Vehicle Choices, Miles Driven, and Pollution Policies

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ABSTRACT

Mobile sources contribute large percentages of each pollutant, but the technology is not yet available to measure and tax emissions from each vehicle. We build a behavioral model of household choices about vehicles and miles traveled. The ideal-but-unavailable emissions tax would encourage drivers to abate emissions through many behaviors, some of which involve market transactions that can readily be observed for feasible market incentives: tax engine size, subsidize newer cars, or tax gasoline. Our model can calculate behavioral effects of each such price and thus calculate car choices, miles, and emissions.

A two-level nested logit structure is used to model individual households' discrete choices among different vehicle bundles. We also consider continuous choices of miles driven and the age of each vehicle. We propose a consistent estimation method for both discrete and continuous demands in one step, to capture the interactive effects of simultaneous decisions. Results are compared with those of the traditional sequential estimation procedure.

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The standard economic case for market-based incentives requires that a tax or permit price on each unit of emissions. Each form of abatement is then pursued up to the point where the marginal cost of reducing a unit of pollution exactly matches the tax per unit of pollution. The resulting combination of abatement technologies is the social-cost minimizing combination (Pigou, 1920). For vehicles, a price or tax on emissions could induce drivers to: (1) buy a newer, cleaner car, (2) buy a smaller, more fuel efficient car, (3) fix their broken pollution control equipment, (4) buy cleaner gasoline, (5) drive less, (6) drive less aggressively, and (7) avoid cold start-ups.[1] Moreover, economic efficiency requires different combinations of these methods for different consumers: some lose little by switching to a smaller car, some could easily walk, and some just pay the tax.

Yet the technology is not available to measure each car's emissions in a reliable and cost-effective manner. On-board diagnostic equipment is too costly because millions of vehicles would need to be retrofitted (Harrington et al., 1994). Remote sensing is less expensive but cannot distinguish emissions clearly enough to tax each car (Sierra Research, 1994, p. 17). Moreover, vehicle emissions are important. In 1997, vehicles in the U.S. contributed 32 percent of total carbon dioxide (CO_2) emissions, 36 percent of hydrocarbons (HC), 41 percent of nitrogen oxides (NO_x), and 61 percent of carbon monoxide (CO) emissions (http://www.bts.gov/btsprod/nts/).

For these reasons, vehicle emission policies have relied almost solely on mandates: new cars must meet required emission rates, refineries must make cleaner gasoline, and households in certain areas must bring their cars for inspection and maintenance (I/M) programs (U.S. National Research Council, 2001).[2] These command and control (CAC) policies miss the opportunity to reduce social costs by harnessing individual incentives, however, as the mandated combination of abatement methods is unlikely to match the combination that households would choose if faced with a tax per unit of emissions. In fact, the cost of abatement using such mandates can be several times the minimum cost achieved by using an emissions tax (Newell and Stavins, 2003).

[1] Because of cold start-up emissions, Burmich (1989) finds that a 5-mile trip has almost three times the emissions per mile as a 20-mile trip. Sierra Research (1994) finds that a car driven aggressively has CO emissions that are almost 20 times higher than when driven normally.

[2] In the U.S., new cars face emissions standards of .254 grams/km of HC's, 2.11 grams/km of CO, and .248 grams/km of NO_x. Light trucks face a variety of weaker standards, but all are scheduled to become more stringent. These figures pertain to a test in the U.S. with a cold start-up phase, a transient phase at different speeds, and a hot start phase, for a total distance of 18 km at an average speed of 34 km/h.

While the inability to measure emissions may preclude a vehicle emissions tax, it does not preclude any use of incentives. Price mechanisms can still apply to observable behavior, especially market transactions that generate an invoice for verification or where the retailer can collect the tax or pay the subsidy. Those who sell new or used cars or light-trucks can collect tax on vehicle characteristics that are associated with emissions, or provide subsidy for vehicles with low emissions. Most states charge annual registration fees that can be made to depend on vehicle characteristics. Such policies might reduce emission rates, while changes in the gasoline tax might reduce miles driven.[3]

What vehicle characteristics or behaviors should be targeted by a tax or subsidy? How would consumers react to those new incentive instruments? How much would each instrument reduce emissions? To address these questions, we build a general purpose model of discrete choices by households regarding how many cars to own and what types of cars to own, plus continuous choices about how far to drive. Our model is based on Dubin and McFadden (1984), who use a two-step procedure to estimate a discrete choice model (for household appliances) and then a continuous choice (usage hours). Others extend this model to a discrete choice among vehicle bundles and a continuous choice of miles (e.g. Train, 1986, Goldberg, 1998, and West, 2004). We further extend this work in several ways. First, we allow for two continuous choices of miles – in each vehicle of a two-vehicle household. These choices are bundle-specific. Thus, in response to a higher price of gas, a one-car family reduces miles by one amount, a one-SUV family can decrease miles by a different amount, and each two-vehicle family can decrease miles by a bundle-specific amount.[4] Second, we allow for two more continuous choices, for the age of each vehicle of a two-vehicle family. Third, we capture the simultaneity of these decisions by proposing a method for consistent estimation of both discrete and continuous choices in one step. Whereas the Dubin-McFadden method corrects for selection of

[3] The trading of permits may not work for millions of drivers, but a tax or subsidy can still be provided to individual drivers. A new higher gas tax may be politically unlikely, yet it is still worth studying to know its power as an emissions-reduction tool. And even if governments are unlikely to use tax dollars to pay for the various subsidies we study here, these incentives might instead be provided to drivers by private companies that want to purchase "offsets" – reductions in vehicle emissions to offset their increases from stationary sources. For all of these reasons, we find it important to study specific incentives to drivers.

