Estimation of the Joint Demand for Vehicles and Miles: Analyzing the Impacts of Alternative Car Pollution Control Policies

by

Sarah E. West

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Department of Economics
Macalester College
1600 Grand Ave.
St. Paul MN 55105

e-mail: wests@macalester.edu

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ABSTRACT

By driving more miles in larger vehicles, Americans continue to frustrate efforts to reduce automobile pollution. Because a tax per unit of emissions is not yet possible, researchers seek feasible alternative policies that could reduce emissions. Such policies include a gas tax, and taxes or subsidies on vehicle characteristics such as size and vintage. To determine the likely distributional effects of such policies, and to calculate price and income elasticities of the demand for miles and gasoline, I estimate a two-stage model that controls for the endogeneity of vehicle choice in the demand for miles. I use data from the 1994 Consumer Expenditure Survey and from the California Air Resources Board. Results indicate that households with higher incomes prefer newer, larger vehicles. Thus a subsidy to vehicle "newness" is likely to be regressive, while a size tax is likely to be progressive. For the lower half of the income distribution, the average share of total expenditures spent on gasoline *increases* as total expenditures increase. Only across middle- and upper-income groups is the gasoline tax regressive. Regressions that correct for endogeneity result in price elasticity estimates that are up to 38 percent larger in absolute value than those from regressions that do not account for endogeneity.

Sarah E. West
Department of Economics
Macalester College
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St. Paul, MN 55105
wests@macalester.edu

By driving more miles, American households continue to frustrate efforts to reduce automobile pollution.[1] Renewed love for large, less efficient vehicles means that future vehicle fleets may use more gasoline and therefore emit more pollutants per mile driven.[2] Because a tax per unit of emissions is not yet possible, researchers seek feasible alternative policies that could reduce emissions.[3] Instruments that perform most like an emissions tax target two components of pollution creation: the number of miles driven, and the process in which gasoline is burned. Fullerton and West (1999a and 1999b) analyze a policy combination that uses a gasoline tax to reduce miles, and a tax on engine size and subsidy to vehicle "newness" to reduce emissions per mile. In this paper, I estimate a more general empirical model of the discrete choice of vehicle, including the choice of vintage and engine size, and the continuous choice of vehicle-miles-traveled *(VMT)*. I use results from this estimation to describe the likely distributional effects of a gas tax, size tax, and newness subsidy, and to calculate the price and income elasticities of demand for *VMT* and gasoline.

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, an individual that lives far from work may gain more enjoyment from commuting in a large, comfortable vehicle. Residence location also makes it likely that the individual will drive more miles. The two choices are also related through the effect that vintage and engine size have on fuel efficiency, and thus on the price per mile. The price per mile is the price per gallon of gasoline divided by fuel efficiency (miles per gallon), which is itself a function of vintage and engine size. Since the demand for *VMT*

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[1] According to data from the Nationwide Personal Travel Survey, a household, on average, drove 11,739 miles per year in 1983, 18,161 in 1990, and 20,895 in 1995 (ORNL, 1998, p. 10-10). Ten metropolitan areas remain listed in the extreme or severe categories of ozone non-attainment areas (USEPA, http://www.epa.gov/oar/oaqps/greenbk).

[2] 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. The car industry predicts that larger vehicles will continue to account for the majority of sales in 1999 (Warner, December 3, 1998).

[3] See for example Devarajan and Eskeland (1996), Innes (1996), Kohn (1996), Plaut (1998), and Sevigny (1998).

depends on the price per mile, and thus fuel efficiency, the household's choice of vehicle affects their demand for miles, and vice versa.

Because an automobile is a durable, and miles-driven is the service provided by an automobile through gasoline use, an appropriate framework for modeling this joint choice is found in Dubin and McFadden (1984).[4] They derive models to estimate the joint demand for durables and energy use, and apply them to the demand for appliances and electricity.

Five studies use the Dubin and McFadden framework to estimate the joint demand for vehicles and miles. Two use data from the 1970s. Mannering and Winston (1985) develop a dynamic model of vehicle ownership and utilization using a discrete-type choice model, in which utilization is the sum of miles driven by 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. While both studies explicitly incorporate the endogeneity of vehicle choice in the demand for miles, their results using 1970s vehicles may not apply today. Goldberg (1998), uses data 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 mode choice. Hensher et al (1992) use Australian panel data from 1981 to 1985 to estimate a dynamic model of vehicle holdings and use.

Each of these studies uses one method to control for the endogeneity of vehicle choice in estimation of miles demand. All except Train (1986) treat vehicles as durable goods. However, none of these studies uses recent data from the United States. In addition, all use traditional measures of income. Since current income includes transitory components, a better measure of permanent income is current

[4] Several studies examine either the choice of vehicle or vehicle characteristics, or the demand for miles. Many that were conducted in the 1970s estimate the aggregate demand for vehicles using time-series data (see, for example, Hess (1977) and Johnson (1978)). Some studies estimate the discrete choice of vehicle, but not the demand for miles (Berkovec (1985), Berkovec and Rust (1985), McCarthy (1996)). Other researchers use hedonic analysis to estimate the contributions of vehicle characteristics to vehicle price, and then use these estimates for second-stage estimation of the demand for characteristics (Agarwal and Ratchford (1980), Arguea, Hsiao, and Taylor (1994), Atkinson and Halvorsen (1984), Bitros and Panas (1990), and Goodman (1983)). While many 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)). Hundreds of studies of gasoline demand do not include vehicle choice at all (see Dahl (1986), Dahl and Sterner (1991), and Espey (1996) for reviews of gas demand literature).

total expenditures (Bohi (1981), Poterba (1991), and Slesnick (1994)). Finally, no study models vehicle choice in a way that can be used to determine the effects of household characteristics on the demand for newness and engine size, attributes that are important for analyzing emission-reduction policies.

This paper fills those gaps. It implements the Dubin and McFadden framework using data from the 1994 U.S. Consumer Expenditure Survey (CEX), the California Air Resources Board (CARB) Light-Duty Surveillance Program (Series 13), and the American Chamber of Commerce Researchers Association (ACCRA). The CEX contains a preferred measure of income, household total expenditures.

I estimate a model of the joint determination of miles driven and vehicle attributes (including newness and engine size) in two stages. The first stage estimates a conditional logit of households' choices from among 19 possible vehicle bundles. Bundles are first classified according to the number of vehicles: 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.[5] Then, within the one- and two-vehicle categories, bundles are further classified according to vintage and engine size. By classifying bundles in this way, I explicitly link vehicle characteristics and the price per mile; each bundle is assigned a price per mile that depends on vintage and engine size.

The second stage estimates the demand for VMT as a function of price per mile, permanent income, and household characteristics. I control for the endogeneity of vehicle choice by implementing three methods proposed by Dubin and McFadden (1984).

Results from the first-stage regression provide insight into the demand for vintage and engine size. Households with higher incomes prefer newer, larger vehicles. Thus a newness subsidy is likely to be regressive, while a size tax is likely to be progressive. Households with male or less-educated heads or that live in regions other than the Northeast would be hardest hit by a size tax. White, more-educated, male-headed households would benefit the most from a newness subsidy.

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[5] In the 1994 CEX, 86% of households own zero, one, or two cars. These households own 67% of all cars, and purchase 75% of all gas consumed by households in the survey.

As in previous studies, my results indicate that the demand for *VMT* is price-inelastic. The income elasticity is positive and less than one, which indicates that the gas tax may be regressive. As in Poterba (1991), however, for the lower half of the income distribution, the average share of total expenditures spent on gasoline *increases* as total expenditures increase. This is due to the fact that many of the lowest-income households do not own any vehicles. Only across middle- and upper-income groups is the gasoline tax regressive.

In the *VMT* regressions, including indicator variables for vehicle choice changes coefficient estimates quite dramatically, and correcting for the endogeneity of vehicle choice further changes the estimates. Regressions that correct for endogeneity result in price elasticity estimates that are up to 38 percent larger in absolute value than those from regressions that do not account for endogeneity.

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 results from the two stages of estimation. Section IV offers conclusions and directions for future research.

I. Model

This section presents a model of the joint discrete choice of vehicle bundle and the continuous choice of miles. First, I use general functional forms to provide the intuition behind the framework. Second, I specify a functional form for conditional indirect utility, derive the probability that a vehicle bundle is chosen, and solve for the conditional demand-for-miles equation used in estimation.

Households face the discrete choices of the number of vehicles to own, the engine size, vintage, and the make and model of each vehicle. They also face the continuous choice of vehicle-miles-traveled, *VMT*. To model these related choices, I combine the choice of the number, engine size, and vintage of vehicles into one choice, the choice of vehicle bundle, b. A household chooses from among a set of mutually exclusive, exhaustive vehicle bundles. Given bundle b, the consumer has a conditional indirect utility function:

$$V_b = f(b, y - r_b, p_b, c_b, h, \varepsilon_b, \eta) \tag{1}$$

where y is household quarterly total expenditures, r_b is the quarterly[6] life-cycle cost of bundle b, p_b is the cost per mile for vehicles in bundle b, c_b is observable attributes of bundle b, h is observed household characteristics, ε_b is unobserved attributes of bundle b, and η is unobserved household characteristics.

Given b and using Roy's identity, the number of miles that the household will travel is:

$$VMT_b = \frac{-\partial V_b(b, y - r_b, p_b, c_b, h, \varepsilon_b, \eta) \big/ \partial p_b(b, y - r_b, p_b, c_b, h, \varepsilon_b, \eta)}{\partial V_b(b, y - r_b, p_b, c_b, h, \varepsilon_b, \eta) \big/ \partial y(b, y - r_b, p_b, c_b, h, \varepsilon_b, \eta)} \tag{2}$$

A household chooses the vehicle bundle to maximize conditional indirect utility. That is, the household chooses bundle b^* if and only if

$$V_{b^*} > V_b \qquad \text{for all } b \text{ other than } b^*$$

Thus, the probability that the household chooses bundle b^* is

$$P_{b^*} = \text{Prob}(V_{b^*} > V_b) \qquad \text{for all } b \text{ other than } b^* \tag{3}$$

[6] 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.

