, ε_{nb} is unobserved attributes of bundle b , and η is unobserved household characteristics.

Second, given n and b, the number of miles that the household will travel is, by Roy's identity:

$$VMT_{nb} = \frac{-\partial V_{nb}(b, y - r_{nb}, p_{nb}, c_{nb}, h, \varepsilon_{nb}, \eta) \big/ \partial p_{nb}}{\partial V_{nb}(b, y - r_{nb}, p_{nb}, c_{nb}, h, \varepsilon_{nb}, \eta) \big/ \partial y} \qquad (2)$$

---

[11] Usually this life-cycle cost is expressed as the annualized cost of the vehicle bundle. Since the data used in this paper are quarterly, this cost is also quarterly.

The household chooses vehicle number n^* and bundle b^* to maximize conditional indirect utility, that is, it chooses bundle b if and only if

$$V_{n^*b^*} > V_{nb} \qquad \text{for all } \; n, b, \text{ other than } n^*, b^*$$

Thus, the probability that the household chooses vehicle number n^* and bundle b^* is

$$P_{n^*b^*} = \text{Prob}(V_{n^*b^*} > V_{nb} \text{ for all } n, b \text{ other than } n^*, b^*)$$

To evaluate this probability, recall that V_{nb} is composed of both observed and unobserved vehicle and household attributes. Combine the effects of all unobserved variables into one composite unobserved variable, take the mean of V_{nb} over this unobserved variable and label this mean $\overline{V}_{nb}$. This mean can be further decomposed into terms that represent the mean utility over number n, $\overline{V}_n$, and the mean utility over bundles b, $\overline{V}_{b|n}$. Including a third term for deviations from the means, μ_{nb}, write this decomposition as

$$V_{nb} = \overline{V_n} + \overline{V}_{b|n} + \mu_{nb} \tag{3}$$

Then, the joint probability of choosing a particular vehicle bundle and make/model combination, P_{nb}, is

$$P_{nb} = P_n P_{b|n} \tag{4}$$

where P_n is the marginal probability of choosing vehicle number n, and $P_{b|n}$ is the probability of choosing bundle b conditional upon vehicle number n.

If one assumes that μ_{nb} in (3) for all n and b are jointly distributed according to a generalized extreme value function, then the appropriate estimation technique is nested logit, where the upper nest contains the number of vehicles, and the lower nests the vehicle bundles.

To derive the model used in estimation, a functional form for conditional indirect utility must be specified. The choice of a vehicle and the conditional demand for miles is analogous to Dubin and McFadden's (1984) choice of appliance and the conditional demand for electricity. They derive an electricity demand function that is linear in prices and net income, and conditional on appliance choice. To apply their form to estimating the conditional demand for miles, I follow Goldberg (1998) and modify it to include a price per mile that is conditional on the choice of vehicle bundle.[12] The resulting conditional indirect utility function is

$$V_b = (\alpha_0^b + \frac{\alpha_1}{\beta} + \alpha_1 p_b + h'\gamma + \beta(y - r_b) + \eta)e^{-\beta p_b} + \varepsilon_b \qquad (5)$$

where α_0^b is a bundle-specific constant and α_1, β, and the vector γ are parameters to be estimated (and super- and sub-scripts indicating vehicle number have been suppressed for simplicity).[13]

The quarterly life-cycle cost of bundle b can be broken into two components:

$$r_b = p_b q_b + \rho r_{kb} \qquad (6)$$

where q_b is *typical* quarterly miles driven by a household in bundle b, ρ is an exogenous discount factor, and r_{kb} is the capital cost of bundle b. Typical quarterly miles represents the number of miles that a household expects to drive in a vehicle bundle. Typical miles multiplied by the price per mile, $p_b q_b$, is the vehicle bundle's total quarterly operating cost *(TOPCOST$_b$)*.

Application of Roy's identity to equation (5), taking into account the dependence of life-cycle cost r_b on the price per mile in (6), yields the quarterly demand for miles conditional on vehicle bundle choice b:

$$VMT_b = q_b + \alpha_0^b + \alpha_1 p_b + h'\gamma + \beta(y - r_b) + \eta \qquad (7)$$

Decompose quarterly life cycle costs into total operating cost *(TOPCOST$_b$)* and capital cost *(r_{kb})* and rewrite (7) in a more convenient form for estimation:

$$VMT_b - q_b = \sum_i \alpha_0^b \delta_{bi} + \alpha_1 \sum_i p_b \delta_{bi} + h'\gamma + \beta(y - \sum_i TOPCOST_b \delta_{bi}) - \beta\rho \sum_i r_{kb}\delta_{bi} + \eta \qquad (8)$$

[12] Another approach would be to choose a simple demand function and solve its corresponding differential equation to obtain the associated indirect utility function. De Jong (1990) does this, and applies the econometrics of nonlinear budget sets to include the discrete choice component of car use. I use Goldberg's framework because unlike De Jong's, it is consistent with the nested logit specification.

[13] As Goldberg (1998) says, the presence of the term $e^{-\beta p_b}$ in (1) "complicates the specification" (p. 5). I therefore follow her approach and apply a Taylor's series expansion around the mean operating cost per mile. Doing so preserves the computational advantages of the generalized extreme value distribution (the distribution that corresponds to nested logit) assumed here.

where δ_{bi} is an indicator variable equal to one when $i = b$. To consider the distributional effects of a tax on miles or on gasoline, I include an interaction between income and the operating cost per mile in the estimation.[14]

If vehicle bundle choice and the additive error η in the demand for miles in (8) are statistically independent, then estimation of equation (8) yields unbiased parameter estimates. But, an unobserved household characteristic that affects the utility of miles driven in a particular vehicle bundle is likely to affect both its probability of selection and its intensity of use. For example, a large household may gain more enjoyment from driving in a spacious vehicle. The household may also have to drive children to more activities, and so they may drive more miles. Moreover, factors that affect the intensity of use will affect the probability of choosing particular vehicle bundles. A person that lives in a region with long commutes drives more miles and may be more likely to choose a vehicle bundle that has low operating costs. Cases such as these imply that the residuals η are correlated with the choice indicators δ_{bi}, and thus the expectation of η given bundle-choice b does not equal zero.

The conditional expectation correction method is consistent in the presence of correlation of the residual η and the bundle-choice indicators (see Dubin and McFadden (1984)). To implement this method, solve for the expectation of η given vehicle number n and bundle-choice b:

$$\sum_{i \neq n} \sum_{j \neq b} \left[\frac{\hat{P}_{nb} \ln \hat{P}_{nb}}{1 - \hat{P}_{nb}} + \ln \hat{P}_{ij} \right] \tag{9}$$

where $\hat{P}_{nb}$ are the estimated probabilities that a household would select bundles b other than the bundle it actually chose and $\hat{P}_{ij}$ is the estimated probability the household chooses the bundle that it actually owns. Addition of term (9) to equation (8) permits one to use OLS to consistently estimate the parameters in (8).

II. Data and Summary Statistics

[14] Inclusion of interaction terms means that the demand function in (4) does not correspond directly to the indirect utility function in (1). To derive the indirect utility function that corresponds to the demand function used here, one can first use Roy's identity to write the demand function as a differential equation (Hausman (1981), p. 674). One can then solve for the indirect utility function, but cannot find a closed form solution.

To estimate the model discussed above, one needs data on individual expenditures, prices, and household and vehicle characteristics. This section describes the three main sources of data used in this study: the Consumer Expenditure Survey (CEX), the California Air Resources Board (CARB) Light-Duty Surveillance Program, and the American Chamber of Commerce Researchers' Association (ACCRA) cost-of-living index. Then it explains the classification of vehicle bundles, describes the derivation of variables used in the estimation, and provides summary statistics.

A. General Data Description

The 1997 Consumer Expenditure Survey (CEX) is the main component of the data. The CEX includes the amount spent on gasoline, total expenditures, and detailed information on each household's vehicles. Variables in the vehicle file include year, make, model, number of cylinders, the amount paid for the vehicle, and other characteristics. I use data for each household from the first quarter in which the household appears.

To construct a operating cost per mile variable the fuel efficiency of each vehicle and gas prices are needed. Since the CEX does not contain data on fuel efficiency, I rely on the CARB for this variable. In two phases of its Light-Duty Surveillance Program, the CARB tested the fuel efficiency of 667 vehicles in California.[15] In addition, they compiled vehicle information such as make, model, year, and number of cylinders. These data allow me to estimate fuel efficiency as a function of number of cylinders and vehicle vintage.

For gas prices, I use the ACCRA cost-of-living index. This index compiles prices of many goods as well as overall price indexes for approximately 300 cities in the United States. It is most widely used to calculate the difference in the overall cost-of-living between any two cities. It also lists average prices of regular unleaded national-brand gasoline for each city in the survey each quarter. Since the CEX reports state of residence of each

---

[15] The Light-Duty Vehicle Surveillance Program, Series 13 and 14, was conducted as part of an ongoing effort by the CARB to accumulate vehicle emissions data, to investigate vehicle maintenance practices and deficiencies, and to determine the frequency and effect of tampering with pollution control equipment. The CARB tested candidate vehicles from a randomized set of registered vehicles belonging to households within a 25-mile radius of the CARB office in El Monte, California.

household, and not city, I average the city gas prices to obtain a state gasoline price for each calendar quarter. Then I assign a gas price to each CEX household based on state of residence and CEX quarter.[16]

B. Classification of Vehicle Bundles

Vehicle bundles are classified according to three characteristics: number of vehicles, vintage, and engine size. I use vintage and engine size rather than other characteristics because they, of the vehicle characteristics included in the CEX, have the most measurable effect on the price per mile.[17] This classification also enables me to estimate the effects of household characteristics on the demand for engine size and vintage.