[4] Some households might drive fewer miles in their SUV and *more* miles in their car. We do not estimate separately the miles in each vehicle, but we do estimate a change for the (Car, SUV) bundle that might differ from the (Car, Car) bundle. A couple of other papers have estimated substitution between vehicles within the family, but they treat the vehicles as given rather than chosen. Greene and Hu (1985) find that this kind of substitution occurs to a large extent in some households, while Sevigny (1998) finds small effects.

vehicle on the choice of miles, our simultaneous procedure also allows for fuel demand to affect the choice of vehicle. Fourth, we use the estimated parameters not only to predict changes in choices about vehicles and miles, but also how those choices affect emissions.[5]

Several papers explore market incentives that could be used in place of a tax on vehicle emissions.[6] In addition, several papers estimate models of the discrete choice among vehicle bundles (including number, size, and age categories).[7] Some models estimate the demand for gasoline or for vehicles-miles traveled (*VMT*) as functions of prices and incomes.[8] As well, we note that other models predict emissions.[9] A major contribution of our research, then, is to include all such choices simultaneously. In general, we capture the effect of any price change on each household's choices about the number of cars to buy, the age and size of each, the consequent emissions rates, the miles driven in each car, and the consequent total emissions. And we capture heterogeneity, which is important because a single policy can affect each household differently.[10]

For two reasons, however, our discrete choice model does not use discrete vehicle size and age categories. First, as in Fullerton and West (2000), regressions below find that engine size is not an important determinant of emission rates (controlling for type of vehicle). Instead, we distinguish the vehicle type, whether car or "sports utility vehicle" (SUV, for short, but including all light trucks and vans). This distinction matters most for emissions, because emission standards for new SUV's have not been as strict as those for cars. In contrast, for each of those two vehicle types, the emission rules for new vehicles do not depend on engine size. Second, those regressions find that vehicle age is a very important determinant of emission rates. We wish not to lose information by aggregating vehicles into finite age categories (e.g. new vs. old). Age is a continuous variable, and the consumer's choice of vehicle age is a continuous demand that affects emissions.

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[5] Our household responses represent market outcomes only if supply curves were horizontal. However, our demand system could be combined with some other estimates of supply to calculate equilibrium outcomes.

[6] For examples, see Eskeland and Devarajan (1996), Innes (1996), Kohn (1996), Train et al (1997), Plaut (1998), Sevigny (1998), and Fullerton and West (2000, 2002).

[7] For examples, see McFadden (1979), Train (1986), Brownstone et al (1996), Goldberg (1998), Brownstone and Train (1999), West (2004), and other papers reviewed in McFadden (2001).

[8] See the review of this literature in Harrington and McConnell (2003).

[9] For example, the U.S. Environmental Protection Agency (U.S. EPA, 1998, p.3-68) discusses the use of EPA's MOBILE5a model or California's EMFAC7F model.

[10] Fullerton and West (2000) simulate the effects of incentives with heterogeneous households, but they do not model discrete choices like the number of cars, and they calibrate rather than estimate parameters.

We therefore model continuous choice of miles and of vehicle age. If a household in our model chooses to own two vehicles, then it has four continuous choices: age of each vehicle and miles to drive each vehicle.[11]

Age is normally measured in years, of course, but our model requires a price that does not depend on the amount demanded. The price of age is not linear, because owning a brand-new car costs more depreciation per year than owning an old car. Instead of using age in years, we therefore construct a continuous choice variable called "*Wear*" that measures the fraction of the vehicle that has depreciated (between 0 and 1). A constant rate of depreciation means that *Wear* is a nonlinear function of age, but then the price per unit of *Wear* does not depend on its amount (for each vehicle type, as estimated from hedonic price regressions below). Next, in order to separate this choice of vehicle attribute from the choice of vehicle, we assume that the discrete choice is about a brand-new "concept vehicle." Then the household gets reimbursed by the price of *Wear* for accepting an older car. In other words, in our model, a household makes simultaneous decisions about which concept vehicles, how old, and miles to drive. This simultaneity is important because the cum-tax price of gasoline affects not only choices about gasoline and miles, but also choices about what cars to drive. Similarly, any incentive policy that affects the cost of particular cars will affect choices about both cars and miles.

The next section describes a behavioral choice model for one-vehicle households and then extends it to consider two-vehicle bundles. It also presents a new method designed for jointly estimating all discrete and continuous choices. Section II describes data sources and provides summary statistics, while Section III provides estimation results for both discrete choices and continuous demands. Finally, Section IV concludes.