Assuming ε_b in (1) are independently and identically distributed in accordance with an extreme value distribution,[7] the probability of choosing bundle b is:[8]

$$P_b = \frac{\exp(V_b)}{\sum_{b'} \exp(V_{b'})} \tag{4}$$

where b' is the set of all vehicle bundles.

To derive the model used in estimation, a functional form for conditional indirect utility must be specified. Dubin and McFadden (1984) derive a form that generates an energy-use demand function that is linear in prices and net income. They use this function to estimate the conditional demand for electricity. To apply their form to estimating the conditional demand for miles, I modify it to include a price per mile that is conditional on the choice of vehicle bundle. The resulting conditional indirect utility function is

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

where α_0^b is a bundle-specific constant, and α_1, β, and the vector γ are parameters to be estimated.

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

$$r_b = p_b q_b + \rho r_{kb} \tag{6}$$

[7] The extreme value distribution is also known as a Weibull distribution. To assume that the error terms are distributed according to this distribution imposes the assumption of independence of irrelevant alternatives (IIA). Since the IIA assumption rarely holds, and probably does not hold for the vehicle choice model in this paper, a nested logit would be the more appropriate estimation strategy. Measures are taken in this paper in an attempt to mitigate the potential problems involved with violating IIA, and are discussed in Section III.

[8] See McFadden (1973).

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 fuel costs *($TFCOST_b$)*.

Replace r_b in equation (5) with equation (6), and the bundle choice probabilities in equation (5) then become:

$$P_b = \frac{\exp\left[(\alpha_0^b - \beta p_b q_b - \beta\rho r_{kb})(e^{-\beta p_b})/\psi\right]}{\sum_{b'} \exp\left[(\alpha_0^{b'} - \beta p_{b'} q_{b'} - \beta\rho r_{kb'})(e^{-\beta p_{b'}})/\psi\right]} \qquad (7)$$

where ψ is a positive scale factor (see Dubin and McFadden (1984)).

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:

$$VMT_b = q_b + \alpha_0^b + \alpha_1 p_b + h'\gamma + \beta(y - r_b) + \eta \qquad (8)$$

Decompose quarterly life cycle costs into total fuel cost *($TFCOST_b$)* and capital cost *(r_{kb})* and then rewrite (8) in a more convenient form for estimation:

$$VMT_b - q_b = \sum_b \alpha_0^b \delta_{bi} + \alpha_1 \sum_b p_b \delta_{bi} + h'\gamma + \beta(y - \sum_b TFCOST_b \delta_{bi}) - \beta\rho \sum_b r_{kb} \delta_{bi} + \eta \qquad (9)$$

where δ_{bi} is an indicator variable equal to one when $i = b$.

If vehicle bundle choice and the additive error η in the demand for miles in (9) are statistically independent, then estimation of equation (9) 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 household with many children may gain more enjoyment from driving in a spacious vehicle. The household may also have to drive the 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 living 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.

Dubin and McFadden (1984) suggest three alternative methods that are consistent in the presence of correlation of the residual η and the bundle-choice indicators: the conditional expectation correction method (CE), the instrumental variable method (IV), and the reduced form method (RF). To implement the CE method, solve for the expectation of η given bundle-choice b:

$$\sum_{b \neq i} \mu_i \left[\frac{\hat{P}_b \ln \hat{P}_b}{1 - \hat{P}_b} + \ln \hat{P}_i \right] \qquad (10)$$

where μ_i are parameters to be estimated, $\hat{P}_b$ are the estimated probabilities that a household would select bundles b other than the bundle it actually chose, and $\hat{P}_i$ is the estimated probability that the household chooses the bundle that they actually own. Addition of the terms in (10) to equation (9) permits one to use OLS to consistently estimate of the parameters in (9).

For the IV method, the estimated probabilities $\hat{P}_b$ from the discrete choice model are used as instruments for the bundle-choice indicators δ_{bi}. The instruments include the household's demographic characteristics, $\sum_b p_b \hat{P}_b$, $y - \sum_b TFCOST_b \hat{P}_b$, $\sum_b r_{kb} \hat{P}_b$, and the $\hat{P}_b$.

Finally, the reduced-form method entails applying OLS to equation (9), where the bundle-choice indicators δ_{bi} have been replaced by the estimated probabilities $\hat{P}_b$. Thus OLS is applied to the equation:

$$VMT_b - q_b = \sum_b \alpha_0^b \hat{P}_b + \alpha_1 \sum_b p_b \hat{P}_b + h'\gamma + \beta(y - \sum_b TFCOST_b \hat{P}_b) - \beta\rho \sum_b r_{kb} \hat{P}_b + \varepsilon_{rf} \qquad (11)$$

Here each household faces its *expected* price per mile, total fuel cost, and capital cost.[9]

II. Data and Summary Statistics

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 1994 Consumer Expenditure Survey (CEX) is the main component of the data. It is published annually by the Bureau of Labor Statistics of the U.S. Department of Labor, and provides

[9] The CE estimations method is a Heckman type method that "embodies specific assumptions regarding the joint distribution of η and ε_b" while the IV and RF methods "are more robust in this sense" (Dubin and McFadden (1984), p. 359).

comprehensive and detailed information on the quarterly expenditures of approximately 5000 consumer units. Each consumer unit participates in the survey for five consecutive interview quarters. The CEX includes the amount spent on gasoline, total expenditures, and detailed information on each consumer unit's vehicles. Variables in the vehicle file include year, make, model, number of cylinders, the amount paid for the vehicle, and a variety of other characteristics. The CEX is a rotating panel survey. Each quarter, 20 percent of the sample is rotated out and replaced by new consumer units. I use data for each household from the first quarter in which the household appears.

To construct a variable for price per mile, the fuel efficiency of each vehicle bundle and the price per gallon of gasoline are needed. Since the CEX does not contain data on fuel efficiency, for this variable I rely on the CARB. Between November 1995 and March 1997, the CARB tested the fuel efficiency of 342 vehicles in California.[10] 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 household, and not city, I average the city gas prices to obtain a state gasoline price for each calendar quarter.[11] Then I assign a gas price to each CEX household based on state of residence and CEX quarter.

[10] The Light-Duty Vehicle Surveillance Program, Series 13, was conducted as part of an ongoing effort by the California Air Resources Board 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. To undertake this project, 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.

[11] Because gas prices from municipalities that are not Metropolitan Statistical Areas (MSAs) are incomplete, non-MSAs have been removed from the sample. All households in the sample from the CEX live within a MSA.

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 impact on the price per mile.[12] 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. Then, within the one- and two-vehicle categories, I further classify each vehicle according to vintage and engine size. Since I am primarily concerned with the effect of vintage on fuel efficiency, initially I hoped to divide vehicles into vintage groups in accordance with when larger-than-average changes in Corporate Average Fuel Economy Standards (CAFE) took effect. Doing so would imply cut-off dates of pre-1981, 1981 to 1989, and 1990 and newer.[13] However, the CEX 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 on 8-cylinder (big).

This classification generates nine one-vehicle bundles and nine two-vehicle bundles. Table 1 describes each bundle and the lists total number of households choosing each bundle. Households that own no cars make up 27 percent of the sample, 41 percent own one car, and 32 percent own two cars. The most common bundle is one 4-cylinder 1980s-vintage car, and the next most common bundle is one 6-cylinder 1980s-vintage car. The most common two-car bundle is a combination of those same two cars.

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[12] 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.

[13] For a table of CAFE standards across time, see ORNL (1996), p. 3-43.

Table 1: Vehicle Bundle Description and Statistics

Bundle Number	Bundle Description			Frequency	Percent of total
	Number of vehicles	Engine Size	Vehicle Age		
1	1	small	old	45	.78
2	1	small	newer	632	11.01
3	1	small	newest	371	6.46
4	1	medium	old	61	1.06
5	1	medium	newer	483	8.41
6	1	medium	newest	302	5.26
7	1	large	old	158	2.75
8	1	large	newer	212	3.69
9	1	large	newest	68	1.18
10	2	small	old	3	.05
11	2	small	newer	166	2.89
12	2	small	newest	200	3.48
13	2	medium	old	16	.28
14	2	medium	newer	329	5.73
15	2	medium	newest	476	8.29
16	2	large	old	36	.63
17	2	large	newer	384	6.69
18	2	large	newest	257	4.48
19	0	-	-	1541	26.85
			Total	5740	100.00

C. Derivation of Bundle-Specific Attributes and VMT

Three key bundle-specific attributes appear in the model in Section I. They are price per mile (p_b) , typical miles-driven (q_b), and capital cost (r_{kb}). The price per mile for each vehicle is the price of gasoline divided by fuel efficiency. The ACCRA gives the price per gallon of gasoline. 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. The results of this regression appear in Table 2.

Table 2: Fuel Efficiency Regression

Dependent Variable	Constant	6-cylinder	8-cylinder	1980s	1990s	R^2	F-stat
MPG	21.74	-6.36	-9.34	2.43	4.75	.68	175.27
	(.51)	(.40)	(.51)	(.51)	(.56)		

Standard errors are in parentheses; the number of observations is 342.
Given the omitted indicator variables, the constant represents the estimated fuel efficiency of a 4-cylinder, pre-1980 vehicle.