First I classify bundles according to three number of vehicles categories: zero, one, or two. Households that own three or more vehicles are not included, as that would increase the total number of bundle choices to hundreds.[18] Then, within the one- and two-vehicle categories, I further classify each vehicle according to vintage and engine size. Larger than average changes in Corporate Average Fuel Economy Standards (CAFE) standards occurred in 1981 and 1990.[19] One might like to divide vehicles into vintage categories according to these cut-off points. The CEX, however, lumps 1980- through 1982-vintage cars into the same category. So, I divide vehicles into these vintage categories: all pre-1980 (old), at least one 1980 to 1989 and no 1990 and newer (newer), or at least one 1990 and newer (newest). For engine size, the three categories are all 4-cylinder (small), at least one 6-cylinder and no 8-cylinder (medium), or at least one 8-cylinder (large).

[16] Within-state variation in gas prices is small. For example, for the fourth quarter of 1997, the average standard deviation of within-state gas prices is .04 (4 cents) per gallon.

[17] To classify vehicles, Train (1986), and Mannering and Winston (1985) use vintage but no measure of vehicle size. Berkowitz et al. (1990) classify bundles using vintage and type (sedan or truck), which is one measure of size. They estimate fuel efficiency but do not reveal whether they include type in this estimation. Hensher et al. (1992) uses type but not vintage to classify bundles. Goldberg's (1998) model includes choices between new and used and among classes of vehicle type.

[18] Eighty-two percent of 1997 CEX households own zero, one, or two vehicles (the 1995 Nationwide Personal Transportation Survey lists this number as 81 percent (ORNL (2000)). The CEX data for households with more than two vehicles is very spotty; seventy percent of these households have missing data for size or vintage of at least one vehicle. Inclusion of multiple-vehicle bundles would also be difficult because bundle choices would be spread very thinly across the sample. Even with two-car bundles, this thinness presents problems for estimation, as discussed below. Households with three or more vehicles have higher average expenditures as the households included here; by ignoring them this study focuses on a less-wealthy portion of the income distribution.

This classification generates nine one-vehicle bundles and nine two-vehicle bundles. Two of the two-vehicle bundles have very few observations, which creates problems in estimation. I combine these bundles into one bundle that contains the following combinations: two 4-cylinder, 1970s-vintage; one 4-cylinder 1970s-vintage and one 6-cylinder 1970s-vintage; and two 6-cylinder 1970s-vintage.[20] Households that own no cars make up 24 percent of the sample, 45 percent own one car, and 31 percent own two cars. The most common one-car bundle is a 4-cylinder 1990s-vintage car, and the next most common one-car bundle is a 6-cylinder 1990s-vintage car. The most common two-car bundle is a combination of those same two cars.

C. Derivation of Bundle-Specific Attributes and VMT

Three key bundle-specific attributes appear in the model in Section I. They are operating cost per mile (p_b), typical miles-driven (q_b), and capital cost (r_{kb}). The operating cost per mile for each vehicle is the price of gasoline divided by fuel efficiency, plus maintenance and tire costs per mile.[21] The ACCRA gives the price per gallon of gasoline. The ORNL (1998) provides maintenance and tire costs per mile, by vehicle vintage.

To obtain fuel efficiency, I use the CARB to estimate a regression of *MPG* on indicator variables for the three size categories and for the three vintage categories.[22] Fuel efficiency decreases in both vehicle age and

---

[19] For a table of CAFE standards across time, see ORNL (1998), p. 6-14.

[20] Two households own the first bundle, three own the second or third bundle.

[21] Two variable operating costs not included here are time cost and expected accident cost. These costs are large components of the price per mile (more than double the fuel, tire, and maintenance costs per mile), and so I experimented with operating costs that include them. Because these costs are determined primarily by the wage, they reflect income more than anything else. So, not surprisingly, in *VMT* regressions, coefficients on operating costs that include time and accident costs are positive. This result may also be explained by the fact that these costs affect miles traveled through mode or residential location choice, choices not included in estimation. The data used here do not contain sufficient information to estimate a model with such choices, and so rather than introduce bias by including time and accident costs in the absence of mode and location choice, I omit these costs and take mode and location choice as given (see Small (1992) for discussion time costs and transportation modeling). While it is difficult to determine the direction of the bias due to this omission, because fuel costs are a larger proportion of poor households' full cost of driving, we might expect price elasticities to be biased downward for these households, and thus incidence measures to be biased toward regressivity.

[22] The fitted equation is (standard errors in parentheses):

$$\underset{(.34)}{\text{Estimated MPG} = 21.24} - \underset{(.28)}{6.22}\text{*six-cylinder} - \underset{(.35)}{9.19}\text{*eight-cylinder} + \underset{(.35)}{2.29}\text{*1980s-vintage} + \underset{(.38)}{4.60}\text{*1990s-vintage}$$

The adjusted R^2 equals .68; the number of observations is 667. Given the omitted variables, the constant represents the estimated fuel efficiency of a 4-cylinder, pre-1980 vehicle. In regressions that include interaction terms, coefficients on the interaction terms are not statistically significant, and the adjusted R-squared is lower that in this reported regression.

engine size. For one-vehicle bundles, fuel efficiency is calculated directly from the regression results. For two-vehicle bundles, first I calculate the fuel efficiency of each two-car pair within the bundle by averaging the two cars' estimated efficiencies. Then, I assign the two-vehicle bundles that consist of more than one possible two-vehicle pair the average of the pairs' average efficiencies.

Unfortunately, the CEX only lists the total gas expenditure for each household, not the gas expenditure for each vehicle. Thus I cannot assign VMT to each vehicle, and must use total VMT by a household. To calculate VMT, first I divide the household's gas expenditure by its gas price to get gallons of gas consumed. Then, I multiply gallons by fuel efficiency to obtain VMT for the household.[23]

Typical miles-driven appears in the estimated model as part of the quarterly life cycle costs of a vehicle bundle, and represents the number of miles a household expects to drive. If true miles driven by a household were used to measure expected miles, the problems caused by the endogeneity of this variable would make estimation very difficult. To construct an exogenous measure of the typical miles driven by a household, I calculate the average number of miles driven in each bundle over all households. Then, to allow typical miles to vary across households that own the same bundle, I regress these averages on total expenditures and the number of drivers, and use these estimates to assign typical miles to each household.

For capital costs, I use the average purchase price of a bundle.[24] Households in the CEX are asked how much they paid for each vehicle they own, and what year they bought the vehicle. I use prices of new and used vehicles purchased in 1997 to calculate the current capital cost of each size-vintage combination. For two-vehicle bundles, I calculate the capital cost of each two-car pair within the bundle by adding the two cars'

---

[23] My estimates of VMT yield means that are somewhat lower than those from the 1995 Nationwide Personal Transportation Survey (NPTS). My one-car households drive an average of 11,780 miles per year; those in the 1995 NPTS drive 12,379 miles per year. My two-car households drive 18,100 miles per year; those in the 1995 NPTS drive 25,126 miles per year. Also, using total VMT versus the VMT in each vehicle ignores the possibility that households respond to changes in gasoline price by driving more in one vehicle and less in another. Thus, estimates of the elasticity of VMT with respect to the price per mile are likely to be biased downwards. Green and Hu (1985) find that substitution among vehicles within a household in response to changes to the price per mile is negligible, and so the bias is not likely to be large.

[24] In addition to the vehicle purchase price, other fixed costs that vary across vehicle types include depreciation, insurance, finance charges, and license fees. These costs vary closely with purchase price, and so purchase price appears to be a good proxy for overall fixed costs.

average prices. Then, I assign the two-vehicle bundles that consist of more than one possible two-vehicle pair the average of the pairs' capital costs.

D. Summary Statistics: Household and Vehicle Characteristics

Table 1 lists summary statistics by number of vehicles. Not controlling for other variables, the number of vehicles owned increases with total expenditures, household size, the number of household members older than 15 (this variable is meant to proxy for the number of drivers), the number of income earners, and homeownership. Based on the distribution of percentages across number of vehicles, the probability that a household chooses a vehicle bundle with more vehicles may increase if the household head is male, white, has more than a high school education or lives in the Midwest or South. The likelihood that a household chooses bundles with more vehicles appears to decrease if the household lives in a large metropolitan area.

The relationship between total expenditures and engine size does not appear to be monotonic; total expenditures for those with medium-sized vehicles are higher than for those with small vehicles, but expenditures for those with large vehicles are lower than those with medium vehicles. Larger households and those that live in the West appear to prefer larger cars. Less-educated, male, and older household heads also appear to choose larger vehicles. Households that live in larger cities are less likely to own larger vehicles. As predicted by the fuel efficiency regression, the operating cost per mile increases with size.[25]

Newer vehicles are owned by households with higher total expenditures. Newer vehicles also appear to be preferred by households with more members above the age of 15, more income earners, and with white, male, and more-educated heads. Households living in large metro areas, the Northeast, the Midwest, or the South also appear more likely to own newer vehicles, while households with older heads, or living in the West seem more likely to own older vehicles. As indicated by the fuel efficiency regression, the operating cost per mile increases with vehicle age.

---

[25] The tables with summary statistics for households by engine size and vehicle vintage are available in the Appendix.

III. Estimation and Results

Estimation of the model described in Section I is undertaken in two stages. The first estimates a nested logit specification of the discrete choice of vehicle bundle as a function of household and vehicle bundle characteristics. Then, the second stage estimates the demand for vehicle-miles traveled using the method described in Section I.