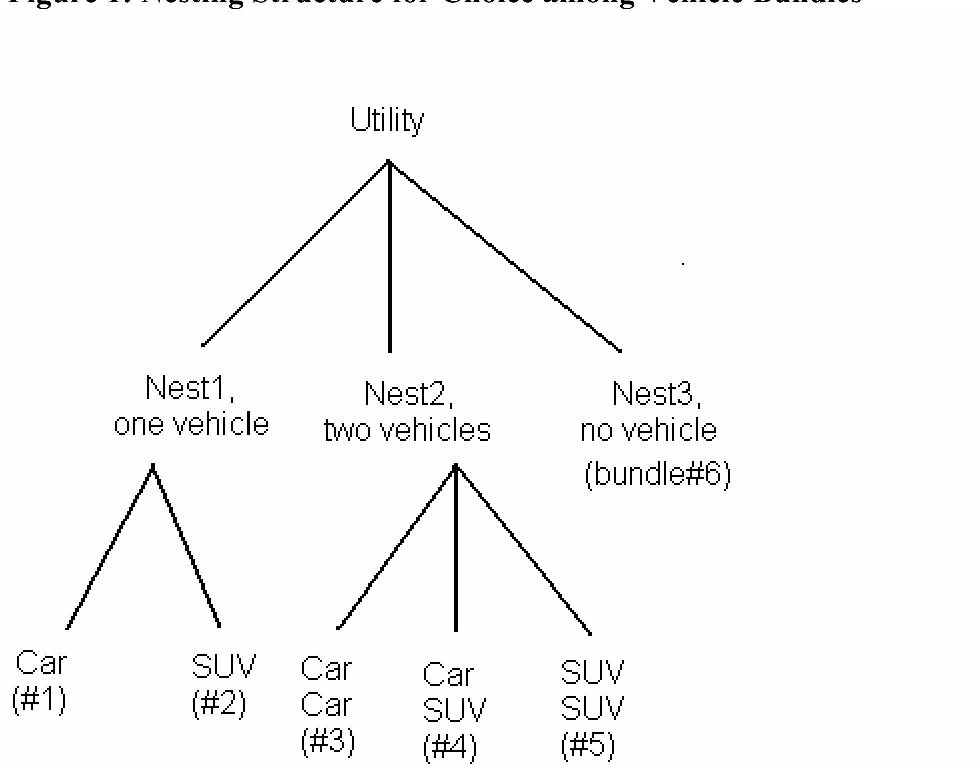
I. The Model and Estimation

In our model, an agent representing each household faces a discrete choice among a finite number of vehicle bundles. The nesting structure is shown in Figure 1. One choice is the number of vehicles (0, 1, or 2), and another choice for each vehicle is the type of vehicle (a car or an SUV). We thus have in six final bundles, as shown in the

[11] In the model of Fullerton and West (2000), utility depends directly on continuous choices for car size (in cubic inches), car age (in years), and vehicle miles traveled (*VMT*). That model avoids discrete choices, but it considers only one car per agent. In our model, we need discrete choices to consider the household's number of cars. Utility still depends on car size and age in our model, but only through choice of bundle.

figure and listed in Table 1. In addition, for each vehicle, the household makes continuous choices about vehicle miles traveled (*VMT*) and vehicle age. Vehicle age is important because each year affects the vehicle's emissions rate. We construct a variable called "*Wear*" that measures age in a non-linear way, yielding a linear price. It is the fraction of the vehicle used up by depreciation, and it is calculated for each car in our sample by assuming 20% depreciation per year, so $Wear = 1 - (1 - 0.2)^{age}$.

Figure 1: Nesting Structure for Choice among Vehicle Bundles



Then, since choice of age is considered separately, each discrete vehicle bundle must be defined in a way that is independent of age. For this reason, we define each "concept" vehicle as a bundle of attributes of a brand-new vehicle (car or SUV). The household must pay the price of that brand-new vehicle (the "capital cost"), but then it gets back some money for accepting *Wear* on that vehicle (the "reimbursement" price of *Wear*).

Our demand system now has several distinguishing characteristics. First, it incorporates all of these discrete and continuous choices simultaneously. Second, some unobserved characteristics might affect both kinds of choices. For example, an agent who lives far from work may drive more and thus prefer a larger, more comfortable car.

Yet, a more comfortable car may increase the satisfaction of driving and thus induce more driving. Third, many households have two cars with multiple continuous choices. Consequently, the substitution structure in *VMT* and *Wear* among different vehicles is important in order to understand the effects of policy on driving behavior.

Since the model of Dubin and McFadden (1984) involves only two discrete choices, that paper's logit model does not need to be generalized. Our model with six choices requires a more general logit structure, however, so we use the nested logit. The next sub-section describes the simple case for households with only one vehicle, and the second subsection considers multi-vehicle households. In the third and fourth sub-sections, we discuss the estimation procedure and elasticity calculations.

A. Our Model of Car Choice and Miles Driven

This description starts with the choices of miles and *Wear*, assuming that a one-car household has already chosen vehicle number-and-type bundle i. Given bundle i, an agent's direct utility is a function of *VMT*, *Wear*, and another consumption good c. That is, $U = U(VMT_i, Wear_i, c_i)$. Given income y, the budget constraint is given by:

$$\frac{p_g}{MPG_i} VMT_i - q_i Wear_i + c_i = y - r_i\,, \tag{1}$$

where p_g is the price of gasoline (in dollars per gallon), and MPG_i is fuel efficiency (in miles per gallon), so that $p_i \equiv p_g/MPG_i$ is the price per mile in the ith vehicle bundle. The "reimbursement" price of *Wear* for vehicle type i is denoted as q_i. The price of the other consumption good is normalized to be 1. The annualized cost of the concept-vehicle bundle is r_i. Thus, gasoline is the only cost per mile, whereas capital cost is a fixed cost of each bundle. The indirect utility for bundle i is a function of household income and prices, denoted as $V(y\text{-}r_i, p_i, q_i)$.