The regression shows that fuel efficiency decreases in both vehicle age and 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 weighted 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.[14]

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. 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 vehicles purchased in 1994 to calculate the 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' average prices. Then, I assign the two-vehicle bundles that consist of more than one possible two-vehicle pair the weighted average of the pairs' capital costs.

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[14] 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. However, Green and Hu (1985) find that substitution among vehicles in response to changes to the price per mile is negligible, and so the bias is not likely to be large.

D. Summary Statistics: Household and Vehicle Characteristics

This section presents summary statistics of household and vehicle characteristics by number of vehicles, engine size, and vintage. These statistics allow hypotheses to be made about the effects of these characteristics on the probability that a vehicle bundle is chosen.

Table 3 lists summary statistics by a CEX household's number of vehicles. Not controlling for other variables, the number of vehicles owned increases with 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 total expenditures. 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 head of household is male, white, has more than a high school education or lives in the Midwest. The likelihood that a household chooses bundles with more vehicles appears to decrease if the household lives in a large metropolitan area.

Table 3: Summary Statistics by Number of Vehicles

Household and Vehicle Characteristics*	Number of Vehicles			
	0	1	2	All
Number of households	1541	2332	1867	5740
Household size	2.00	2.01	2.94	2.30
% Households with kids	23.3	24.2	48.1	31.7
Number in household > 15 years old	1.43	1.52	2.12	1.69
Number of income earners	.712	.981	1.62	1.12
% Household heads that are male	34.1	49.8	72.7	53.0
Age of household head	47.0	48.6	45.0	47.0
% HH heads that are white	67.2	82.9	87.5	80.2
% HH heads with educ. > high school	34.6	53.0	57.4	49.5
% HH in metro area with pop. > 4 million	23.0	11.6	10.7	14.4
% HH in Northeast	32.5	19.4	16.8	22.1
% HH in Midwest	22.1	22.6	26.6	23.8
% HH in South	30.1	35.8	35.1	34.1
% HH in West	15.2	22.1	21.5	20.1
Total quarterly expenditures	3725	5816	8962	6278
Average purchase price (1994 $)	0	5882	11630	6172
Price per mile (p_b)	0	.056	.055	.041
p_b*typical miles-driven (*TFCOST*)[a]	0	207	226	158
Actual miles driven	0	2981	4943	2819
Ln (number of make/models in bundle)	0	5.17	11.6	5.88

* Mean values are given unless otherwise noted.
[a] Typical miles is an exogenous variable calculated using the following regression, where the dependent variable is the average 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)

Statistics by engine size appear in Table 4. The likelihood that a household chooses a vehicle with larger engine size appears to increase with household size, the number of members older than 15, and age of the household head. More educated household heads appear to choose smaller vehicles, and households in the Midwest and South or with male heads of household to choose larger vehicles. As predicted by the fuel efficiency regression, the price per mile increases with engine size.

Table 4: Summary Statistics by Vehicle Engine Size (Households with Vehicles)

Household and Vehicle Characteristics	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	1417	1667	1115	4199
Household size	2.14	2.53	2.63	2.42
% Households with kids	29.9	37.8	36.7	34.8
Number in household > 15 years old	1.62	1.84	1.92	1.79
Number of income earners	1.21	1.33	1.25	1.27
% Household heads that are male	50.5	61.5	69.6	60.0
Age of household head	42.7	47.7	49.5	46.5
% HH heads that are white	84.3	85.6	84.8	85.0
% HH heads with educ. > high school	63.8	55.7	42.6	55.0
% HH in metro area with pop. > 4 million	9.81	12.8	10.5	11.2
% HH in Northeast	19.3	19.7	14.7	18.2
% HH in Midwest	20.9	26.0	26.5	24.4
% HH in South	35.3	34.5	37.3	35.5
% HH in West	24.6	19.9	21.5	21.9
Total quarterly expenditures	6470	7824	7249	7215
Average purchase price (1994 $)	7287	9711	7997	8438
Price per mile (p_b)	.044	.057	.069	.056
p_b*typical miles-driven (*TFCOST*)[a]	166	221	269	215
Actual miles driven	3722	4078	3685	3853
Ln(number of make/models in bundle)	6.63	8.56	9.04	8.04

Finally, Table 5 contains summary statistics by vintage. Newer vehicles appear to be preferred by households with children, with more members above the age of 15, more income earners, larger total expenditures, and with white, male, and more educated heads. Households living in large metro areas also appear more likely to choose newer vehicles, while households with older heads seem more likely to choose older vehicles. As indicated by the fuel efficiency regression, the price per mile increases with vehicle age.

Table 5: Summary Statistics by Vehicle Age (Households with Vehicles)

Household and Vehicle Characteristics	Age of Vehicles in Bundle			
	Older: All 1979 or older	Old: At least one 1980s, no 1990s	New: At least one 1990s	All
Number of households	319	2206	1674	4199
Household size	2.26	2.46	2.41	2.42
% Households with kids	27.9	35.1	35.7	34.8
Number in household > 15 years old	1.59	1.79	1.83	1.79
Number of income earners	0.92	1.24	1.37	1.27
% Household heads that are male	50.5	57.9	64.5	60.0
Age of household head	49.2	46.4	46.0	46.5
% HH heads that are white	78.7	83.0	88.8	85.0
% HH heads with educ. > high school	34.8	51.8	63.0	55.0
% HH in metro area with pop. > 4 million	6.58	11.2	12.1	11.2
% HH in Northeast	12.9	19.9	17.1	18.2
% HH in Midwest	18.2	23.9	26.2	24.4
% HH in South	34.2	34.4	37.2	35.5
% HH in West	34.8	21.8	19.5	21.9
Total quarterly expenditures	4381	6407	8819	7215
Average purchase price (1994 $)	875	3331	16609	8438
Price per mile (p_b)	.078	.057	.050	.056
p_b *typical miles driven (*TFCOST*)[a]	282	217	201	215
Actual miles driven	2106	3530	4612	3853
Ln(number of make/models in bundle)	5.58	7.81	8.80	8.04

These statistics provide insight into the probable determinants of bundle choice, and they inform the selection of variables to include in the discrete-choice estimation detailed next.

III. Estimation and Results

Estimation of the model described in Section I is undertaken in two stages. The first estimates a conditional 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 *VMT* using the three methods described in Section I.

A. Stage 1: The Discrete Choice of Vehicle Bundle

The conditional logit is estimated using full information maximum likelihood.[15] The names and definitions of variables included in the estimated model are in Table 6. For estimation, demographic characteristics are interacted with choice indicators. I leave out the indicators and interaction terms that involve the zero-vehicle choice so that the remaining coefficients are probabilities of bundle-choice relative to the zero-vehicle bundle. To represent a measure of the variety of vehicles in each bundle, I include the log of the number of makes and models. Since I do not include this variable in the *VMT* regression, it also serves to identify the two-equation model.

[15] Estimating vehicle choice using the logit specification imposes the assumption of independence of irrelevant alternatives (IIA). This assumption means that the ratio of choice probabilities between two alternatives does not depend on any alternatives other than the two. McFadden (1975) shows that if the appropriate terms are added to utility in the logit model, then IIA is not a problem. For example, if households were truly indifferent between owning a small new car and a large new car, adding choice-specific constants to the estimation would enable the model to represent situations in which IIA does not hold. If this is not the case, however, a different adjustment to utility is needed. If the researcher cannot determine the necessary adjustments a priori, then the estimated logit will not represent the true probabilities. In the conditional logit estimation, I include choice-specific indicator variables. If the relationships among pairs are similar to that described above, then doing so mitigates to some extent the problems due to violation of IIA. Since I do not have any a priori information about the degree of substitutability between vehicles within various pairs, I do not make any further adjustments that might correct the problem. The natural solution to this problem is to use a nested logit structure, wherein households first choose the number of vehicles, the vintage, then size.

Table 6: Definition of Bundle-Choice Model Variables

Variable Name	Variable Definition
BUNx	Bundle indicator variables (x is the bundle number 1 through 19)
CAPCOST	Bundle's average purchase price
*INC*CAPCOST*	Total expenditures times average purchase price
TFCOST	Total fuel cost (price per mile*typical miles driven)
PMILE	Price of a mile (gas price/*MPG*)
MALE	Equals one if head of household is male
EDUC	Equals one if head of household has more than high school education
WHITE	Equals one if head of household is white
METRO	Equals one if household lives in metro area with population>4 million
KIDS	Equals one if household has kids
FAMSIZE	Number of household members
DRIVERS	Number of household members older than 15 years
EARNERS	Number of income earners in household
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
REGION1	Equals one if household lives in the Northeast
REGION2	Equals one if household lives in the Midwest
REGION3	Equals one if household lives in the South
REGION4	Equals one if household lives in the West

Table 7 shows the estimation results for the bundle-specific attributes. For the full results, see Table A.1 in the Appendix. The coefficients on average purchase price and the price per mile have the expected signs: both are negative. The coefficient on the interaction term of average purchase price and income is positive; households with higher incomes are more likely to choose bundles that are more expensive.

Table 7: Conditional Logit Results for bundle-specific attributes

Variable	Coefficient	Standard Error	z-statistic[a]
CAPCOST	-.000065	.000039	-1.65
*INC*CAPCOST*	.000000008	.0000000005	15.88
TFCOST	.027	.003	7.91
PMILE	-96.25	15.72	-6.12

[a] The z-statistic is the conditional logit's analog to the t-statistic.

The signs of other interactions between demographic characteristics and choice indicators tend to confirm the apparent results of the summary statistics in Section II.D, and in some cases provide additional information not evident in the summary statistics. The more positive the coefficient on an interaction term is, the more likely the household is to choose the vehicle bundle with which the household characteristic is interacted. And, the more negative a coefficient is, the less likely the household is to choose the interacted bundle.