A. Stage 1: The Discrete Choice of Vehicle Bundle

The nested logit is estimated using full information maximum likelihood. Using Hausman's (1978) specification test, I test the model for independence of irrelevant alternatives (IIA). The assumption of IIA is rejected; the test rejects the notion that the choice of number of vehicles, vintage, and size is made jointly and suggests that the nested model is appropriate. Likelihood ratio tests, reported below Table 2, confirm the appropriateness of the nest. For estimation, demographic characteristics are interacted with choice indicators.

Table 2 summarizes the estimation results.[26] For the three continuous variables in the estimation (capital cost, total operating cost, and operating cost per mile), I report coefficient estimates and standard errors. The rest of the variables enter the nested logit as interactions with vehicle bundle indicators. I report qualitative results for these variables rather than listing the coefficients and standard errors for each of the vehicle bundle interaction terms for each variable.

The upper nest includes variables that might affect a household's vehicle number choice, including gender, family size, whether the household owns a home or lives in a large metropolitan area, and the number of earners and potential drivers in the household. It also includes inclusive values from the lower vintage-size nests that indicate the average utility that a household can expect from the vintage-size alternatives in the one- and two-vehicle subsets. Due to problems with multicollinearity, income is not included in the upper nest. Instead, it appears only in the lower vintage-size choice nests as interactions between indicators for households' quintiles in the income distribution and vehicle bundle. It is still possible to determine the effect of income on vehicle

[26] Full results can be found in the Appendix.

number choice by comparing the magnitude of the coefficients on these interactions for one-car households with those from two-car households. Also included in the vintage and engine size nest are variables presented in the summary statistics section.

First consider the results for the number of vehicles nest. Households headed by males are more likely to own cars than they are to own no cars. Since coefficients on the two-car bundles are more positive than those on the one-car bundles, male-headed households are even more likely to own two vehicles than they are to own one. Households with more income earners and members over the age of 15 are more likely to own two cars than they are to own one, as are households that own homes. Overall family size does not affect vehicle number choice.

The coefficients on average purchase price and the operating cost per mile have the expected signs: both are negative. An increase in purchase price or operating cost per mile for any vehicle can be expected to decrease the likelihood that vehicle is purchased. So policies that tax age or engine size through increases in the purchase price or operating cost per mile can be expected to decrease purchases of older and larger cars.

As predicted using summary statistics, households with male, older, or less-educated heads are more likely to choose bundles with larger vehicles. Households that live in the Midwest or South are more likely to own larger cars than similar households in the Northeast. Those headed by males and that own 1980s-vintage vehicles are less likely to own larger vehicles. Despite what summary statistics indicate, neither residence in a metropolitan area nor family size appear to be important determinants of engine size choice.

Households with male, older, more-educated household heads, or that live in the Midwest are more likely to own newer bundles. Number of drivers and metro residence do not appear to affect vintage choice.

Coefficients on terms that interact quintiles and indicators for the newest bundles are larger for wealthier quintiles. Coefficients, on the other hand, that interact quintiles and indicators for the older bundles are smaller for wealthier quintiles. Higher-income households therefore prefer newer cars.

The relationship between income and engine size choice is not so straightforward; the results depend on which vintage of vehicle we consider. Coefficients on medium and large vehicles in 1990s-vintage bundles are higher for the wealthiest quintiles– higher-income households with new vehicles generally prefer larger cars.

This is not true for owners of 1970s- or 1980s-vintage vehicles. Coefficients on large vehicles are highest for the third quintile, and then fall with the fourth and fifth quintiles– middle-income households with older vehicles prefer larger cars.

B. Stage 2: Estimation of the Demand for Vehicle-Miles-Traveled

For the second stage regression analysis, I use equation (8) and the conditional expectation correction approach explained in Section I. To determine whether different income groups respond differently to price changes, I include a price and income interaction term. Table 3 shows the results of OLS with neither vehicle-choice indicators nor correction for correlation (OLS1), results using OLS including actual bundle-choice indicators but not correcting for the correlation between the error term and the bundle-choice indicators (OLS2), and results using the conditional expectation correction method.

As expected, all three sets of results show that higher operating costs per mile decrease *VMT* while increases in income increase *VMT*. The positive coefficients on average purchase price *(CAPCOST)* indicate that households have positive discount rates. All of the regressions show that demand for *VMT* increases if the household is headed by a male. Miles also increase if the household lives in a large metro area or has more income earners, which emphasizes the importance of the commute. Two of the three regressions show that education reduces *VMT*. Those households whose heads are past retirement age also drive less.

Because it includes bundle-choice indicators, the OLS2 regression accounts for the effect that bundle choice has on *VMT*, but does not correct for the potential correlation between the bundle-choice indicators and the error term. Still, the differences between the results from OLS1 and those from OLS2 show the effect that (endogenous) bundle-choice has on *VMT*. Including the bundle-choice indicators reduces the coefficient on income by about one third and increases the coefficient on vehicle capital cost by four times. Both regressions, on the other hand, yield similar estimates for operating costs per mile.

The conditional expectation correction method corrects for the bias due to the fact that the bundle-choice indicators are correlated with the error term. While the estimates for the operating cost and income terms are of the same sign and similar magnitude to those from OLS2, some of those for demographic characteristics, notably those for region, age, and race, differ in magnitude and even sign. The *BIAS* term is statistically significant; estimates from regressions that do not include this term are biased. The differences in coefficient estimates demonstrate the importance of incorporating bundle choice *probabilities* to obtain the most accurate estimates.

C. Elasticities and Distributional Effects of Vehicle Pollution Control Policies

1. Elasticities of Demand for *VMT* with respect to operating costs and expenditures

The results in Table 3 can be used to calculate several different measures of the elasticity of demand for *VMT* with respect to operating costs, all conditional on vehicle choice. Each of the three sets of regression results, for example, can be used to calculate this elasticity evaluated at sample means of miles, operating costs per mile, and total expenditures. Using the OLS1 results and sample means yields an elasticity of –1.03. Inclusion of bundle choice indicators in OLS2 results in a less-elastic –.89, and controlling for the endogeneity of vehicle choice in the CE regression results in a still less-elastic –.87.

The expenditure elasticity of demand for miles calculated at sample means using CE results is .02. This estimate is smaller than estimates from previous studies and implies that a tax on miles or on gasoline would be quite regressive.[27] This estimate, however, conceals two critical characteristics of miles demand that vary across the income distribution. First, a large proportion of lower income households do not own vehicles, and therefore do not spend any money on miles.[28] In the lower half of the income distribution, as expenditures increase, spending on miles as a proportion of total expenditures also increases. Second, lower income households are more responsive to price changes than are high income households.

Columns 4 and 7 in Table 4 list elasticities of demand by decile for the OLS2 and CE regressions respectively, where households in decile 1 have the lowest expenditures and those in decile 10 have the

[27] OLS1 and OLS2 results yield expenditure elasticities of .10 and .04 respectively. Mannering and Winston (1985) finds a *VMT* income elasticity of .04 on average. Hensher et al. finds *VMT* elasticities ranging from .05 to .14. The only other study to define income as total expenditures (but not net income) is Archibald and Gillingham (1981). Their *VMT* expenditure elasticity estimates range from .23 to .47.

highest.[29] Both sets of elasticities are higher in absolute value for low income households than for high income households. Elasticities calculated using CE results are all smaller in absolute value than those using OLS2 results. These elasticities range from –1.51 in the poorest decile to –.75 in decile 8. Because of how vehicle bundles and operating costs are defined, these elasticities are not strictly comparable to estimates from previous studies. However, the results presented here are generally larger in absolute value than others.[30]

2. Distributional Effects of Vehicle Pollution Control Policies

a. A tax on miles or on gasoline

To see what variation in operating cost responsiveness implies for the distributional effects of miles or gas taxes, Table 4 simulates an increase in the operating cost per mile. Parry and Small (2002) update Small and Kazimi (1995) to find that environmental costs of local vehicle pollution are approximately 2 cents per mile.[31] I therefore assess a per mile tax of 2 cents, on top of existing gas taxes. At an average fuel efficiency of 20 miles per gallon, this tax on miles is equivalent to a 40 cent increase in gas prices, or about a doubling of the existing gas tax rate.[32]

The simulations in Table 4 show short-run responses, where only *VMT* is affected. They hold vehicle choice constant and use operating cost elasticities to calculate the average change in *VMT*, by decile, in response to the change in operating costs.[33] Columns 2 through 6 use estimates from the OLS2 regression, assuming a

---

[28] In the lowest decile, 61% of households own no vehicles, and in the second to the lowest decile, 43% of households own no vehicles. This characteristic is also pointed out in Poterba (1991).

[29] I use indicators for quintiles rather than deciles in the discrete choice model because they must be interacted with so many vehicle bundles. I use deciles here so that results may be compared directly with those from previous studies.

[30] For example, Walls et al. (1994) has *VMT* price elasticity estimates that range from -0.120 to -0.583. Berkowitz et al. (1990) estimate a *VMT* price elasticity of -.21. Similarly, Mannering and Winston (1985) find a *VMT* price elasticity of -.228, and Hensher et al.'s (1992) results range from -.28 to -.39. Sevigny's (1998) *VMT* estimates are the only ones that are in the same neighborhood as mine; they range from -.85 to -.94.

[31] The U.S. FHWA (2000) also estimates the costs of local vehicle pollution to be about 2 cents per mile.

[32] The current federal gas tax is 18.4 cents per gallon and the average state gas tax is about 19 cents per gallon.

[33] This simulation ignores the long-run effects of a gas tax on fuel efficiency. Nested logit results are used to form the bias variable for the *VMT* regression, to ensure that estimated elasticities and thus changes in miles driven are unbiased; the

constant demand elasticity (columns 2 and 3) and demand elasticities that vary across deciles (columns 4 through 6). Columns 7 through 9 use estimates from the CE regression, with elasticities that vary across deciles.