One common way to obtain the indirect utility function is to use parametric demand and then solve a system of partial differential equations using Roy's identity (Hausman, 1981). As in other studies, we would want *VMT* demand as a log-linear function of the price per mile p_i, available income $y\text{-}r_i$, and a vector of observed socio-demographic variables x. When we add the reimbursement price q_i to that equation, we have:

$$\ln(VMT_i) = \alpha_V^i + \alpha_p^i p_i - \alpha_q q_i - \beta\left(y - r_i\right) + x'\gamma + \eta\,, \tag{2}$$

where η represents an agent-specific unobserved factor (see below).[12] Also, we assume

$$r_i = (\delta+\rho)k_i, \tag{3}$$

where k_i is the total capital value of bundle i (depreciated or market value), δ is the annual rate for further depreciation of that value, and ρ represents the interest and maintenance cost. When we plug (3) into (2) and integrate, the implied indirect utility is:

$$V_i = \frac{1}{\beta}\exp\left(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta\right) - \frac{1}{\alpha_p^i}\exp(\alpha_p^i p_i - \alpha_q q_i) + \varepsilon_i\,, \tag{4}$$

where $\beta_1 = \beta(\delta+\rho)$.[13] This equation includes an extra additive error ε_i that is bundle-specific. As in the usual discrete choice model, this error term represents the difference between true individual utility at choice i and the calculated utility level.[14]

Note that the simple addition of the price of *Wear* to equation (2) dictates the form of indirect utility in (4). This indirect utility then implies specific forms for both demands:

$$\ln(VMT_i) = \alpha_V^i + \alpha_p^i p_i - \alpha_q q_i - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{5a}$$

$$\ln(Wear_i) = \alpha_W^i + \ln\left(\alpha_q / \alpha_p^i\right) + \alpha_p^i p_i - \alpha_q q_i - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{5b}$$

This specification has pros and cons. One limitation is using specific functional forms, but these forms are comparable to prior literature and allow us to use two different demand function (5a and 5b) that are consistent with a single indirect utility function (4). An advantage of this specification is that it allows the price of *Wear* (q_i) to enter the *VMT* demand, and price of *VMT* (p_i) to enter the *Wear* demand, but a limitation is that the expression $\alpha^i_p p_i + \alpha_q q_i$ enters both demands the same way.[15] Also, both continuous

[12] A more general demand function for *VMT* such as a translog demand or almost ideal demand system (AIDS) implies a much more complicated indirect utility function that could not be estimated.

[13] Our model provides estimates of β and β_1, and these can be used to calculate $(\delta+\rho)$, but we do not provide separate estimates of δ and ρ. Some of our data work requires an assumption about δ, and we use 20 percent for this purpose. Estimates of the depreciation rate for automobiles range from 33% (Jorgenson, 1996) or 30% (Hulten and Wykoff, 1996) to 15%, the rate implicit in the vehicle depreciation schedule currently used by the Bureau of Economic Analysis. We use 20% because it falls between these bounds.

[14] Note that the intercept in (4) may be different from the intercept in (2).

[15] Thus, a change in p_i must have the same effect on *Wear* that it has on miles. We tried other models, including one where indirect utility has separate terms $\exp(\alpha^i_p p_i)$ and $\exp(\alpha_q q_i)$, so that p_i would have no effect on *Wear*, and q_i would have no effect on *VMT*. That model would not converge, and anyway it is restrictive by assuming no cross-price effects. We also tried models with more coefficients, to relax these restrictions, and we tried many starting points, but only the model in (4) and (5) could be estimated simultaneously for discrete and continuous choices (especially for two-vehicle bundles considered below).

demands have the same income effect, β. A more general model could not be estimated. Note, however, that we have added generality where it matters most. In particular, the price per mile has a bundle-specific coefficient (α^i_p), to allow for different effects on the demand for miles in each type of vehicle. Thus a gas tax might decrease miles in an SUV more than in a car, in a way that depends on fuel efficiency, and the change in miles of a two-car household can differ from the change in miles of a household with two SUV's (or one car and one SUV).

B. Two-Vehicle Households

So far, the model above considers only decisions about miles and age for one car. Yet many households have two cars and thus have two continuous choices of miles and two continuous choices of *Wear*. We have the observed choice of *VMT* and *Wear* for each vehicle, so we can build a model that incorporates all four continuous choices: miles driven and *Wear* for each vehicle.[16] The direct utility for a two-car household choosing bundle i is $U(VMT_{i1}, VMT_{i2}, Wear_{i1}, Wear_{i2}, c_i)$. The budget constraint is given by:

$$\frac{p_g}{MPG_{i1}}VMT_{i1} + \frac{p_g}{MPG_{i2}}VMT_{i2} - q_{i1}(Wear_{i1}) - q_{i2}(Wear_{i2}) + c_i = y - r_i, \tag{6}$$

where q_{ij} are reimbursement prices for *Wear* in the two vehicles of bundle i ($j = 1, 2$). Also, $p_{ij} \equiv p_g/MPG_{ij}$ is the price per mile using the jth car of bundle i. We consider the indirect utility function as follows:

$$V_i = \frac{1}{\beta}\exp\left(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta\right) - \frac{1}{\alpha^i_{p1}}\exp(\alpha^i_{p1}p_{i1} + \alpha^i_{p2}p_{i2} - \alpha_{q1}q_{i1} - \alpha_{q2}q_{i2}) + \varepsilon_i \tag{7}$$