For example, to see how living in a large metropolitan area affects the number of cars that a household owns, consider Table A.1 and note that all of the coefficients that interact *METRO* with vehicle bundle are negative. Thus households that live in metro areas are less likely to own cars than they are to own no cars. Second, the coefficients on the two-car bundles are more negative than those on the one-car bundles: households that live in metro areas are even less 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 with kids. The same is true for households with male, white, or more-educated heads.

To examine how household characteristics affect the likelihood that a household chooses vehicles of a particular engine size, compare the terms *across* sets of three. For example, bundles 4 through 6 and 13 through 15 are medium-sized vehicle bundles. Compare the likelihood of a household choosing medium versus small vehicles by examining how the coefficients on those groups of three compare with those on the bundles 1 through 3 and 10 through 12. 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, South, or West are more likely to own larger cars than similar households in the Northeast. Those that live in large metropolitan areas are *less* likely to own large vehicles. Race and family size do not appear to be an important determinant of engine size choice.

To analyze the probability that a household chooses a newer vehicle, examine the coefficients *within* the sets of three (bundle 4 is an old car, 5 a newer car, and 6 a “newest” car). Households with male, white, and more-educated household heads are more likely to own newer bundles. Despite what the summary statistics indicate, age and children do not appear to affect vintage choice.

Terms that interact income with bundle indicators would be collinear with the *INC*CAPCOST* term, and thus I do not include them in the same estimation. To see how income affects the probability of choosing bundles that are larger or newer, I estimate another conditional logit, include terms that interact income with bundles, and leave out the *INC*CAPCOST* term. Results from this estimation appear in Table A.2 in the Appendix. Table 8 reproduces just the coefficients on the income terms.

Table 8: Coefficients from income-bundle choice interaction terms

Variable	Coefficient	Standard Error	z-statistic
*INC*BUN1*	.0002024	.0000939	2.16
*INC*BUN2*	.0002842	.000063	4.52
*INC*BUN3*	.0003246	.0000585	5.55
*INC*BUN4*	.0001731	.0001158	1.49
*INC*BUN5*	.0003608	.0000835	4.32
*INC*BUN6*	.0004283	.0000744	5.76
*INC*BUN7*	.0003222	.0001231	2.62
*INC*BUN8*	.0004327	.0000998	4.34
*INC*BUN9*	.0004713	.000088	5.35
*INC*BUN10*	.0002324	.000244	.95
*INC*BUN11*	.0003533	.000065	5.44
*INC*BUN12*	.0004299	.0000602	7.14
*INC*BUN13*	.0003746	.0001185	3.17
*INC*BUN14*	.0004176	.0000757	5.51
*INC*BUN15*	.0004553	.0000708	6.43
*INC*BUN16*	.0002898	.0001283	2.26
*INC*BUN17*	.0004039	.0000894	4.52
*INC*BUN18*	.0004905	.0000802	6.12

Within each set of three vehicles, beginning with the set that contains bundles 1 through 3, the newer the vehicles, the higher the coefficient. Thus households with higher incomes prefer newer vehicles. Comparing the coefficients across sets of three, households with higher incomes generally prefer larger cars.

These results provide preliminary information about the probable distributional effects of a size tax and newness subsidy across income, demographic characteristics, and regions. Since households that purchase larger cars have more income, a size tax would likely be progressive– perhaps surprisingly. However, since households with more income also prefer newer cars, a newness subsidy would be regressive– as might be expected. Households with male, older, or less-educated heads that live in regions other than the Northeast would be hardest hit by a size tax. White, more educated, male-headed households would benefit the most from a newness subsidy.

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

The second stage regression involves estimating equation (9) and using the three procedures explained in Section I. Table 9 shows the results of the three estimation methods and also lists results using OLS including actual bundle-choice indicators but not correcting for the correlation between the error term and the bundle-choice indicators (OLS1), and OLS with neither vehicle-choice indicators nor correction for correlation (OLS2).

As expected, as shown in all five sets of results, the demand for *VMT* decreases in the price per mile and increases in income. The coefficient on average purchase price *(CAPCOST)* indicates that households have positive discount rates.

All of the regressions show that demand for *VMT* increases if the household lives in the South or West. Miles also increase if the household lives in a large metro area. Three of the five regressions indicate that the number of income earners increases demand for miles, which emphasizes the influence of commuting. However, miles demand decreases with the number of potential drivers, the number of household members older than 15. Those households whose heads are past retirement age also drive less. Race, education, having children, and family size cannot be conclusively said to affect miles driven.

Table 9: Results from *VMT* regressions, all households
VMT minus typical miles is the dependent variable (t-statistics in parentheses)

Variable	Reduced Form Method	Instrumental Variables Method	Conditional Expectation Correction Method	OLS with choice dummies (OLS1)	OLS with no choice dummies (OLS2)
PMILE	-46950.16 (-3.92)	-38158.18 (-3.03)	-31360.41 (-3.29)	-34235.22 (-3.60)	-18312.15 (-14.34)
(INC-TFCOST)	.10 (3.41)	.03 (3.60)	.06 (4.26)	.03 (3.74)	.03 (4.54)
CAPCOST	.21 (6.80)	.09 (2.32)	.13 (3.86)	.11 (3.43)	.07 (13.22)
REGION2	82.31 (.47)	4.59 (.05)	154.00 (1.45)	11.13 (.12)	85.49 (.94)
REGION3	756.73 (3.73)	415.28 (4.39)	560.02 (4.28)	420.25 (4.52)	447.63 (4.89)
REGION4	732.13 (2.65)	180.74 (1.69)	337.52 (1.94)	171.71 (1.65)	120.75 (1.19)
MALE	94.79 (.60)	173.26 (2.66)	213.03 (1.83)	176.72 (2.72)	240.95 (3.70)
EDUC	-161.92 (-.68)	-63.45 (-.95)	-343.11 (-2.27)	-60.00 (-.90)	-66.73 (-1.01)
WHITE	43.17 (.25)	-46.61 (-.58)	-152.45 (-1.44)	-50.71 (-.64)	-22.18 (-.28)
NUMEARNER	-177.63 (-1.30)	288.50 (5.45)	63.77 (.70)	290.39 (5.50)	369.20 (6.98)
FAMSIZE	-41.92 (-.50)	30.60 (.77)	126.99 (2.16)	34.77 (.87)	28.86 (.72)
NUMDRIVER	-406.50 (-2.95)	-212.01 (-3.00)	-451.41 (-3.94)	-214.76 (-3.05)	-121.68 (-1.72)
AGE2	-307.78 (-1.76)	138.67 (1.27)	134.20 (1.03)	133.79 (1.23)	192.24 (1.75)
AGE3	-421.87 (-1.64)	37.67 (.32)	223.19 (1.23)	32.58 (.28)	76.81 (.64)
AGE4	-708.00 (-2.44)	-373.08 (-2.94)	90.68 (.39)	-364.07 (-2.88)	-293.84 (-2.30)
KIDS	131.60 (.75)	209.33 (2.22)	-62.64 (-.49)	211.42 (2.25)	277.94 (2.93)
METRO	701.49 (3.05)	101.23 (1.03)	289.68 (2.36)	105.89 (1.08)	33.63 (.34)
constant	. .	533.57 (.45)	. .	. .	-535.72 (-3.61)
Adjusted R^2	.0925	.1456	.1477	.1474	.1199
Number of obs.	5740	5740	5740	5740	5740

Because it includes bundle-choice indicators, the OLS1 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 η. Still, the differences between the results from OLS1 and those from

OLS2 show the importance of accounting for the effect that (endogenous) bundle-choice has on *VMT*. Including the bundle-choice indicators dramatically affects the coefficient on the price per mile; it nearly doubles the coefficient. Use of the OLS2 coefficients results in elasticity estimates that are biased downward (see Table 10 below).

Even though the OLS1 regression accounts for the effects of vehicle-bundle choice on *VMT*, it does not correct for the bias due to the fact that the bundle-choice indicators are correlated with the error term. The other three methods make this correction. While the estimates for the bundle-specific terms for the three methods are of the same size and magnitude to those from OLS1, some of those for demographic characteristics differ in magnitude and even sign. Thus the estimates from regressions that do not include conditional expectation correction terms are biased. The differences in coefficient estimates demonstrate the importance of incorporating bundle choice *probabilities* to obtain the most accurate estimates. The discrete choice model does fairly well in predicting the actual bundle chosen by the household, but does not do so perfectly.[16] Improvements in the first-stage estimation would further increase the additional explanatory accuracy gained by performing the three methods suggested by Dubin and McFadden (1984) in the second-stage estimation of vehicle-miles-traveled.[17]

C. Price and Income Elasticities

In addition to gaining information about the probable distributional effects of a size tax and newness subsidy, a second goal of this paper is to produce reliable estimates of the price and income elasticities of demand for vehicle-miles-traveled and gasoline. Two sets of elasticities can be calculated

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[16] In almost half of the cases, the highest probability of choosing a bundle corresponds with the household's actual bundle choice.

[17] Two issues regarding these results should be noted. First, if the model violates the assumption of IIA, then the estimated probabilities from the discrete-choice estimation are biased and thus so are the coefficient estimates in the second stage. It is somewhat reassuring, however, that the regression results for OLS1, which does not use bundle choice probabilities, are similar those from the regressions that do incorporate choice probabilities. Second, since I include probabilities estimated in the second-stage regression, the variances of the estimates are affected. Dubin and McFadden (1984) use a different corrected covariance matrix for each of the three procedures to arrive at unconditional variance estimates in the second-stage regressions.

using the regressions estimated in this paper. First, "short-run" elasticities, conditional on a particular choice of vehicle bundle and assuming that the household cannot change its bundle, can be calculated using the coefficient estimates from the second-stage regression. Second, "long-run" elasticities, which include the effect of what Dubin and McFadden (1984) call "portfolio shift", incorporate the change in the probability that a bundle is chosen into "expected" elasticities. To calculate these long-run elasticities, one must know the effect of a change in gas price on the probability of bundle choice. Calculation of these changes in probabilities is more complicated, and is left for future research.