Table 4 shows tax incidence in two ways. First, it shows the proportion of spending on miles tax after responding to the tax as a percentage of total expenditures. All simulations show that spending on miles tax as a percentage of total expenditures increases over the lowest deciles, and decreases over the top deciles. Taxes on miles or on gasoline are progressive across the lower-income households, and regressive across higher-income households.

The Suits Index can be used to compare the tax's regressivity for each of the three sets of elasticities used in Table 4.[34] All Suits Indices calculated here are negative; the tax on *VMT* is regressive overall. When demand elasticities are allowed to vary across deciles, Suits Indices get closer to zero; the tax is less regressive. This can be seen by comparing the constant demand elasticity Suits Index under columns 2 and 3, –0.153, with the Index under columns 5 and 6, –0.142, which uses the same regression results but allows elasticities to vary across deciles. The greater degree of price-responsiveness on the part of low-income households enhances the degree of progressivity in the poorest deciles and mitigates the regressivity in the upper deciles.

To see how controlling for the endogeneity of vehicle choice affects distributional results, compare the Suits Index under columns 5 and 6 with the Suits Index under columns 8 and 9. Use of estimates from the CE regressions yield a Suits Index of –0.139, which is less regressive than the Suits Index based on OLS2 estimates do not control for the endogeneity of vehicle choice.[35]

---

simulation does not use the nested logit results to estimate long-run responses. The discrete choice results themselves do show, however, that the higher a vehicle's operating cost per mile, the less likely a household will own that vehicle. If poorer households are also more responsive to the operating cost per mile when making their vehicle choices, and substitute towards more fuel-efficient vehicles more readily than high-income households, they might reduce gasoline consumption by more than wealthy households, but not miles consumption. In this case, the incidence of a gas tax would be less regressive than a miles tax.

[34] The Suits Index is similar to the Gini coefficient. It is bounded by –1 and 1. A proportional tax has a Suits Index equal to zero, progressive tax has a value greater than zero, a regressive tax has a value less than zero. For details see Suits (1977).

[35] These results are less regressive than Sevigny's (1998) result, using annual income, –0.226, and about equally as regressive as that in Walls and Hanson (1999), also using annual income.

Second, Table 4 shows the change in consumer surplus as a percentage of total expenditures. Since these simulations measure short-run responses and do not allow for households to change the number or type of vehicle they own in response to higher operating costs, the consumer surplus measure is a *conditional* consumer surplus, conditional on the vehicle bundle currently owned by the household. Since low-income households are more price-responsive than high-income households, we should expect the incidence measure based on tax payments alone to be biased toward progressivity. The middle and right-hand sets of columns confirms this; the Suits Index equivalent for consumer surplus are a more regressive –0.148 and –0.147 respectively.

Table 5 considers tax burdens for vehicle owners only. Among those households that would actually pay the tax on *VMT*, the tax is regressive over all deciles. The Suits Index equivalent for consumer surplus, –0.206, reflects this greater degree of regressivity among vehicle owners.

b. Subsidies to Newness or Taxes on Size

Since my analysis of gasoline or miles taxes considers short-run responses, where households do not respond to taxes by changing the number or type of vehicle they own, I consider subsidies to newness or taxes on size in the same context. The discussion below might be best thought of as an analysis of the likely effects of a vehicle registration fee based on vehicle newness or size, before households adjust to the policy by changing the type of vehicles they own.[36]

Results from the nested logit show that wealthy households are more likely to own newer vehicles and may benefit the most from a direct subsidy applied to new cars. To determine whether a newness subsidy would indeed be regressive, I correlate newness with total expenditures across deciles and calculate the Suits Index for any arbitrary subsidy to newness. The Index, for all households, is –0.34, which indicates that a subsidy to

---

[36] Neither the results from the nested logit nor the *VMT* regression can be used to allow for behavioral responses to analyze incidence of these vehicle taxes. To do this, one would need to estimate elasticities with respect to newness and size prices. An appropriate extension to this paper would be to first use hedonic regression analysis to estimate such prices for each household, include these prices in the discrete choice estimation, and estimate newness and size elasticities for different income groups.

newer cars would be significantly more regressive than a miles tax. Accelerated vehicle retirement programs, however, by paying poorer households to dispose of older vehicles, would be progressive.

Policies such as CAFE standards and gas guzzler taxes increase the relative price of new vehicles that are large (Goldberg (1998)). The discrete choice estimates indicate that since households that purchase large new cars have more income, these implicit *size* taxes on *new* vehicles may be progressive. On the other hand, wealthy households that own 1980s-vintage vehicles tend to own smaller cars.[37] Vehicle registration fees apply to vehicles that have already been purchased. If these fees were made higher for older, bigger cars, to reflect the fact that such vehicles pollute more per mile, the discrete choice estimates indicate that the burden may fall most heavily on middle-income households and be regressive across the upper half of the income distribution.

Scrutiny of the likely burdens across deciles, however, reveals that in the short-run a size tax on new vehicles would actually be even more regressive than a size tax on older vehicles. Because households in the upper half of the income distribution are more likely to own larger new cars, they would spend more on size taxes than poor households. Wealthy owners of 1990s vehicles, however, have much higher incomes than poor owners of these new vehicles. So, size tax payments as a proportion of expenditures are lower for them than poor households. And, the income distribution for owners of 1990s vehicles is more unequal than the income distribution for owners of 1980s vehicles. The Suits Index for a size tax on new 1990s vehicles is –.30, while the Suits Index for a size tax on 1980s vehicles is –.29.

c. Implications for the Incidence of Emissions per Mile Standards

Aside from gasoline taxes, emissions per mile standards are the main vehicle emissions policies used in the United States. These standards require car manufacturers to certify that their vehicles' emissions of non-methane organic gases, carbon monoxide, particulate matter, and oxides of nitrogen (all local pollutants) fall below specified limits.

[37] A referee suggests that this apparent change in behavior on the part of wealthy households may be explained by the fact that in the 1980s engine size correlated much better with overall car size than in the 1990s. The idea is that wealthy households have consistently wanted large cars with small engines but were unable to buy such vehicles until the 1990s.

Because the U.S. government has made these standards more stringent over time, vehicle manufacturers spend more on pollution control equipment for newer models (Berry et al., 1996). And, because larger cars have lower fuel efficiencies and thus higher emissions per mile, vehicle manufacturers must install more pollution control equipment on larger cars. So newer, larger cars are made more expensive by emissions per mile standards. To the extent that increases over time in standard stringency increase the price of newer cars, emissions per mile standards are likely to be progressive. On the other hand, to the extent that larger cars are made more expensive, the standards are likely to be regressive.

IV. Conclusion

This paper estimates a model of the discrete choice of vehicle bundle and the continuous choice of vehicle-miles-traveled. Since both of these choices are endogenous, I use exogenously determined estimates of a household's typical miles-driven for the vehicle choice model, and then use predicted probabilities of vehicle bundle-choice in addition to vehicle-bundle-choice indicator variables in the estimation of the demand for miles. I use data on over 7,000 households from the 1997 Consumer Expenditure Survey, combined with fuel efficiencies estimated using data from the California Air Resources Board, and state-level gas prices from the ACCRA cost of living indexes.

By dividing vehicle choices into 18 bundles, and using nested logit, I isolate the effects of income and household characteristics on the choice of vehicle number, engine size, and vintage. Estimation of the vehicle choice model, however, is limited by the data. While the CEX contains excellent data on expenditures and reasonably detailed information on vehicles, it does not contain many of the attributes that affect vehicle choice. To capture the effects of attributes such as styling or legroom on vehicle choice probabilities, and thus demand for miles, one would have to combine the CEX data with information from other sources. In addition, a model that includes mode and location choice would provide insight into ways in which households respond to vehicle pollution policies in the long run. For example, poor households might be more likely to respond to taxes on miles or gasoline by taking public transportation.

This paper uses a partial equilibrium model, holding producer behavior fixed. Producers may, however, respond to increases in the cost of polluting cars, and pass along some of this cost to their employees. A general equilibrium model, using appropriate elasticities of supply and substitution, would provide more evidence on the overall incidence of vehicle pollution control policies. Such a model might also determine whether carmakers introduce cleaner vehicles in response to the policies, and trace out the long-run adjustment of household behavior to the introduction of these new vehicles.

The gasoline tax's regressivity is often cited as one of the strongest arguments against increasing this tax. This paper finds that a tax on miles or gasoline is regressive only across upper income groups. This is because many lower income households do not own any vehicles and, in response to a price increase, poorer households reduce miles by more than do wealthy households. The greater degree of price-responsiveness on the part of low-income households enhances the degree of progressivity in the lower-income groups and mitigates the degree of regressivity in the upper-income groups.

While policy makers remain averse to raising gas tax rates, they have shown a greater willingness to experiment with policies that implicitly tax large vehicles or subsidize new vehicles. On distributional grounds, however, these policies appear to be less attractive than gasoline taxes. Policies that implicitly tax engine size such as the gas-guzzler tax are likely to be significantly more regressive than taxes on miles or on gasoline. The distributional implications of subsidies to new cars depend on how the subsidy is implemented. Direct subsidies to new cars would be significantly more regressive than gasoline taxes, while accelerated vehicle retirement programs are progressive.

Acknowledgements

For their helpful comments, I thank Dietrich Earnhart, Don Fullerton, Jim Gale, Larry Goulder, Kevin Rask, Raymond Robertson, Dan Slesnick, Richard Wall, Pete Wilcoxen, Paul Wilson, Ann Wolverton, and three anonymous referees. For providing data, I thank the California Air Resources Board, Satya Devesh, Mary Hostak, and Raphael Susnowitz. Support for this project was provided in part by the Public Policy Institute of California (PPIC). Any opinions expressed here are mine and not those of the PPIC.