The indirect utility in (7) is similar to (4) except for two extra terms related to the second vehicle's gasoline price p_{i2} and reimbursement price q_{i2}. By Roy's identity, given that the household has chosen bundle i in (7), the four continuous demands are:

$$\ln(VMT_{i1}) = \alpha^i_{V1} + \alpha^i_{p1}p_{i1} + \alpha^i_{p2}p_{i2} - \alpha_{q1}q_{i1} - \alpha_{q2}q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8a}$$

$$\ln(VMT_{i2}) = \alpha^i_{V2} + \ln(\alpha^i_{p2}/\alpha^i_{p1}) + \alpha^i_{p1}p_{i1} + \alpha^i_{p2}p_{i2}$$
$$- \alpha_{q1}q_{i1} - \alpha_{q2}q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8b}$$

[16] Another interesting question is about each household member's choice of miles driven (in either car), but we have no such data. As described below, we have only data on miles driven in each vehicle.

$$\ln(Wear_{i1}) = \alpha^i_{W1} + \ln(\alpha_{q1} / \alpha^i_{p1}) + \alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2}$$
$$- \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \qquad (8c)$$
$$\ln(Wear_{i2}) = \alpha^i_{W2} + \ln(\alpha_{q2} / \alpha^i_{p1}) + \alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2}$$
$$- \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \qquad (8d)$$

The demand for VMT_{i1} in (8a) generalizes that for a one-vehicle household in (5a) by including terms for p_{i2} and q_{i2} (so we refer to all demands in (8)). The demand for VMT_{i2} is symmetric to VMT_{i1} in explanatory variables, but it is non-linear in parameters of both p_{i1} and p_{i2}. The demands for $Wear_{ij}$ $(i, j = 1, 2)$ are similarly defined.

C. A Procedure to Estimate Discrete and Continuous Demands Simultaneously

Note that the same parameters appear in both discrete and continuous choice functions, yet previous literature has estimated these choice models separately. Often the estimates for the same parameters are different not only in magnitude but also in sign. In this sub-section, we propose a procedure for simultaneous estimation of bundle choice, vehicle age, and miles driven. We start with separate discussion of car choice and miles driven, and then how we combine them in a single estimation procedure.

Following McFadden's random utility hypothesis, vehicle bundle i is chosen if and only if: $V_i \geq V_j$ for all $j \neq i$. The unconditional expected share for bundle i then is:

$$S_i = \int \Pr(V_i > V_j, \forall j \neq i \mid \eta) f(\eta) d\eta, \qquad (9)$$

where S_i is the share choosing bundle i, and $f(\eta)$ is the probability density function of the agent-specific error η. We are now in a position to describe the importance of η. On the one hand, individual heterogeneity represented by η could directly affect the choice of bundle. On the other hand, demands for VMT and $Wear$ are estimated conditional on that choice. Since the choice of vehicle bundle is typically a control variable that may be endogenous because of η, the estimated demands of VMT and $Wear$ could be biased without considering the influence of η. The joint model of VMT, $Wear$ and vehicle bundle choice helps us to solve this problem. In the model of Dubin and McFadden (1984), the error term η can be cancelled out from the inequality $\{V_i > V_j, \forall j \neq i\}$, which simplifies the calculation of probabilities (that is, the integration over η in equation (9) is not necessary). In such a model, individual heterogeneity does not affect the choice of vehicle bundle directly, but our purpose here is to *retain* heterogeneity through individual-specific η. Therefore, the evaluation of probabilities in our model will involve integration over all error components: (ε, η) where $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$ and where K is the number of possible vehicle bundles. In our model, the ε_i are assumed to be distributed with a generalized extreme value (GEV) distribution, and η follows an unknown distribution with a zero mean across individuals. Conditional on η, we integrate over the GEV distribution to obtain conditional choice probabilities as a general nested logit model:

$$\Pr\left(V_{ni} > V_{lm}, \forall m \neq i, \forall n, l \middle| \eta\right) = \frac{\exp(V_i/\lambda_n)\left(\sum_{j \in B_k} \exp\left(V_j/\lambda_n\right)\right)^{\lambda_n - 1}}{\sum_{l=1}^{K}\left(\sum_{j \in B_l} \exp\left(V_j/\lambda_l\right)\right)^{\lambda_l}} \quad , \tag{10}$$

where n and l represent nests, i is an alternative within nest n, and m is an alternative within nest l. The nesting structure adopted in this paper is illustrated in Figure 1.

We also integrate over the distribution of η to obtain unconditional probabilities. The literature offers no guidance on the distribution of the η.[17] To reduce the numerical difficulty in estimation, we let η be uniformly distributed in the interval [-0.5, 0.5].