The short-run elasticities presented in Table 10 include the effects of a change in gasoline price on net income, defined simply as the difference between income and total fuel cost. The elasticities are evaluated at the means of price per mile, income, and fuel efficiency.

Table 10: Short-run price and income elasticities of demand for vehicle-miles-traveled and gasoline

	Reduced Form Method	IV Method	Conditional Expectation Correction Method (CE)	OLS1	OLS2
Elasticity of VMT with respect to price per mile	-.67	-.54	-.45	-.49	-.26
Elasticity of VMT with respect to net income	.23	.06	.13	.06	.07
Elasticity of gasoline with respect to price per mile	-.60	-.49	-.40	-.44	-.23
Elasticity of gasoline with respect to net income	.20	.05	.12	.05	.07

Regressions that include bundle-choice indicators imply price elasticities larger in absolute value than those in the OLS2 equation do, but all three indicate that the demand for *VMT* is quite inelastic. Because of how vehicle bundles are defined, these price elasticities are not strictly comparable to estimates from previous studies. However, the results presented here are generally larger in absolute value than others.[18] The income elasticity estimates are similar to those found in the two previous studies that define income as net annual income.[19]

In general, studies that examine distributional effects of gas taxes find that using total expenditures rather than annual income result in less regressive results (see for example Poterba (1991)). My results are consistent with these findings. In addition, as pointed out by Poterba (1991), a large proportion of households in the lower income deciles do not spend any money on gasoline. Thus, to give a more accurate picture of the potential distributional effects of a gas tax, Table 11 presents average gasoline expenditures as a percent of total expenditure, by decile.

Table 11: Average Share of Income spent on Gasoline, by Decile

Decile	Average Gasoline Expenditure as Percent of Total Expenditures, all Households	Average Gasoline Expenditure as Percent of Total Expenditures, Vehicle Owners Only
1	3.0	5.9
2	3.0	4.5
3	3.4	4.4
4	3.5	4.2
5	3.6	3.7
6	3.4	3.6
7	3.2	3.2
8	3.0	2.9
9	2.6	2.4
10	1.7	1.7

The first column lists average total expenditure shares spent on gasoline for all households. These results confirm Poterba's finding that a gas tax would be regressive only across upper-income groups, in this case only in the top half of the income distribution. The second column lists average shares across deciles of only those households that own vehicles, and shows that among car-owners, a gas tax would clearly be regressive.

[18] 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) estimates are the only ones that are larger than mine: she finds *VMT* elasticities that range from -.85 to -.94.

[19] The first, Mannering and Winston (1985) finds a *VMT* income elasticity of .04 on average. The other, Hensher et al, finds *VMT* elasticities ranging from .05 to .14. The only other study to define income as total expenditures

IV. Conclusion

This paper estimates a model of the discrete/continuous choice of vehicle bundle and 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 5000 households from the 1994 Consumer Expenditure Survey, combined with fuel efficiency numbers estimated using data from the California Air Resources Board Light-Duty Surveillance Program, and state-level gas prices from the ACCRA cost of living indexes.

By dividing vehicle choices into 19 possible bundles, categorized by number of vehicles, vintage, and engine size, I can isolate the effects of income and other household characteristics on demand for these bundle attributes. However, combining the choice of number of vehicles with choices of vehicle attributes into one decision ignores the fact that these decisions are typically made in related, but separate stages. In addition, the model likely violates the assumption of independence of irrelevant alternatives. A nested logit would be a more natural structure for vehicle choice, and its use would avoid problems due to violation of IIA.

In addition, the first-stage estimation of vehicle bundle choice 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. Previous studies have found that vehicle choice is affected by shoulder room, acceleration, horsepower, luggage space, safety, and reliability. None of these variables is in the CEX. To capture the effects of these attributes on choice probabilities, and thus demand for miles, one could have to combine the CEX data with information on vehicles from other sources.

(but not net income) is Archibald and Gillingham (1981). Their *VMT* income elasticity estimates range from .23 to .47 and their elasticities of gasoline with respect to income range from .29 to .56.

Results from the first-stage conditional logit estimation of bundle choice indicate that households with higher incomes prefer newer, larger vehicles. Thus a newness subsidy is likely to be regressive, while a size tax is likely to be progressive. Households with male, older, or less-educated heads that live in regions other than the Northeast would be hardest hit by a size tax. White, more educated, male-headed households would benefit the most from a newness subsidy.

Estimates of short-run price elasticity of demand for miles range from -.45 to -.67. These estimates are larger than those found in most previous studies. The gasoline price elasticity estimates range from -.40 to -.60, and the income elasticity estimates range from .06 to .23, which indicates that *VMT* is a necessity and therefore a gas tax may be regressive. However, for the lower half of the income distribution, the average share of total expenditures spent on gasoline *increases* as total expenditures increase. This is because many lower income households do not own any vehicles. Only across upper income groups is the gasoline tax regressive. Including indicator variables for actual vehicle choice changes coefficient estimates quite dramatically, and correcting for the endogeneity of vehicle choice in miles demand further changes the estimates. Regressions that correct for endogeneity result in price elasticity estimates that are up to 38 percent larger in absolute value than those from regressions that do not account for endogeneity.

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Appendix

Table A.1: Conditional Logit Estimation
(Probabilities from this Estimation used in Second Stage)

Variables	Coefficient	Standard Error	z-statistic
BUN1	-2.710	.946	-2.865
BUN2	1.129	.312	3.617
BUN3	.383	.483	.793
BUN4	-.804	.805	-.999
BUN5	.730	.436	1.674
BUN6	-1.175	.633	-1.855
BUN7	.175	.779	.225
BUN8	-1.561	.653	-2.392
BUN9	-2.544	1.043	-2.438
BUN10	-20.429	46.288	-.441
BUN11	-1.407	.600	-2.343
BUN12	-.184	.610	-.301
BUN13	-10.518	36.470	-.288
BUN14	.088	.531	.166
BUN15	.078	.564	.139
BUN16	-2.172	1.271	-1.708
CAPCOST	-.00006	.00004	-1.653
*INC*CAPCOST*	.000000008	.0000000005	15.883
TFCOST	.027	.003	7.914
PMILE	-96.249	15.723	-6.122
*MALE*BUN1*	.471	.316	1.491
*MALE*BUN2*	.228	.104	2.203
*MALE*BUN3*	.206	.127	1.623
*MALE*BUN4*	.414	.281	1.473
*MALE*BUN5*	.449	.113	3.971
*MALE*BUN6*	.592	.139	4.260
*MALE*BUN7*	.547	.180	3.048
*MALE*BUN8*	.998	.161	6.191
*MALE*BUN9*	1.525	.307	4.959
*MALE*BUN10*	-4.576	6.096	-.751
*MALE*BUN11*	.789	.185	4.269
*MALE*BUN12*	.682	.169	4.037
*MALE*BUN13*	.611	.532	1.149
*MALE*BUN14*	1.035	.143	7.254
*MALE*BUN15*	.981	.132	7.436
*MALE*BUN16*	1.096	.380	2.882
*MALE*BUN17*	1.129	.136	8.298
*MALE*BUN18*	1.587	.184	8.636
*EDUC*BUN1*	.121	.325	.373
*EDUC*BUN2*	.729	.107	6.845
*EDUC*BUN3*	.754	.134	5.625
*EDUC*BUN4*	-.309	.295	-1.049
*EDUC*BUN5*	.320	.117	2.739
*EDUC*BUN6*	.483	.142	3.408
*EDUC*BUN7*	-.345	.193	-1.784
*EDUC*BUN8*	.104	.163	.638
*EDUC*BUN9*	-.326	.268	-1.217
*EDUC*BUN10*	-.900	1.340	-.672
*EDUC*BUN11*	1.005	.188	5.340
*EDUC*BUN12*	.896	.180	4.980
*EDUC*BUN13*	.033	.535	.061
*EDUC*BUN14*	.452	.138	3.266
*EDUC*BUN15*	.709	.133	5.350
*EDUC*BUN16*	-.849	.402	-2.110
*EDUC*BUN17*	-.058	.133	-.433
*EDUC*BUN18*	.102	.157	.647
*RACE*BUN1*	.888	.429	2.072
*RACE*BUN2*	.693	.127	5.453
*RACE*BUN3*	.923	.170	5.417
*RACE*BUN4*	.325	.317	1.025
*RACE*BUN5*	.401	.133	3.023
*RACE*BUN6*	1.061	.201	5.284
*RACE*BUN7*	.257	.209	1.228
*RACE*BUN8*	.621	.198	3.131
*RACE*BUN9*	1.091	.414	2.637
*RACE*BUN10*	7.979	31.443	.254
*RACE*BUN11*	1.091	.245	4.451
*RACE*BUN12*	.651	.217	3.000
*RACE*BUN13*	1.306	.790	1.652
*RACE*BUN14*	1.058	.183	5.769
*RACE*BUN15*	1.348	.194	6.929
*RACE*BUN16*	.743	.445	1.667
*RACE*BUN17*	1.053	.172	6.131
*RACE*BUN18*	1.217	.238	5.117
*METRO*BUN1*	-1.473	1.091	-1.351
*METRO*BUN2*	-.921	.165	-5.567
*METRO*BUN3*	-.625	.210	-2.977
*METRO*BUN4*	-.268	.443	-.605
*METRO*BUN5*	-.977	.175	-5.586
*METRO*BUN6*	-.359	.205	-1.754
*METRO*BUN7*	-1.263	.363	-3.474
*METRO*BUN8*	-.650	.250	-2.605
*METRO*BUN9*	-1.298	.477	-2.722
*METRO*BUN10*	-2.199	31.857	-.069
*METRO*BUN11*	-1.240	.318	-3.899
*METRO*BUN12*	-1.739	.319	-5.446
*METRO*BUN13*	-9.084	36.880	-.246
*METRO*BUN14*	-1.165	.228	-5.111