References

Alberini, A., Harrington, W., and McConnell, V., 1996. Estimating an Emissions Supply Function from Accelerated Vehicle Retirement Programs. The Review of Economics and Statistics 78 (2), 251-263.

Archibald, R., Gillingham, R., 1981. A Decomposition of the Price and Income Elasticities of the Consumer Demand for Gasoline. Southern Economic Journal 47 (4), 1021-1031.

Baumol, W.J., Oates, W.E., 1988. The Theory of Environmental Policy. Cambridge University Press, Cambridge, UK.

Berkovec, J., 1985. New Car Sales and Used Car Stocks: A Model of the Automobile Market. Rand Journal of Economics 16 (2), 195-214.

Berkovec, J., Rust, J., 1985. A Nested Logit Model of Automobile Holdings for One Vehicle Households. Transportation Research 19B (4), 275-285.

Berkowitz, M.K., Gallini, N.T., Miller, E.J., Wolfe, R.A., 1990. Disaggregate Analysis of the Demand for Gasoline. Canadian Journal of Economics 23 (2), 253-275.

Berry, S. Kortum, S., Pakes, A., 1996. Environmental Change and Hedonic Cost Functions for Automobiles. Proceedings of the National Academy of Sciences 93 (23), 12731-12738.

Brooks, N., Sethi, R., 1997. The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics. Journal of Environmental Economics and Management 32 (2), 233-250.

Dahl, C., 1986. Gasoline Demand Survey. The Energy Journal 7 (1), 67-82.

Dahl, C., Sterner, T, 1991. Analyzing Gasoline Demand Elasticities: A Survey. Energy Economics 13 (3), 203-210.

De Borger, B., 2001. Discrete Choice Models and Optimal Two-part Tariffs in the Presence of Externalities: Optimal Taxation of Cars. Forthcoming, Regional Science and Urban Economics.

De Jong, G.C., 1990. An Indirect Utility Model of Car Ownership and Private Car Use. European Economic Review 34, 971-985.

Devarajan, S., Eskeland G., 1996. Taxing Bads by Taxing Goods: Pollution Control with Presumptive Charges. The World Bank, Washington, DC.

Dubin, J.A., McFadden, D.L., 1984. An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. Econometrica 52 (2), 345-362.

Espey, M., 1996. Explaining the Variation in Elasticity Estimates of Gasoline Demand in the United States: A Meta-Analysis. The Energy Journal 17 (3), 49-60.

Fullerton, D., West, S., 2000. Tax and Subsidy Combinations for the Control of Car Pollution. NBER Working Paper No. 7774.

Goldberg, P., 1998. Effects of the Corporate Average Fuel Efficiency Standards in the U.S. Journal of Industrial Economics 46 (1), 1-33.

Greene, D.L., Hu, P.S., 1985. The Influence of the Price of Gasoline on Vehicle Use in Multi-vehicle Households. Transportation Research Record 988, 19-24.

Harrington, W., 1997. Fuel Economy and Motor Vehicle Emissions. Journal of Environmental Economics and Management 33 (3), 240-252.

Hausman, J., 1978. Specification Tests in Econometrics. Econometrica 46 (6), 1251-1271.

Hausman, J., 1981. Exact Consumer's Surplus and Deadweight Loss. American Economic Review 71 (4), 662-676.

Hensher, D.A., Smith, N.C., Milthorpe, F.W., Barnard, P., 1992. Dimensions of Automobile Demand: A Longitudinal Study of Household Automobile Ownership and Use. North-Holland, Amsterdam.

Innes, R., 1996. Regulating Automobile Pollution Under Certainty, Competition, and Imperfect Information. Journal of Environmental Economics and Management 31 (2), 219-239.

Kayser, H. 2000. Gasoline Demand and Car Choice: Estimating Gasoline Demand Using Household Information. Energy Economics 22 (3), 331-348.

Kohn, R.E., 1996. An Additive Tax and Subsidy for Controlling Automobile Pollution. Applied Economics Letters 3 (7), 459-462.

Mannering, F., Winston, C., 1985. A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. Rand Journal of Economics 16 (2), 213-236.

McCarthy, P.S., 1996. Market Price and Income Elasticities of New Vehicle Holdings. Review of Economics and Statistics 78 (3), 543-547.

Metcalf, G.E., 1999. A Distributional Analysis of Green Tax Reforms. National Tax Journal 52 (4), 355-681.

Oak Ridge National Laboratory (ORNL), Davis, S., 1998. Transportation Energy Data Book, 18th ed. Oak Ridge National Laboratory, Oak Ridge, TN.

Oak Ridge National Laboratory (ORNL), Davis, S., 2000. Transportation Energy Data Book, 20th ed. Oak Ridge National Laboratory, Oak Ridge, TN.

Parry, I., Small, K.A., 2002. Does Britain or America Have the Right Gasoline Tax? Working paper, Resources for the Future and University of California-Irvine.

Plaut, P., 1998. The Comparison and Ranking of Policies for Abating Mobile-Source Emissions. Transportation Research D 3 (4), 193-205.

Poterba, J.M., 1991. Is the Gasoline Tax Regressive? In: Bradford, D. (Ed.), Tax Policy and the Economy 5. MIT Press, Boston, pp. 145-164.

Sevigny, M., 1998. Taxing Automobile Emissions for Pollution Control. Edward Elgar Publishing Ltd., Cheltenham, UK and Northhampton, MA.

Sipes, K.N., Mendelsohn, R., 2001. The Effectiveness of Gasoline Taxation to Manage Air Pollution. Ecological Economics 36 (2), 299-309.

Slesnick, D.T., 2001. Consumption and Social Welfare: Living Standards and Their Distribution in the United States. Cambridge University Press, Cambridge, UK and New York.

Small, K.A., 1992. Urban Transportation Economics. Harwood Academic Publishers, Chur, Switzerland.

Small, K.A., Kazimi, C., 1995. On the Costs of Air Pollution from Motor Vehicles. Journal of Transport Economics and Policy 29 (1), 7-32.

Suits, D.B., 1977. Measurement of Tax Progressivity. American Economic Review 67 (4) , 747-752.

Train, K., 1986. Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand. The MIT Press, Cambridge, MA.

U.S. FHWA, 2000. Addendum to the 1997 Federal Highway Cost Allocation Study Final Report. U.S. Federal Highway Administration, Washington, DC.

Walls, M., Hanson, J., 1999. Distributional Aspects of an Environmental Tax Shift: The Case of Motor Vehicle Emissions Taxes. National Tax Journal 52 (1), 53-65.

Walls, M.A., Krupnick, A.J., Hood, H.C., 1994. Estimating the Demand for Vehicle-Miles Traveled Using Household Survey Data: Results from the 1990 Nationwide Transportation Survey. Discussion Paper 93-25 Rev. Resources for the Future, Washington, DC.

Warner, F., 1998. U.S. Truck Sales Reach Major Milestone. The Wall Street Journal (December 3), A2.

Table 1: Summary Statistics by Number of Vehicles

Household and Vehicle Characteristics[a]	**Number of Vehicles**			
	0	**1**	**2**	**All**
Number of households	1,730	3,181	2,162	7,073
Total quarterly expenditures	4,606	6,350	9,297	6,824
Household size	2.01	2.09	2.90	2.32
Number in household > 15 years old	1.43	1.55	2.10	1.69
Number of income earners	.81	1.01	1.58	1.14
% Household heads that are male	37.1	48.6	69.3	52.1
Age of household head	45.3	46.5	45.5	45.9
% Household heads that are white	69.5	81.4	85.8	79.9
% Household heads with education > high school	41.3	56.6	59.8	53.8
% Households in metro area with population > 4 million	38.5	28.8	27.5	30.8
% Households in Northeast	29.8	18.4	17.4	20.9
% Households in Midwest	23.1	23.7	24.2	23.7
% Households in South	27.1	34.0	36.7	33.1
% Households in West	20.0	23.9	21.6	22.3
% Home owners	25.7	48.3	72.2	50.1
Vehicle bundle purchase price (1997 $)	0	4,024	10,189	4,924
Operating cost per mile (p_b)[b]	0	.10	.10	.07
p_b*typical miles-driven (*TOPCOST*)[c]	0	252	315	210
Actual quarterly miles driven	0	2,945	4,525	2,707

[a] Mean values are given unless otherwise noted.
[b] The price per mile includes costs of gasoline, maintenance, and tires.
[c] Typical miles is an exogenous variable calculated using the following regression, where the dependent variable is the average quarterly miles driven in each vehicle bundle (standard errors in parentheses):

Miles driven = 2710.131 + .060*quarterly expenditure + 395.386*number HH members > 15 years old
(41.98) (.003) (21.04)

Table 2: Nested Logit Summary Results

Number of Vehicles Nest		
Variable	**Coefficient**	**Standard Error**
*Male Household Head*One Car*	0.331	0.202
Family Size One Car*	-0.005	0.356
*Own Home*One Car*	0.741	0.078
*Metro. Area Pop.> 4 million*One Car*	-0.492	0.425
*Number of Drivers*One Car*	-0.377	0.286
Number of Earners One Car*	0.237	0.062
Inclusive Value for One Car Vintage-Size	0.696	0.469
*Male Household Head*Two Car*	0.654	0.327
*Family Size*Two Car*	0.047	0.197
*Own Home*Two Car*	1.261	0.091
*Metro Area Pop.> 4 million*Two Car*	-0.724	0.478
*Number of Drivers*Two Car*	-0.337	0.412
*Number of Earners*Two Car*	0.570	0.070
Inclusive Value for Two Car Vintage-Size	1.436	0.511
Vintage and Engine Size Nest		
Variable	**Coefficient**	**Standard Error**
Capital Cost	-0.0002	0.00001
Total Operating Cost	0.002	0.0008
Price per Mile	-37.863	3.266
	Relationship to Vintage (+ indicates increase in likelihood of owning newer car)	**Relationship to Engine Size (+ indicates increase in likelihood of owning larger car)**
Quintile	+	– for 1980s, + for 1990s
Household Head's Education> High School	+	–
Male Household Head	+	+
Midwest	+	+
South	none	+
West	none	none
Family Size	none	none
Age	+	+
Number of Drivers	none	none
Metro Area Population > 4 million	none	none
White Household Head	none	– for 1980s, none for 1990s

Estimation using 7073 households. Log likelihood=-15249.662; χ^2 = 10387.87. The likelihood ratio test for nesting against the null hypothesis of nonnesting (inclusive value parameters set to 1) gives χ^2 = 216.71, which supports the use of nested logit.