As pointed out by Dubin and McFadden (1984), the random error η does not have a zero mean conditional on each chosen bundle, due to the endogeneity of bundle choice. This can be seen clearly if we rewrite equations (8) into a more convenient form for estimation (using just equation 8a, as an example):

$$\begin{aligned}\ln(VMT_{i1}) = \sum_j \alpha_{V1}^j d_{ij} + \sum_j \alpha_{p1}^j p_{j1} d_{ij} + \sum_j \alpha_{p2}^j p_{j2} d_{ij} \\ - \alpha_{q1} \sum_j q_{j1} d_{ij} - \alpha_{q2} \sum_j q_{j2} d_{ij} - \beta y + \beta_1 \sum_j k_j d_{ij} + x'\gamma + \eta\end{aligned} \tag{11a}$$

where d_{ij} is a choice indicator variable equal to one when $i = j$. The random error η is correlated with the choice indicators d_{ij}. Dubin and McFadden (1984) suggest sequential estimation to solve this endogeneity problem (a procedure later adopted by Goldberg (1998) and West (2004)). First, the discrete choice model is estimated and the predicted probabilities are calculated. They then suggest three alternative methods that yield consistent estimates of parameters for continuous demands: the instrumental variable method (IV), the reduced form method (RF), and the conditional expectation correction

[17] Dubin and McFadden (1984) assume η has a particular form of mean and variance, in order to derive an explicit conditional expectation.

method (CE). They derive the correction terms in terms of probabilities for the CE method based on the assumption of an *i.i.d.* extreme value distribution of ε_i. However, since we assume a GEV distribution of ε_i, these correction terms cannot be used in our model. We want a method that can be used both for sequential estimation and for our simultaneous estimation, in order to compare them, and so we employ the RF method. It is an application of OLS to all equations (11a-d), except that all the choice dummies d_{ij} are replaced by the estimated shares $\hat{S}_j$ when continuous demands are estimated.

As noted earlier, the same parameters appear in both discrete and continuous choice functions. To capture this simultaneity, we propose a joint estimation method. In particular, we obtain a set of parameters that maximize the following objective function:

$$\begin{aligned} F(\Theta|y, p_1, p_2, q_1, q_2, k, x) &= -\sum_n(\ln(VMT_1) - f_1)^2 - \sum_n(\ln(VMT_2) - f_2)^2 \\ &- \sum_n(\ln(Wear_1) - g_1)^2 - \sum_n(\ln(Wear_2) - g_2)^2 + \sum_n \ln L \end{aligned} , \tag{12}$$

where f_1, f_2, g_1, and g_2 represent the right hand sides of the four equations (11a-d) that correspond to (8a-d), lnL is the log likelihood function of the nested logit, and Θ represents the set of parameters to be estimated by maximizing equation (12).

As is consistent with Dubin and McFadden (1984) and other papers in this literature, the maintained hypotheses are that the utility functional form is correct and that consumers maximize it. Under these hypotheses, our procedure produces consistent estimates of parameters. The reasoning is as follows: if the components of (12) were maximized separately, and if some single set of parameters were the solution to all those separate maximizations, then this set of parameters would also maximize the combined objective function. To compare the results, we estimate our model by both the sequential method and the simultaneous estimation method.

D. Elasticities

Once we obtain the parameter estimates, we are ready to calculate elasticities. To see the marginal effects of prices on indirect utility, and therefore on bundle choice, we use equation (7) to obtain explicit formulas for those derivatives. First, define $\exp(\cdot) \equiv \exp(\alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2} - \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2})$. Then:

$$\frac{\partial V_i}{\partial p_{i1}} = -\exp(\cdot) \ , \qquad \frac{\partial V_i}{\partial p_{i2}} = -\frac{\alpha^i_{p2}}{\alpha^i_{p1}}\exp(\cdot) \tag{13a}$$

$$\frac{\partial V_i}{\partial q_{i1}} = \frac{\alpha_{q1}}{\alpha^i_{p1}}\exp(\cdot)\,, \qquad \frac{\partial V_i}{\partial q_{i2}} = \frac{\alpha_{q2}}{\alpha^i_{p1}}\exp(\cdot) \tag{13b}$$

and the marginal effects of income or capital cost on utility take similar forms:

$$\frac{\partial V_i}{\partial y} = \exp(-\alpha^i_0 + \beta y - \beta_1 k_i - x'\gamma - \eta) \tag{14a}$$

$$\frac{\partial V_i}{\partial k_i} = -\frac{\beta_1}{\beta}\exp(-\alpha^i_0 + \beta y - \beta_1 k_i - x'\gamma - \eta) \tag{14b}$$

Then we derive the elasticity of choice i with respect to a change in variable z_j (where z_j may be any of the price variables, income y, or capital cost k_j):

$$g^i_{z_j} = \frac{\partial S_i}{\partial z_j}\cdot\frac{z_j}{S_i} = \frac{\partial S_i}{\partial V_j}\cdot\frac{\partial V_j}{\partial z_j}\cdot\frac{z_j}{S_i} \tag{15}$$

Since these formulas involve the unconditional probability of vehicle bundle i, calculating each bundle elasticity requires integration over η. In contrast, calculations of VMT elasticites do not involve integration over η. For bundle i ($i = 1, \ldots, 5$), the own- and cross- price elasticities of VMT demand are calculated by:

$$e^i_{V1p1} = \frac{\partial \ln(VMT_{i1})}{\partial \ln p_{i1}} = \alpha^i_{p1} p_{i1} = e^i_{V2p1} \ , \qquad e^i_{V2p2} = \frac{\partial \ln(VMT_{i2})}{\partial \ln p_{i2}} = \alpha^i_{p2} p_{i2} = e^i_{V1p2} \tag{16}$$