*METRO*BUN15*	-1.207	.197	-6.126
*METRO*BUN16*	-2.240	1.061	-2.112
*METRO*BUN17*	-1.155	.211	-5.475
*METRO*BUN18*	-1.052	.250	-4.202
*KIDS*BUN1*	-.196	.508	-.386
*KIDS*BUN2*	.206	.174	1.184
*KIDS*BUN3*	-.125	.237	-.526
*KIDS*BUN4*	.321	.432	.742
*KIDS*BUN5*	-.051	.180	-.286
*KIDS*BUN6*	.146	.245	.596
*KIDS*BUN7*	-.819	.304	-2.696
*KIDS*BUN8*	-.198	.255	-.776
*KIDS*BUN9*	.570	.477	1.194
*KIDS*BUN10*	-4.633	7.697	-.602
*KIDS*BUN11*	.712	.239	2.981
*KIDS*BUN12*	.266	.239	1.114
*KIDS*BUN13*	.670	.639	1.049
*KIDS*BUN14*	.307	.188	1.630
*KIDS*BUN15*	.468	.184	2.536
*KIDS*BUN16*	.897	.477	1.882
*KIDS*BUN17*	.278	.180	1.539
*KIDS*BUN18*	.162	.223	.725
*FAMSIZE*BUN1*	.041	.210	.198
*FAMSIZE*BUN2*	-.134	.080	-1.682
*FAMSIZE*BUN3*	-.144	.111	-1.300
*FAMSIZE*BUN4*	.179	.162	1.105
*FAMSIZE*BUN5*	.107	.073	1.462
*FAMSIZE*BUN6*	-.148	.112	-1.325
*FAMSIZE*BUN7*	.260	.105	2.465
*FAMSIZE*BUN8*	.180	.097	1.848
*FAMSIZE*BUN9*	-.451	.246	-1.836
*FAMSIZE*BUN10*	-.380	.881	-.431
*FAMSIZE*BUN11*	-.043	.100	-.427
*FAMSIZE*BUN12*	-.412	.121	-3.421
*FAMSIZE*BUN13*	-.147	.274	-.538
*FAMSIZE*BUN14*	.010	.078	.125
*FAMSIZE*BUN15*	-.142	.080	-1.766
*FAMSIZE*BUN16*	.019	.180	.104
*FAMSIZE*BUN17*	.028	.073	.377
*FAMSIZE*BUN18*	-.036	.092	-.386
*DRIVERS*BUN1*	-.470	.395	-1.190
*DRIVERS*BUN2*	-.449	.149	-3.007
*DRIVERS*BUN3*	-.900	.204	-4.404
*DRIVERS*BUN4*	-1.345	.353	-3.809
*DRIVERS*BUN5*	-.823	.161	-5.105
*DRIVERS*BUN6*	-.545	.196	-2.776
*DRIVERS*BUN7*	-1.286	.255	-5.045
*DRIVERS*BUN8*	-.931	.212	-4.392
*DRIVERS*BUN9*	-.263	.356	-.737
*DRIVERS*BUN10*	.713	1.346	.529

*DRIVERS*BUN11*	.164	.188	.869
*DRIVERS*BUN12*	.482	.199	2.420
*DRIVERS*BUN13*	.155	.461	.337
*DRIVERS*BUN14*	-.061	.161	-.382
*DRIVERS*BUN15*	-.027	.158	-.171
*DRIVERS*BUN16*	-.474	.347	-1.367
*DRIVERS*BUN17*	-.178	.161	-1.109
*DRIVERS*BUN18*	-.004	.182	-.023
*EARNERS*BUN1*	-.043	.280	-.152
*EARNERS*BUN2*	.343	.094	3.657
*EARNERS*BUN3*	.591	.133	4.445
*EARNERS*BUN4*	.452	.246	1.837
*EARNERS*BUN5*	.434	.098	4.436
*EARNERS*BUN6*	.298	.125	2.392
*EARNERS*BUN7*	-.080	.161	-.500
*EARNERS*BUN8*	.402	.133	3.030
*EARNERS*BUN9*	.177	.229	.771
*EARNERS*BUN10*	.177	.885	.200
*EARNERS*BUN11*	.878	.140	6.255
*EARNERS*BUN12*	1.017	.146	6.988
*EARNERS*BUN13*	.751	.378	1.987
*EARNERS*BUN14*	.906	.110	8.242
*EARNERS*BUN15*	1.005	.106	9.496
*EARNERS*BUN16*	.399	.259	1.538
*EARNERS*BUN17*	.784	.101	7.740
*EARNERS*BUN18*	.548	.121	4.520
*AGE2*BUN1*	.258	.436	.592
*AGE2*BUN2*	.318	.153	2.074
*AGE2*BUN3*	.552	.192	2.870
*AGE2*BUN4*	.113	.451	.250
*AGE2*BUN5*	.617	.205	3.007
*AGE2*BUN6*	.869	.289	3.011
*AGE2*BUN7*	.566	.318	1.779
*AGE2*BUN8*	.657	.334	1.969
*AGE2*BUN9*	.702	.556	1.263
*AGE2*BUN10*	7.059	29.931	.236
*AGE2*BUN11*	.720	.325	2.212
*AGE2*BUN12*	1.104	.329	3.351
*AGE2*BUN13*	8.282	36.450	.227
*AGE2*BUN14*	1.146	.275	4.166
*AGE2*BUN15*	1.160	.289	4.015
*AGE2*BUN16*	.820	.769	1.066
*AGE2*BUN17*	1.392	.312	4.461
*AGE2*BUN18*	.617	.324	1.904
*AGE3*BUN1*	-.066	.525	-.125
*AGE3*BUN2*	.398	.173	2.296
*AGE3*BUN3*	.313	.224	1.400
*AGE3*BUN4*	.350	.505	.692
*AGE3*BUN5*	1.167	.216	5.396
*AGE3*BUN6*	1.231	.301	4.088

*AGE3*BUN7*	.600	.347	1.727
*AGE3*BUN8*	1.423	.339	4.193
*AGE3*BUN9*	1.173	.570	2.059
*AGE3*BUN10*	6.178	29.941	.206
*AGE3*BUN11*	.784	.348	2.250
*AGE3*BUN12*	.677	.357	1.893
*AGE3*BUN13*	8.293	36.451	.227
*AGE3*BUN14*	1.061	.294	3.607
*AGE3*BUN15*	1.362	.301	4.529
*AGE3*BUN16*	1.486	.787	1.889
*AGE3*BUN17*	1.860	.320	5.805
*AGE3*BUN18*	.890	.337	2.641
*AGE4*BUN1*	-.695	.618	-1.124
*AGE4*BUN2*	.222	.189	1.176
*AGE4*BUN3*	.445	.249	1.787
*AGE4*BUN4*	.959	.521	1.840
*AGE4*BUN5*	1.241	.230	5.390
*AGE4*BUN6*	1.554	.317	4.909
*AGE4*BUN7*	.777	.357	2.177
*AGE4*BUN8*	1.781	.358	4.978
*AGE4*BUN9*	1.031	.625	1.649
*AGE4*BUN10*	.484	32.993	.015
*AGE4*BUN11*	.306	.462	.663
*AGE4*BUN12*	.763	.424	1.801
*AGE4*BUN13*	7.452	36.464	.204
*AGE4*BUN14*	1.318	.328	4.024
*AGE4*BUN15*	1.899	.324	5.855
*AGE4*BUN16*	1.182	.887	1.333
*AGE4*BUN17*	1.888	.346	5.460
*AGE4*BUN18*	1.441	.363	3.964
*REGION2*BUN1*	.652	.773	.844
*REGION2*BUN2*	.326	.147	2.224
*REGION2*BUN3*	.582	.193	3.022
*REGION2*BUN4*	.015	.439	.035
*REGION2*BUN5*	.408	.158	2.587
*REGION2*BUN6*	1.234	.205	6.032
*REGION2*BUN7*	1.000	.301	3.326
*REGION2*BUN8*	.983	.240	4.105
*REGION2*BUN9*	.926	.395	2.343
*REGION2*BUN10*	1.636	18.756	.087
*REGION2*BUN11*	.902	.279	3.230
*REGION2*BUN12*	.713	.255	2.796
*REGION2*BUN13*	-.624	1.163	-.537
*REGION2*BUN14*	.776	.203	3.818
*REGION2*BUN15*	1.202	.180	6.661
*REGION2*BUN16*	2.072	.794	2.608
*REGION2*BUN17*	1.364	.196	6.964
*REGION2*BUN18*	1.224	.232	5.275
*REGION3*BUN1*	1.322	.671	1.971
*REGION3*BUN2*	.108	.145	.746
*REGION3*BUN3*	.795	.186	4.272
*REGION3*BUN4*	.723	.394	1.837
*REGION3*BUN5*	.222	.157	1.414
*REGION3*BUN6*	1.015	.217	4.686
*REGION3*BUN7*	.777	.298	2.606
*REGION3*BUN8*	1.003	.242	4.140
*REGION3*BUN9*	.853	.382	2.236
*REGION3*BUN10*	5.483	16.047	.342
*REGION3*BUN11*	.450	.284	1.588
*REGION3*BUN12*	.437	.246	1.775
*REGION3*BUN13*	-.127	.781	-.162
*REGION3*BUN14*	.582	.201	2.894
*REGION3*BUN15*	.606	.188	3.230
*REGION3*BUN16*	1.670	.786	2.126
*REGION3*BUN17*	.960	.201	4.786
*REGION3*BUN18*	.982	.236	4.152
*REGION4*BUN1*	2.223	.653	3.405
*REGION4*BUN2*	.389	.156	2.495
*REGION4*BUN3*	.413	.211	1.954
*REGION4*BUN4*	.557	.448	1.243
*REGION4*BUN5*	.101	.181	.560
*REGION4*BUN6*	.933	.236	3.949
*REGION4*BUN7*	1.447	.299	4.832
*REGION4*BUN8*	.776	.273	2.839
*REGION4*BUN9*	.115	.476	.241
*REGION4*BUN10*	6.406	16.035	.399
*REGION4*BUN11*	.971	.287	3.380
*REGION4*BUN12*	.245	.275	.893
*REGION4*BUN13*	.996	.703	1.417
*REGION4*BUN14*	.566	.221	2.557
*REGION4*BUN15*	.464	.208	2.224
*REGION4*BUN16*	2.105	.791	2.661
*REGION4*BUN17*	.751	.225	3.340
*REGION4*BUN18*	.802	.261	3.073
LNMAKE	-.491	.073	-6.682