Table 3: Results from *VMT* regressions, vehicle-owning households[a]

VMT minus typical miles is the dependent variable (robust standard errors in parentheses)

Variable	OLS with no choice indicators (OLS1)	OLS with choice indicators (OLS2)	Conditional Expectation (CE) Correction Method
Operating Cost Per Mile($)	-27,670.41 (4,845.68)	-24,932.58 (10,606.00)	-25,220.31 (10,590.92)
Income Net of Total Operating Costs($)	0.17 (0.07)	0.11 (0.07)	0.08 (0.07)
*Operating Costs*Net Income ($)*	-1.49 (0.70)	-1.14 (0.69)	-0.94 (0.68)
Vehicle Capital Cost ($)	0.04 (0.01)	0.18 (0.05)	0.13 (0.05)
Midwest	46.32 (105.99)	39.05 (111.02)	-106.56 (113.47)
South	204.00 (102.73)	199.25 (110.54)	-26.05 (117.86)
West	-36.58 (129.79)	17.52 (128.66)	-126.38 (134.98)
Male Head of Household	212.64 (72.00)	134.30 (70.71)	165.44 (70.59)
Head's Education More than High School	-47.80 (98.81)	-140.50 (99.65)	-360.28 (102.56)
White Head of Household	146.42 (92.16)	111.88 (89.43)	-144.78 (101.66)
Number of Income Earners	299.56 (73.45)	197.31 (74.57)	137.18 (74.31)
Family Size	127.01 (52.22)	145.19 (50.60)	15.64 (50.48)
Number of Drivers	-244.27 (92.14)	-369.73 (90.78)	-205.45 (88.76)
24< Age of Household Head < 45	215.46 (125.98)	108.20 (123.89)	-103.11 (131.94)
44< Age of Household Head < 65	58.98 (135.94)	-60.61 (134.47)	-331.85 (138.37)
64< Age of Household Head	-746.70 (159.15)	-887.11 (158.97)	-1,143.03 (162.03)
Metro Area Population > 4 million	312.68 (95.63)	344.25 (95.09)	532.33 (95.62)
Bias	. .	. .	-16.29 (2.93)
Constant	2,527.24 (489.08)	. .	. .
R^2	.079	.171	.175
Number of observations	5343	5343	5343

[a] Standard errors were computed using the Huber/White/sandwich estimator. Vehicle bundle choice indicators are included in the (CE) and (OLS2) regressions. *BIAS* is the term defined in equation (5).

Table 4: *VMT* Demand Elasticities and Tax Burdens by Decile, All Households[a]

	Distributional Effects Using OLS2 Estimates					Distributional Effects Using Conditional Expectation Correction (CE) Estimates		
	Constant Demand Elasticity[b]		Demand Elasticities Vary Across Deciles[c]			Demand Elasticities Vary Across Deciles[c]		
Decile	Tax/Income	Change in Consumer Surplus/ Income	Elasticity of Demand for *VMT* with respect to Operating Costs	Tax/Income	Change in Consumer Surplus/ Income	Elasticity of Demand for *VMT* with respect to Operating Costs	Tax/Income	Change in Consumer Surplus/ Income
1	0.78	0.88	-1.51	0.66	0.82	-1.51	0.66	0.82
2	0.81	0.91	-1.32	0.73	0.87	-1.31	0.73	0.87
3	0.87	0.98	-1.07	0.83	0.96	-1.06	0.83	0.96
4	0.87	0.98	-1.03	0.84	0.96	-1.01	0.84	0.97
5	0.86	0.97	-0.97	0.84	0.96	-0.95	0.85	0.96
6	0.84	0.95	-0.86	0.85	0.95	-0.84	0.85	0.95
7	0.80	0.91	-0.81	0.82	0.92	-0.78	0.83	0.92
8	0.75	0.85	-0.79	0.77	0.86	-0.75	0.78	0.86
9	0.59	0.67	-0.82	0.60	0.67	-0.78	0.61	0.67
10	0.38	0.43	-0.90	0.38	0.43	-0.83	0.39	0.44
	Suits Index = -0.153 Suits Index Equivalent for Consumer Surplus= -0.153			Suits Index = -0.142 Suits Index Equivalent for Consumer Surplus= -0.148			Suits Index = -0.139 Suits Index Equivalent for Consumer Surplus= -0.147	

[a] The tax per mile is set to equal estimated costs of local air pollution, $0.02 (see Parry and Small (2002)) and is imposed on top of existing gas taxes. Miles after tax are calculated using estimated elasticities, miles before tax, and the midpoint formula.
[b] The elasticity of demand for *VMT* using OLS2 estimates and calculated at sample means is -.89.
[c] Demand elasticities are calculated at the mean operating cost per mile, miles, and total expenditures, by decile.

Table 5: *VMT* Demand Elasticities and Tax Burdens by Decile, Vehicle Owners Only[a]

Distributional Effects Using Conditional Expectation Correction (CE) Estimates (Demand Elasticities Vary Across Deciles[b])		
Elasticity of Demand for *VMT* with respect to Operating Costs	Tax/Income	Change in Consumer Surplus/ Income
-1.46	1.29	1.58
-1.09	1.23	1.43
-1.02	1.10	1.26
-0.94	1.03	1.17
-0.86	1.00	1.12
-0.79	0.97	1.07
-0.78	0.87	0.97
-0.77	0.75	0.83
-0.77	0.64	0.71
-0.84	0.41	0.46
Suits Index = -0.198 Suits Index Equivalent for Consumer Surplus= -0.206		

[a] The tax per mile is set to equal estimated costs of local air pollution, $0.02 (see Parry and Small (2002)) and is imposed on top of existing gas taxes. Miles after tax are calculated using estimated elasticities, miles before tax, and the midpoint formula.
[b] Demand elasticities are calculated at the mean operating cost per mile, miles, and total expenditures, by decile.

Appendix

Table A-1: Vehicle Bundle Descriptions and Statistics

Bundle Number	Bundle Description			Frequency	Percent of total
	Number of vehicles	Engine Size	Vehicle Age		
1	1	small	old	37	.52
2	1	small	newer	582	8.23
3	1	small	newest	738	10.43
4	1	medium	old	54	.76
5	1	medium	newer	529	7.48
6	1	medium	newest	730	10.32
7	1	large	old	102	1.44
8	1	large	newer	243	3.44
9	1	large	newest	166	2.35
10	2	small, medium	old	5	.07
11	2	small	newer	112	1.58
12	2	small	newest	344	4.86
13	2	medium	newer	219	3.10
14	2	medium	newest	821	11.61
15	2	large	old	13	.18
16	2	large	newer	228	3.22
17	2	large	newest	420	5.94
18	0	-	-	1,730	24.46
			Total	7,073	100.00

Vehicle age categories are all pre-1980 (old), at least one 1980 to 1989 and no 1990 and newer (newer), or at least one 1990 and newer (newest). For engine size, the three categories are all 4-cylinder (small), at least one 6-cylinder and no 8-cylinder (medium), or at least one 8-cylinder (large).

Bundle 10 contains the following combinations: two 4-cylinder, 1970s-vintage; one 4-cylinder. 1970s-vintage and one 6-cylinder 1970s-vintage; and two 6-cylinder 1970s-vintage.

Table A-2: Summary Statistics by Vehicle Engine Size (Households with Vehicles)

Household and Vehicle Characteristics[a]	**Size of Vehicles in Bundle**			
	Small: All 4 cylinder	**Medium: At least one 6 cylinder, no 8**	**Large: At least one 8 cylinder**	**All**
Number of households	1,818	2,353	1,172	5,343
Total quarterly expenditures	6,879	7,986	7,681	7,542
Household size	2.21	2.50	2.59	2.42
Number in household > 15 years old	1.64	1.81	1.90	1.78
Number of income earners	1.23	1.27	1.23	1.24
% Household heads that are male	50.8	57.4	65.9	57.0
Age of household head	41.8	47.1	50.8	46.1
% Household heads that are white	81.2	84.2	84.3	83.2
% Household heads with education > high school	65.0	57.5	47.7	57.9
% Households in metro area with population > 4 million	30.6	28.2	24.7	28.3
% Households in Northeast	18.4	19.5	14.5	18.0
% Households in Midwest	21.4	25.9	23.6	23.9
% Households in South	33.4	33.0	41.9	35.1
% Households in West	26.8	21.5	20.0	23.0
% Home owners	44.7	63.2	68.1	58.0
Vehicle bundle purchase price (1997 $)	985	4,671	18,811	6,519
Operating cost per mile (p_b) [b]	.09	.10	.12	.10
p_b*typical miles-driven (*TOPCOST*)[c]	230	289	330	278
Actual quarterly miles driven	3,730	3,583	3,360	3,584

[a] Mean values are given unless otherwise noted.
[b] The price per mile includes costs of gasoline, maintenance, and tires.
[c] Typical miles is an exogenous variable calculated using the following regression, where the dependent variable is the average quarterly miles driven in each vehicle bundle (standard errors in parentheses):