The elasticities of demand for $Wear$ with respect to its price have a similar form:

$$e^i_{W1q1} = \frac{\partial \ln(Wear_{i1})}{\partial \ln q_{i1}} = -\alpha_{q1} q_{i1} = e^i_{W2q1} \ , \quad e^i_{W2q2} = \frac{\partial \ln(Wear_{i2})}{\partial \ln q_{i2}} = -\alpha_{q2} q_{i2} = e^i_{W1q2} \tag{17}$$

We can also calculate the income elasticity, given by:

$$e^i_{Vy} = \frac{\partial \ln(VMT_{i1})}{\partial \ln y} = \frac{\partial \ln(VMT_{i2})}{\partial \ln y} = -\beta y \ , \tag{18}$$

and the total capital cost elasticity, given by:

$$e^i_{Vk} = \frac{\partial \ln(VMT_{i1})}{\partial \ln k_i} = \frac{\partial \ln(VMT_{i2})}{\partial \ln k_i} = \beta_1 k_i \, . \tag{19}$$

In equations (15) – (19), elasticities are typically evaluated at each bundle's mean values of y and k, the bundle average of gas prices per mile (p_1 and p_2) and the bundle average of reimbursement prices (q_1 and q_2).

II. Data and Summary Statistics

In order to analyze household choice of vehicles, miles driven, and vehicle *Wear*, we need micro-data on household characteristics, household income or expenditures, and detailed information about household-owned vehicles such as the number of vehicles, miles driven in each, and vehicle characteristics (including miles per gallon, MPG, and emissions per mile, EPM). No single data set contains all such information.

The Consumer Expenditure Survey (CEX) provides data on household income, household characteristics, and household-owned vehicles.[18] For this study, we use the CEX data from 1996 to 2000, supplemented with the corresponding OVB file (Owned Vehicles Part B Detailed questions). This OVB file includes data on each vehicle type, make, year, number of cylinders, purchase expenses and financing, time since purchase, mileage, gasoline expenditure, and other information. We keep only households that satisfy the following criteria. First, the household must be reported consecutively for 4 quarters in the CEX of 1996-2000. Second, the household must possess the same number of vehicles during these four quarters. Third, we remove those households who own more than two vehicles.[19] We also remove households who have vehicles other than automobiles or SUVs (defined to include light trucks or vans). The household's demographic data and detailed vehicle information are taken from the last quarter they appear in the survey. Finally, we are left with 9036 households, of which 2077 own no vehicles, 4213 own one vehicle, and 2746 own two vehicles. We use yearly total expenditure as a proxy for yearly income of each household. Table 2 defines all the variables used in estimations.

Summary statistics are shown in Table 3 for major household characteristics by vehicle bundle. This table shows significant variations in household characteristics across the number of vehicles and bundles. For example, larger households especially with more

[18] The CEX data are collected by the Bureau of Labor Statistics of the U.S. Department of Labor through quarterly interviews of selected households throughout the U.S. Each household is interviewed over five consecutive quarters. In each quarter, twenty percent of households that complete their last interview in the previous quarter are replaced by new households. The CEX data can be obtained free from several sources, including http://elsa.berkeley.edu and http://www.icpsr.umich.edu/.

[19] In the CEX of 1996-2000, 81.60% of households own at most two vehicles.

kids have more vehicles and prefer SUVs. Wealthier households (as measured by total yearly expenditures) possess more vehicles. Households with more workers or income earners have more vehicles. Households with male heads are inclined to have SUVs.

Next, fuel price data are obtained from the ACCRA cost-of-living index for 1996-2000. This index compiles quarterly data for approximately 300 cities in the United States. It also lists average gasoline price for each city for each survey quarter. Since the CEX reports region and state of residence instead of city for each household, we average the city gas prices to obtain a state price for each calendar quarter. For those states reported in the CEX, but not reported in the ACCRA index, we use the average region price as a substitute. Then we assign a gas price to each CEX household based on the state of residence, CEX quarter, and year.

Some of the variables in our model require calculations or additional sources of data. We now describe these extra calculations.

(1) Wear: The vehicle's age is derived by taking the year of the survey minus the year the vehicle was made. We then assume 20% annual depreciation, and calculate *Wear* as the percentage of the vehicle’s value that has wasted away (given all the vehicle characteristics unchanged except vehicle age). *Wear* ranges from zero for a new car, to $Wear = 1$ for a very old car. Specifically, $Wear = 1 - (1 - 0.2)^{\text{age}}$.

(2) Capital value of the vehicle: The vehicle's year of purchase and reported purchase price (*pp*) are available in the OVB file, but we want an estimate of current market value (*cmv*). We calculate the "number of years since purchase" (*#ysp*), and we subtract depreciation for each year, again using 20% as the annual rate of depreciation. The formula is $cmv = pp \times (1 - 0.2)^{\#\text{ysp}}$. If the purchase price or number of years since purchase is missing, we impute *cmv* using a simple hedonic price regression:

$$cvm = a_0 + a_1 \times (cyl) + a_2 \times (tran) + a_3 \times (import) + b \times (1\text{-}Wear) \quad , \qquad (20)$$

where a_0 through a_3, and b are parameters. The variable *cyl* denotes the number of cylinders, while *tran* and *import* are dummy variables indicating if the vehicle has automatic transmission and if it is imported.[20] *Wear* is included in the regression to

[20] The CEX does not include the vehicle’s nation of origin, but we can create the *import* dummy using information on manufacturer and model. We also tried other vehicle characteristics in the regression, such as indicator variables for power steering and air conditioning, but the estimates are not significant. Excluding these variables does not considerably change the estimates of coefficients on other variables.

capture the effects of vehicle age on market value. Separate regressions are run for cars and SUV's, and the estimation results are reported in Table 4. Then, for the brand new "concept" vehicle, we calculate the value with $Wear = 0$:

$$\hat{k} = \hat{a}_0 + \hat{a}_1 \times cyl + \hat{a}_2 \times tran + \hat{a}_3 \times import + \hat{b} \quad , \tag{21}$$

where $\hat{a}_0$ through $\hat{a}_3$ and $\hat{b}$ are estimates of parameters in equation (20).