Estimation using 5740 households times 19 choices equals 109060 observations.
Log Likelihood = -12401.577
χ^2 = 8999.01
Pseudo R^2 = .2662

Table A.2: Conditional Logit Estimation
(Effects of Income on Bundle Choice)

Variables	Coefficient	Standard Error	z-statistic
BUN1	-3.002	1.072	-2.799
BUN2	1.667	.569	2.929
BUN3	-1.777	.734	-2.42
BUN4	-2.065	1.104	-1.87
BUN5	.220	.725	0.304
BUN6	-4.475	1.058	-4.228
BUN7	-2.179	1.272	-1.714
BUN8	-3.528	1.011	-3.489
BUN9	-7.617	1.671	-4.558
BUN10	-18.593	51.572	-0.361
BUN11	2.465	1.308	1.885
BUN12	.740	.657	1.127
BUN13	-8.238	37.884	-0.217
BUN14	4.132	1.379	2.996
BUN15	.898	.606	1.482
BUN17	3.455	1.306	2.646
*INC*BUN1*	.0002024	.0000939	2.156
*INC*BUN2*	.0002842	.0000630	4.515
*INC*BUN3*	.0003246	.0000585	5.551
*INC*BUN4*	.0001731	.0001158	1.494
*INC*BUN5*	.0003608	.0000835	4.319
*INC*BUN6*	.0004283	.0000744	5.758
*INC*BUN7*	.0003222	.0001231	2.619
*INC*BUN8*	.0004327	.0000998	4.335
*INC*BUN9*	.0004713	.0000880	5.353
*INC*BUN10*	.0002324	.0002444	0.951
*INC*BUN11*	.0003533	.0000650	5.439
*INC*BUN12*	.0004299	.0000602	7.136
*INC*BUN13*	.0003746	.0001185	3.162
*INC*BUN14*	.0004176	.0000757	5.513
*INC*BUN15*	.0004553	.0000708	6.434
*INC*BUN16*	.0002898	.0001283	2.259
*INC*BUN17*	.0004039	.0000894	4.516
*INC*BUN18*	.0004905	.0000802	6.117
CAPCOST	.0002	.0001	2.118
TFCOST	-0.048	.021	-2.256
PMILE	172.527	76.898	2.244
*MALE*BUN1*	0.485	0.317	1.531
*MALE*BUN2*	0.200	0.104	1.922
*MALE*BUN3*	0.193	0.127	1.515
*MALE*BUN4*	0.489	0.281	1.738
*MALE*BUN5*	0.417	0.114	3.663
*MALE*BUN6*	0.566	0.140	4.045
*MALE*BUN7*	0.612	0.180	3.394
*MALE*BUN8*	0.958	0.162	5.908
*MALE*BUN9*	1.514	0.307	4.926
*MALE*BUN10*	-4.607	6.188	-0.745
*MALE*BUN11*	0.719	0.186	3.867
*MALE*BUN12*	0.623	0.171	3.642
*MALE*BUN13*	0.587	0.536	1.094
*MALE*BUN14*	0.944	0.144	6.553
*MALE*BUN15*	0.958	0.133	7.224
*MALE*BUN16*	1.186	0.384	3.088
*MALE*BUN17*	1.089	0.137	7.953
*MALE*BUN18*	1.570	0.184	8.528
*EDUC*BUN1*	0.182	0.337	0.541
*EDUC*BUN2*	0.653	0.110	5.948
*EDUC*BUN3*	0.737	0.137	5.363
*EDUC*BUN4*	-0.075	0.305	-0.247
*EDUC*BUN5*	0.238	0.120	1.985
*EDUC*BUN6*	0.408	0.145	2.806
*EDUC*BUN7*	-0.187	0.198	-0.946
*EDUC*BUN8*	0.003	0.167	0.018
*EDUC*BUN9*	-0.338	0.274	-1.235
*EDUC*BUN10*	-0.861	1.395	-0.617
*EDUC*BUN11*	0.804	0.195	4.130
*EDUC*BUN12*	0.733	0.184	3.978
*EDUC*BUN13*	-0.037	0.561	-0.066
*EDUC*BUN14*	0.199	0.144	1.384
*EDUC*BUN15*	0.645	0.134	4.797
*EDUC*BUN16*	-0.641	0.417	-1.538
*EDUC*BUN17*	-0.151	0.138	-1.095
*EDUC*BUN18*	0.058	0.159	0.368
*RACE*BUN1*	0.907	0.431	2.105
*RACE*BUN2*	0.651	0.128	5.082
*RACE*BUN3*	0.918	0.171	5.354
*RACE*BUN4*	0.449	0.321	1.399
*RACE*BUN5*	0.355	0.134	2.651
*RACE*BUN6*	1.021	0.202	5.051
*RACE*BUN7*	0.312	0.210	1.483
*RACE*BUN8*	0.563	0.200	2.818
*RACE*BUN9*	1.083	0.415	2.611
*RACE*BUN10*	8.314	37.713	0.220
*RACE*BUN11*	0.981	0.247	3.973
*RACE*BUN12*	0.550	0.220	2.499
*RACE*BUN13*	1.257	0.793	1.586
*RACE*BUN14*	0.916	0.185	4.951
*RACE*BUN15*	1.318	0.195	6.742
*RACE*BUN16*	0.824	0.451	1.829
*RACE*BUN17*	1.002	0.173	5.793
*RACE*BUN18*	1.195	0.238	5.012
*METRO*BUN1*	-1.437	1.091	-1.318
*METRO*BUN2*	-0.966	0.167	-5.789
*METRO*BUN3*	-0.646	0.211	-3.066
*METRO*BUN4*	-0.142	0.444	-0.321
*METRO*BUN5*	-1.015	0.176	-5.770

*METRO*BUN6*	-0.408	0.206	-1.981
*METRO*BUN7*	-1.204	0.363	-3.317
*METRO*BUN8*	-0.689	0.251	-2.750
*METRO*BUN9*	-1.314	0.477	-2.757
*METRO*BUN10*	-2.485	36.699	-0.068
*METRO*BUN11*	-1.330	0.320	-4.153
*METRO*BUN12*	-1.850	0.323	-5.722
*METRO*BUN13*	-9.444	43.844	-0.215
*METRO*BUN14*	-1.269	0.231	-5.503
*METRO*BUN15*	-1.256	0.198	-6.343
*METRO*BUN16*	-2.207	1.060	-2.082
*METRO*BUN17*	-1.191	0.212	-5.620
*METRO*BUN18*	-1.091	0.250	-4.357
*KIDS*BUN1*	-0.159	0.505	-0.314
*KIDS*BUN2*	0.182	0.175	1.040
*KIDS*BUN3*	-0.128	0.236	-0.545
*KIDS*BUN4*	0.439	0.428	1.028
*KIDS*BUN5*	-0.076	0.181	-0.420
*KIDS*BUN6*	0.129	0.246	0.525
*KIDS*BUN7*	-0.720	0.300	-2.400
*KIDS*BUN8*	-0.228	0.257	-0.890
*KIDS*BUN9*	0.557	0.475	1.172
*KIDS*BUN10*	-4.650	7.843	-0.593
*KIDS*BUN11*	0.642	0.240	2.669
*KIDS*BUN12*	0.225	0.241	0.932
*KIDS*BUN13*	0.645	0.642	1.003
*KIDS*BUN14*	0.224	0.191	1.177
*KIDS*BUN15*	0.452	0.185	2.448
*KIDS*BUN16*	0.962	0.478	2.014
*KIDS*BUN17*	0.249	0.181	1.376
*KIDS*BUN18*	0.149	0.223	0.669
*FAMSIZE*BUN1*	0.041	0.208	0.196
*FAMSIZE*BUN2*	-0.145	0.080	-1.817
*FAMSIZE*BUN3*	-0.148	0.110	-1.337
*FAMSIZE*BUN4*	0.194	0.159	1.225
*FAMSIZE*BUN5*	0.095	0.073	1.303
*FAMSIZE*BUN6*	-0.160	0.112	-1.425
*FAMSIZE*BUN7*	0.255	0.104	2.445
*FAMSIZE*BUN8*	0.167	0.098	1.705
*FAMSIZE*BUN9*	-0.451	0.246	-1.835
*FAMSIZE*BUN10*	-0.396	0.883	-0.449
*FAMSIZE*BUN11*	-0.070	0.101	-0.697
*FAMSIZE*BUN12*	-0.439	0.121	-3.616
*FAMSIZE*BUN13*	-0.155	0.275	-0.565
*FAMSIZE*BUN14*	-0.022	0.079	-0.284
*FAMSIZE*BUN15*	-0.153	0.081	-1.897
*FAMSIZE*BUN16*	0.039	0.180	0.214
*FAMSIZE*BUN17*	0.015	0.074	0.209
*FAMSIZE*BUN18*	-0.044	0.092	-0.480
*DRIVERS*BUN1*	1.056	0.578	1.827