Miles driven = 2710.131 + .060*quarterly expenditure + 395.386*number HH members > 15 years old
(41.98) (.003) (21.04)

Table A-3: Summary Statistics by Vehicle Vintage (Households with Vehicles)

Household and Vehicle Characteristics[a]	**Age of Vehicles in Bundle**			
	Old: All 1979 or older	**Newer: At least one 1980s, no 1990s**	**Newest: At least one 1990s**	**All**
Number of households	211	1,913	3,219	5,343
Total quarterly expenditures	4,691	5,873	8,721	7,542
Household size	2.16	2.44	2.42	2.42
Number in household > 15 years old	1.60	1.73	1.81	1.78
Number of income earners	0.90	1.14	1.33	1.24
% Household heads that are male	52.1	53.7	59.2	57.0
Age of household head	52.3	46.3	45.6	46.1
% Household heads that are white	82.9	82.9	83.4	83.2
% Household heads with education > high school	37.4	48.1	65.1	57.9
% Households in metro area with population > 4 million	23.2	26.8	29.5	28.3
% Households in Northeast	11.4	18.0	18.5	18.0
% Households in Midwest	19.0	22.9	24.8	23.9
% Households in South	32.7	32.7	36.7	35.1
% Households in West	37.0	26.4	20.0	23.0
% Home owners	49.3	48.6	64.1	58.0
Vehicle bundle purchase price (1997 $)	7,584	6,881	6,233	6,519
Operating cost per mile (p_b)[b]	.13	.10	.10	.10
p_b*typical miles-driven (*TOPCOST*)[c]	331	265	282	278
Actual quarterly miles driven	1,804	2,926	4,092	3,584

[a] Mean values are given unless otherwise noted.
[b] The price per mile includes costs of gasoline, maintenance, and tires.
[c] Typical miles is an exogenous variable calculated using the following regression, where the dependent variable is the average quarterly miles driven in each vehicle bundle (standard errors in parentheses):

$$\text{Miles driven} = \underset{(41.98)}{2710.131} + \underset{(.003)}{.060}\text{*quarterly expenditure} + \underset{(21.04)}{395.386}\text{*number HH members} > 15 \text{ years old}$$

Table A-4: Variables in Nests

Variable Name	Variable Definition
Number of Vehicles (0, 1, or 2)	
ONE	Equals one for one-car bundles
TWO	Equals one for two-car bundles
MALE	Equals one if head of household is male
FAMSIZE	Number of household members
OWNHOME	Equals one if household owns home
METRO	Equals one if household lives in metro area with population>4 million
DRIVERS	Number of household members older than 15 years
EARNERS	Number of income earners in household
INVONE	Inclusive value term for size-vintage choice, one-car households
INVTWO	Inclusive value term for size-vintage choice, two-car households
Vintage and Engine Size Nest	
BUNx	Bundle indicator variables (x is the bundle number 1 through 18)
CAPCOST	Bundle's average purchase price
TOPCOST	Total fuel cost (price per mile*typical miles driven)
PMILE	Price per mile (gas price/miles per gallon)
QUINT1	Equals one if household expenditure is in 20th percentile or below*
QUINT2	Equals one if household expenditure is in 21th to 40th percentile
QUINT3	Equals one if household expenditure is in 41th to 60th percentile
QUINT4	Equals one if household expenditure is in 61th to 80th percentile
QUINT5	Equals one if household expenditure is above the 80th percentile
EDUCATION	Equals one if head of household has more than high school education
MALE	Equals one if head of household is male
NORTHEAST	Equals one if household lives in the Northeast*
MIDWEST	Equals one if household lives in the Midwest
SOUTH	Equals one if household lives in the South
WEST	Equals one if household lives in the West
FAMSIZE	Number of household members
AGE1	Equals one if age of household head < 25*
AGE2	Equals one if 24 < age of household head < 45
AGE3	Equals one if 44 < age of household head < 65
AGE4	Equals one if age of household head > 64
DRIVERS	Number of household members older than 15 years
WHITE	Equals one if head of household is white
METRO	Equals one if household lives in metro area with population>4 million

* This is the excluded category in the estimation.

Table A-5: Nested Logit Estimation: Full Results

Number of Vehicles			
Variable	**Coefficient**	**Standard Error**	**z-statistic***
*MALE*ONE*	0.337	0.191	1.77
*FAMSIZE*ONE*	-0.007	0.097	-0.07
*OWNHOME*ONE*	0.815	0.077	10.62
*METRO*ONE*	-0.531	0.219	-2.43
*DRIVERS*ONE*	-0.280	0.196	-1.43
*EARNERS*ONE*	0.264	0.059	4.43
*MALE*TWO*	0.508	0.261	1.94
*FAMSIZE*TWO*	-0.073	0.123	-0.59
*OWNHOME*TWO*	1.47	0.090	16.33
*METRO*TWO*	-0.308	0.267	-1.15
*DRIVERS*TWO*	-0.117	0.233	-0.50
*EARNERS*TWO*	0.617	0.069	8.98
*INV*ONE*	0.556	0.068	8.12
*INV*TWO*	1.431	0.141	10.17

Vintage and Engine Size			
Variable	**Coefficient**	**Standard Error**	**z-statistic**
CAPCOST	-0.0002	0.00001	-12.21
TOPCOST	0.002	0.0008	2.26
PMILE	-37.86	3.27	-11.59
*QUINT2*BUN2*	0.991	0.204	4.85
*QUINT2*BUN3*	1.788	0.223	8.01
*QUINT2*BUN4*	0.918	0.354	2.59
*QUINT2*BUN5*	0.721	0.207	3.48
*QUINT2*BUN6*	1.342	0.213	6.30
*QUINT2*BUN7*	0.634	0.298	2.12
*QUINT2*BUN8*	0.800	0.251	3.18
*QUINT2*BUN9*	1.364	0.353	3.87
*QUINT2*BUN12*	0.170	0.276	0.62
*QUINT2*BUN13*	0.579	0.306	1.90
*QUINT2*BUN14*	1.157	0.205	5.64
*QUINT2*BUN15*	1.270	0.905	1.40
*QUINT2*BUN16*	0.430	0.260	1.65
*QUINT2*BUN17*	1.691	0.346	4.88
*QUINT3*BUN2*	1.429	0.273	5.24
*QUINT3*BUN3*	2.693	0.284	9.47
*QUINT3*BUN4*	0.939	0.474	1.98
*QUINT3*BUN5*	1.441	0.272	5.30
*QUINT3*BUN6*	2.207	0.275	8.01
*QUINT3*BUN7*	0.815	0.388	2.10
*QUINT3*BUN8*	1.716	0.307	5.58
*QUINT3*BUN9*	2.858	0.375	7.62
*QUINT3*BUN12*	0.956	0.255	3.75
*QUINT3*BUN13*	1.207	0.305	3.96
*QUINT3*BUN14*	1.787	0.211	8.46
*QUINT3*BUN15*	1.411	0.937	1.51
*QUINT3*BUN16*	0.792	0.273	2.90
*QUINT3*BUN17*	2.178	0.355	6.14
*QUINT4*BUN2*	1.309	0.297	4.41
*QUINT4*BUN3*	2.614	0.303	8.62
*QUINT4*BUN4*	0.147	0.711	0.21
*QUINT4*BUN5*	1.485	0.295	5.03
*QUINT4*BUN6*	2.595	0.291	8.91
*QUINT4*BUN7*	0.676	0.450	1.50
*QUINT4*BUN8*	1.500	0.341	4.40
*QUINT4*BUN9*	2.916	0.401	7.27
*QUINT4*BUN12*	1.352	0.262	5.17
*QUINT4*BUN13*	1.082	0.322	3.36
*QUINT4*BUN14*	2.212	0.222	9.95
*QUINT4*BUN15*	0.631	1.109	0.57
*QUINT4*BUN16*	0.548	0.296	1.85
*QUINT4*BUN17*	2.534	0.363	6.97
*QUINT5*BUN2*	0.511	0.320	1.60
*QUINT5*BUN3*	2.216	0.318	6.98
*QUINT5*BUN4*	0.219	0.712	0.31
*QUINT5*BUN5*	0.631	0.319	1.97
*QUINT5*BUN6*	2.395	0.303	7.91
*QUINT5*BUN7*	-0.022	0.538	-0.04
*QUINT5*BUN8*	0.663	0.384	1.73
*QUINT5*BUN9*	2.925	0.412	7.10
*QUINT5*BUN12*	1.278	0.283	4.52
*QUINT5*BUN13*	0.577	0.349	1.65
*QUINT5*BUN14*	2.192	0.243	9.03
*QUINT5*BUN15*	0.010	1.349	0.01
*QUINT5*BUN16*	0.070	0.322	0.22
*QUINT5*BUN17*	2.623	0.374	7.01
*ED*BUN2*	0.696	0.153	4.55
*ED*BUN3*	1.129	0.156	7.22
*ED*BUN4*	-0.026	0.309	-0.08
*ED*BUN5*	0.396	0.154	2.57
*ED*BUN6*	0.714	0.152	4.69
*ED*BUN7*	0.036	0.254	0.14
*ED*BUN8*	0.337	0.189	1.78
*ED*BUN9*	0.535	0.214	2.50
*ED*BUN12*	0.700	0.130	5.37
*ED*BUN13*	-0.394	0.155	-2.54
*ED*BUN14*	0.395	0.087	4.51
*ED*BUN15*	-1.164	0.680	-1.71
*ED*BUN16*	-0.241	0.150	-1.60