*DRIVERS*BUN2*	0.893	0.409	2.182
*DRIVERS*BUN3*	0.345	0.403	0.857
*DRIVERS*BUN4*	0.841	0.688	1.222
*DRIVERS*BUN5*	1.001	0.541	1.851
*DRIVERS*BUN6*	1.073	0.498	2.157
*DRIVERS*BUN7*	1.417	0.784	1.809
*DRIVERS*BUN8*	1.256	0.653	1.922
*DRIVERS*BUN9*	1.640	0.642	2.554
*DRIVERS*BUN10*	2.225	1.411	1.577
*DRIVERS*BUN11*	1.536	0.428	3.591
*DRIVERS*BUN12*	1.775	0.414	4.294
*DRIVERS*BUN13*	2.195	0.740	2.968
*DRIVERS*BUN14*	1.614	0.494	3.265
*DRIVERS*BUN15*	1.515	0.464	3.267
*DRIVERS*BUN16*	1.885	0.757	2.489
*DRIVERS*BUN17*	1.788	0.579	3.091
*DRIVERS*BUN18*	1.757	0.530	3.312
*EARNERS*BUN1*	0.017	0.289	0.059
*EARNERS*BUN2*	0.292	0.095	3.060
*EARNERS*BUN3*	0.574	0.134	4.296
*EARNERS*BUN4*	0.593	0.246	2.407
*EARNERS*BUN5*	0.388	0.099	3.914
*EARNERS*BUN6*	0.259	0.126	2.065
*EARNERS*BUN7*	0.035	0.162	0.216
*EARNERS*BUN8*	0.353	0.134	2.633
*EARNERS*BUN9*	0.158	0.229	0.690
*EARNERS*BUN10*	0.196	0.910	0.216
*EARNERS*BUN11*	0.788	0.142	5.533
*EARNERS*BUN12*	0.958	0.147	6.513
*EARNERS*BUN13*	0.706	0.385	1.833
*EARNERS*BUN14*	0.805	0.112	7.209
*EARNERS*BUN15*	0.970	0.106	9.131
*EARNERS*BUN16*	0.506	0.265	1.913
*EARNERS*BUN17*	0.735	0.102	7.197
*EARNERS*BUN18*	0.520	0.121	4.290
*AGE2*BUN1*	0.319	0.449	0.711
*AGE2*BUN2*	0.212	0.157	1.349
*AGE2*BUN3*	0.516	0.197	2.627
*AGE2*BUN4*	0.328	0.463	0.709
*AGE2*BUN5*	0.515	0.207	2.480
*AGE2*BUN6*	0.767	0.291	2.639
*AGE2*BUN7*	0.705	0.322	2.190
*AGE2*BUN8*	0.543	0.335	1.619
*AGE2*BUN9*	0.660	0.558	1.182
*AGE2*BUN10*	7.164	31.021	0.231
*AGE2*BUN11*	0.507	0.329	1.542
*AGE2*BUN12*	0.924	0.333	2.771
*AGE2*BUN13*	8.281	37.850	0.219
*AGE2*BUN14*	0.912	0.278	3.281
*AGE2*BUN15*	1.072	0.290	3.693

*AGE2*BUN16*	0.925	0.776	1.193
*AGE2*BUN17*	1.294	0.314	4.123
*AGE2*BUN18*	0.549	0.325	1.690
*AGE3*BUN1*	0.020	0.540	0.036
*AGE3*BUN2*	0.290	0.177	1.639
*AGE3*BUN3*	0.283	0.228	1.243
*AGE3*BUN4*	0.580	0.515	1.128
*AGE3*BUN5*	1.063	0.219	4.862
*AGE3*BUN6*	1.130	0.304	3.718
*AGE3*BUN7*	0.768	0.352	2.182
*AGE3*BUN8*	1.308	0.342	3.824
*AGE3*BUN9*	1.153	0.573	2.010
*AGE3*BUN10*	6.273	31.031	0.202
*AGE3*BUN11*	0.537	0.354	1.517
*AGE3*BUN12*	0.455	0.364	1.250
*AGE3*BUN13*	8.296	37.851	0.219
*AGE3*BUN14*	0.781	0.298	2.617
*AGE3*BUN15*	1.277	0.303	4.214
*AGE3*BUN16*	1.666	0.795	2.096
*AGE3*BUN17*	1.763	0.323	5.465
*AGE3*BUN18*	0.838	0.339	2.471
*AGE4*BUN1*	-0.612	0.630	-0.971
*AGE4*BUN2*	0.117	0.192	0.607
*AGE4*BUN3*	0.408	0.251	1.624
*AGE4*BUN4*	1.152	0.522	2.208
*AGE4*BUN5*	1.140	0.232	4.906
*AGE4*BUN6*	1.456	0.319	4.570
*AGE4*BUN7*	0.938	0.360	2.608
*AGE4*BUN8*	1.669	0.360	4.632
*AGE4*BUN9*	0.989	0.627	1.578
*AGE4*BUN10*	0.522	34.076	0.015
*AGE4*BUN11*	0.094	0.465	0.203
*AGE4*BUN12*	0.591	0.428	1.380
*AGE4*BUN13*	7.440	37.864	0.196
*AGE4*BUN14*	1.082	0.332	3.264
*AGE4*BUN15*	1.814	0.326	5.566
*AGE4*BUN16*	1.323	0.891	1.485
*AGE4*BUN17*	1.787	0.348	5.137
*AGE4*BUN18*	1.372	0.364	3.764
*REGION2*BUN1*	0.664	0.772	0.860
*REGION2*BUN2*	0.352	0.147	2.393
*REGION2*BUN3*	0.604	0.193	3.129
*REGION2*BUN4*	-0.035	0.437	-0.081
*REGION2*BUN5*	0.429	0.159	2.704
*REGION2*BUN6*	1.262	0.206	6.132
*REGION2*BUN7*	0.990	0.300	3.303
*REGION2*BUN8*	0.999	0.240	4.157
*REGION2*BUN9*	0.923	0.395	2.337
*REGION2*BUN10*	1.690	19.400	0.087
*REGION2*BUN11*	0.956	0.281	3.402

*REGION2*BUN12*	0.769	0.257	2.988
*REGION2*BUN13*	-0.620	1.163	-0.533
*REGION2*BUN14*	0.830	0.205	4.040
*REGION2*BUN15*	1.225	0.181	6.760
*REGION2*BUN16*	2.030	0.793	2.559
*REGION2*BUN17*	1.369	0.197	6.961
*REGION2*BUN18*	1.229	0.232	5.291
*REGION3*BUN1*	1.337	0.669	1.998
*REGION3*BUN2*	0.112	0.146	0.770
*REGION3*BUN3*	0.803	0.186	4.320
*REGION3*BUN4*	0.715	0.390	1.831
*REGION3*BUN5*	0.219	0.158	1.389
*REGION3*BUN6*	1.014	0.218	4.663
*REGION3*BUN7*	0.769	0.297	2.589
*REGION3*BUN8*	0.991	0.243	4.079
*REGION3*BUN9*	0.840	0.381	2.206
*REGION3*BUN10*	5.547	16.555	0.335
*REGION3*BUN11*	0.467	0.285	1.637
*REGION3*BUN12*	0.451	0.249	1.812
*REGION3*BUN13*	-0.157	0.782	-0.201
*REGION3*BUN14*	0.588	0.203	2.893
*REGION3*BUN15*	0.605	0.188	3.217
*REGION3*BUN16*	1.587	0.784	2.023
*REGION3*BUN17*	0.937	0.201	4.651
*REGION3*BUN18*	0.963	0.236	4.074
*REGION4*BUN1*	2.216	0.651	3.403
*REGION4*BUN2*	0.360	0.156	2.305
*REGION4*BUN3*	0.389	0.211	1.840
*REGION4*BUN4*	0.545	0.445	1.225
*REGION4*BUN5*	0.076	0.181	0.418
*REGION4*BUN6*	0.907	0.237	3.826
*REGION4*BUN7*	1.437	0.298	4.825
*REGION4*BUN8*	0.763	0.274	2.786
*REGION4*BUN9*	0.100	0.475	0.210
*REGION4*BUN10*	6.449	16.544	0.390
*REGION4*BUN11*	0.924	0.289	3.198
*REGION4*BUN12*	0.182	0.277	0.656
*REGION4*BUN13*	1.007	0.702	1.434
*REGION4*BUN14*	0.538	0.223	2.411
*REGION4*BUN15*	0.434	0.209	2.082
*REGION4*BUN16*	2.144	0.789	2.717
*REGION4*BUN17*	0.752	0.225	3.350
*REGION4*BUN18*	0.791	0.260	3.039
LNMAKE	-1.245	0.213	-5.844

Estimation using 5740 households times 19 choices equals 109060 observations.
Log Likelihood = -12346.984
χ^2 = 9108.19
Pseudo R^2 = .2695