*ED*BUN17*	-0.014	0.116	-0.12
*MALE*BUN2*	-0.212	0.337	-0.63
*MALE*BUN3*	-0.375	0.337	-1.11
*MALE*BUN4*	-0.224	0.431	-0.52
*MALE*BUN5*	-0.190	0.338	-0.56
*MALE*BUN6*	-0.034	0.336	-0.10
*MALE*BUN7*	0.177	0.385	0.46
*MALE*BUN8*	0.251	0.353	0.71
*MALE*BUN9*	0.333	0.368	0.91
*MALE*BUN12*	0.130	0.210	0.62
*MALE*BUN13*	0.108	0.233	0.46
*MALE*BUN14*	0.039	0.192	0.20
*MALE*BUN15*	0.312	0.600	0.52
*MALE*BUN16*	0.416	0.236	1.76
*MALE*BUN17*	0.426	0.212	2.01
*MIDWEST*BUN2*	0.461	0.199	2.32
*MIDWEST*BUN3*	0.707	0.202	3.51
*MIDWEST*BUN4*	-0.183	0.421	-0.43
*MIDWEST*BUN5*	0.543	0.197	2.75
*MIDWEST*BUN6*	0.651	0.193	3.38
*MIDWEST*BUN7*	0.485	0.337	1.44
*MIDWEST*BUN8*	0.689	0.250	2.76
*MIDWEST*BUN9*	1.002	0.294	3.41
*MIDWEST*BUN12*	0.023	0.175	0.13
*MIDWEST*BUN13*	0.349	0.227	1.54
*MIDWEST*BUN14*	0.108	0.114	0.95
*MIDWEST*BUN15*	0.043	0.978	0.04
*MIDWEST*BUN16*	0.333	0.228	1.46
*MIDWEST*BUN17*	0.597	0.184	3.26
*SOUTH*BUN2*	0.589	0.199	2.96
*SOUTH*BUN3*	1.088	0.199	5.47
*SOUTH*BUN4*	0.019	0.392	0.05
*SOUTH*BUN5*	0.635	0.197	3.22
*SOUTH*BUN6*	0.828	0.193	4.28
*SOUTH*BUN7*	0.760	0.320	2.38
*SOUTH*BUN8*	1.119	0.241	4.64
*SOUTH*BUN9*	1.314	0.286	4.59
*SOUTH*BUN12*	0.370	0.157	2.36
*SOUTH*BUN13*	0.357	0.221	1.61
*SOUTH*BUN14*	0.028	0.114	0.24
*SOUTH*BUN15*	0.987	0.791	1.25
*SOUTH*BUN16*	0.691	0.212	3.26
*SOUTH*BUN17*	0.993	0.175	5.67
*WEST*BUN2*	0.993	0.189	5.25
*WEST*BUN3*	0.812	0.196	4.14
*WEST*BUN4*	0.863	0.363	2.38
*WEST*BUN5*	0.796	0.193	4.12

*WEST*BUN6*	0.473	0.192	2.46
*WEST*BUN7*	1.208	0.314	3.85
*WEST*BUN8*	0.443	0.265	1.67
*WEST*BUN9*	0.805	0.302	2.67
*WEST*BUN12*	0.334	0.169	1.98
*WEST*BUN13*	0.883	0.216	4.09
*WEST*BUN14*	-0.053	0.121	-0.44
*WEST*BUN15*	0.819	0.907	0.90
*WEST*BUN16*	0.722	0.225	3.21
*WEST*BUN17*	0.689	0.187	3.68
*FAMSIZE*BUN2*	-0.031	0.176	-0.18
*FAMSIZE*BUN3*	-0.261	0.177	-1.47
*FAMSIZE*BUN4*	-0.012	0.243	-0.05
*FAMSIZE*BUN5*	0.076	0.176	0.43
*FAMSIZE*BUN6*	-0.118	0.176	-0.67
*FAMSIZE*BUN7*	0.138	0.202	0.68
*FAMSIZE*BUN8*	0.135	0.184	0.73
*FAMSIZE*BUN9*	0.080	0.194	0.41
*FAMSIZE*BUN12*	-0.167	0.104	-1.61
*FAMSIZE*BUN13*	0.254	0.105	2.43
*FAMSIZE*BUN14*	0.026	0.092	0.28
*FAMSIZE*BUN15*	0.158	0.260	0.61
*FAMSIZE*BUN16*	0.169	0.107	1.59
*FAMSIZE*BUN17*	0.062	0.100	0.62
*AGE2*BUN2*	0.606	0.202	3.00
*AGE2*BUN3*	0.741	0.208	3.56
*AGE2*BUN4*	-0.460	0.427	-1.08
*AGE2*BUN5*	0.556	0.208	2.67
*AGE2*BUN6*	0.855	0.215	3.98
*AGE2*BUN7*	0.382	0.370	1.03
*AGE2*BUN8*	0.831	0.294	2.82
*AGE2*BUN9*	0.602	0.359	1.68
*AGE2*BUN12*	-0.069	0.189	-0.36
*AGE2*BUN13*	1.125	0.345	3.26
*AGE2*BUN14*	0.301	0.164	1.83
*AGE2*BUN15*	-0.152	0.882	-0.17
*AGE2*BUN16*	1.461	0.347	4.21
*AGE2*BUN17*	1.398	0.360	3.88
*AGE3*BUN2*	0.313	0.232	1.35
*AGE3*BUN3*	0.319	0.237	1.35
*AGE3*BUN4*	0.187	0.414	0.45
*AGE3*BUN5*	0.794	0.230	3.45
*AGE3*BUN6*	0.949	0.238	3.99
*AGE3*BUN7*	0.997	0.373	2.68
*AGE3*BUN8*	1.345	0.309	4.36
*AGE3*BUN9*	1.054	0.377	2.80
*AGE3*BUN12*	-0.519	0.211	-2.46

*AGE3*BUN13*	1.227	0.354	3.47
*AGE3*BUN14*	0.365	0.175	2.09
*AGE3*BUN15*	0.276	0.879	0.31
*AGE3*BUN16*	1.708	0.350	4.88
*AGE3*BUN17*	1.763	0.365	4.83
*AGE4*BUN2*	0.265	0.246	1.08
*AGE4*BUN3*	0.235	0.258	0.91
*AGE4*BUN4*	0.097	0.408	0.24
*AGE4*BUN5*	0.742	0.243	3.06
*AGE4*BUN6*	1.338	0.249	5.37
*AGE4*BUN7*	1.330	0.359	3.70
*AGE4*BUN8*	1.770	0.310	5.71
*AGE4*BUN9*	1.854	0.374	4.95
*AGE4*BUN12*	-0.852	0.261	-3.26
*AGE4*BUN13*	1.135	0.362	3.14
*AGE4*BUN14*	0.456	0.188	2.43
*AGE4*BUN15*	-0.357	1.012	-0.35
*AGE4*BUN16*	1.447	0.357	4.05
*AGE4*BUN17*	1.994	0.369	5.41
*DRIVERS*BUN2*	0.260	0.334	0.78
*DRIVERS*BUN3*	0.332	0.333	1.00
*DRIVERS*BUN4*	-0.291	0.463	-0.63
*DRIVERS*BUN5*	0.179	0.334	0.53
*DRIVERS*BUN6*	0.166	0.333	0.50
*DRIVERS*BUN7*	0.108	0.381	0.28
*DRIVERS*BUN8*	0.228	0.347	0.66
*DRIVERS*BUN9*	-0.086	0.367	-0.24
*DRIVERS*BUN12*	0.469	0.173	2.71
*DRIVERS*BUN13*	0.005	0.182	0.03
*DRIVERS*BUN14*	0.260	0.158	1.65
*DRIVERS*BUN15*	-0.255	0.458	-0.56
*DRIVERS*BUN16*	0.042	0.184	0.23
*DRIVERS*BUN17*	0.204	0.169	1.21
*WHITE*BUN2*	1.018	0.165	6.18
*WHITE*BUN3*	0.804	0.168	4.79
*WHITE*BUN4*	0.471	0.316	1.49
*WHITE*BUN5*	0.871	0.162	5.38
*WHITE*BUN6*	0.797	0.164	4.85
*WHITE*BUN7*	0.404	0.252	1.60
*WHITE*BUN8*	0.657	0.201	3.27
*WHITE*BUN9*	1.294	0.273	4.74
*WHITE*BUN12*	0.245	0.142	1.73
*WHITE*BUN13*	0.917	0.215	4.27
*WHITE*BUN14*	0.392	0.106	3.68
*WHITE*BUN15*	-0.546	0.553	-0.99
*WHITE*BUN16*	0.668	0.196	3.41
*WHITE*BUN17*	0.591	0.161	3.68
*METRO*BUN2*	0.346	0.385	1.22
*METRO*BUN3*	0.469	0.384	-0.54
*METRO*BUN4*	-0.275	0.507	0.10
*METRO*BUN5*	0.039	0.388	1.05
*METRO*BUN6*	0.404	0.384	0.02
*METRO*BUN7*	0.010	0.445	0.51
*METRO*BUN8*	0.205	0.406	0.58
*METRO*BUN9*	0.242	0.418	-0.51
*METRO*BUN12*	-0.113	0.223	-0.76
*METRO*BUN13*	-0.188	0.248	-1.52
*METRO*BUN14*	-0.311	0.204	-0.2
*METRO*BUN15*	-0.141	0.713	-0.69
*METRO*BUN16*	-0.173	0.250	-1.17
*METRO*BUN17*	-0.262	0.224	1.22

* The z-statistic is the logit's analog to a t-statistic. Estimation using 7073 households. Log likelihood=-15249.66; χ^2 = 10387.87. The likelihood ratio test for nesting against the null hypothesis of nonnesting (inclusive value parameters set to 1) gives χ^2 = 216.71, which supports the use of nested logit.