(3) The price of Wear: In (20), $\hat{b}$ is the extra amount paid for a car with no wear on it (compared to a very old car with the same characteristics). For q, the annual "reimbursement" price of *Wear*, we need the amount saved during a year by an owner who accepts one more unit of *Wear* (an old car instead of a new car). Since a very old car does not depreciate any further, the amount saved is the depreciation during the year from holding a new car. Again assuming 20% depreciation, we have: $q = 0.2 \times \hat{b}$.

(4) Fuel Efficiency: For each type of vehicle, whether new or used, we need fuel efficiency measured in miles per gallon (MPG).[21] The CEX does not contain information on MPG, so we estimate it using data of the California Air Resources Board (CARB, 1997 and 2000). This dataset consists of two sub-samples. The first is "series 13", from November 1995 to March 1997, in which the CARB tested a total of 345 passenger cars, light-duty trucks, and medium-duty vans. The second is "series 14", from November 1997 to August 1999, which sampled 332 vehicles (but which reports only 327 vehicles). In total, our sample has 672 vehicles. We regress MPG against vehicle characteristics in the CARB and then use those estimated coefficients to predict MPG for each vehicle in the CEX. The estimation results are presented in Table 5, where a 4-cylinder SUV is the omitted category. This table shows that fuel efficiency decreases with vehicle age and with engine size, both for cars and for SUV's. Given the same vehicle age and engine size, MPG is higher for cars than for SUV's.

(5) Emissions per mile (EPM): In the same sample of 672 used cars, the CARB tests for several pollutants. Following Fullerton and West (2000), we weight each pollutant by estimates of its damages, with the highest weight on nitrous oxides (NOX, 0.495), followed by hydrocarbons (HC, 0.405), and carbon monoxide (CO, 0.10). Results

[21] For MPG of new cars, http://www.fueleconomy.gov/feg/index.htm is a website of the US Environmental Protection Agency (EPA) and the Department of Energy. The EPA also provides the historical fuel economy of new vehicles at http://www.epa.gov/otaq/mpg.htm or at http://www.epa.gov/otaq/tcldata.htm.

appear in Table 5. Cars pollute less than SUV's because they were produced under stricter standards. Older vehicles pollute more, both because newer vintages had stricter standards and because pollution control equipment deteriorates over time.

(6) Vehicle Miles Traveled (VMT): The OVB file provides data on current cumulative miles on each vehicle, but we need yearly miles driven. We had planned to match households across quarters, take the latest odometer reading minus the earliest one, divide by the number of quarters between these two readings, and multiply by four. Unfortunately, however, some later odometer readings are less than the earlier ones, and many readings are missing. Therefore, we propose a different procedure to calculate *VMT*. For a *one*-car household, we take observed annual expenditure on gasoline, divide by the price per gallon to get number of gallons, and then multiply by MPG to get miles. For a two-vehicle household, we only know the total gasoline expenditure, so we need to allocate it between the two vehicles. Only for this allocation do we use the difference in odometer readings between quarters.[22]

(7) Vehicle bundles: As listed in Table 1, vehicle choices are classified into six categories according to the number and type of vehicles. For bundle 4, with one car and one SUV, the car is always identified as the first vehicle. For bundles 3 and 5, the first vehicle is identified as the one with higher yearly *VMT*. If two vehicles have the same yearly *VMT*, the identification is arbitrary. If *VMT* is missing, then the vehicle with an earlier purchase year is taken as the first vehicle. If the purchase year and miles-driven are both missing, the identification is arbitrary.

III. Estimation Results

The model described in Section I is estimated by both the sequential and the simultaneous estimation methods. The mean values of key variables are reported by bundle in Table 6. We average the values within each bundle for each bundle-specific variable except gas price per mile. Gas price per mile is calculated by dividing gas price

[22] If the difference in odometer readings is positive for both vehicles, then we divide it by MPG to obtain an estimate of each vehicle's gas consumption. Each of these gasoline amounts divided by their sum gives the *share* of gas consumption. We then use these shares to assign the observed total gas consumption to each vehicle. Each vehicle's gallons divided by MPG yields *VMT*. If the difference in odometer readings is positive only for one of two vehicles, we use this figure as *VMT* and calculate the gasoline consumption for this vehicle. Then total gas consumption minus the gas used in this vehicle gives residual gas, which is allocated to the other vehicle. Dividing this residual gas consumption by MPG yields *VMT* for the other vehicle. If the difference in odometer readings is positive for neither vehicle, then we undertake imputations based on households with similar characteristics.

per gallon by a bundle-specific MPG listed in Table 1. Thus, gas prices per mile vary both within and between bundles. The presence of collinearity between the fixed effects α_0^i ($i = 1, ..., 6$) and the bundle-specific variables such as k_i ($i = 1, ..., 5$) force us to normalize the fixed effect of bundle one (α_0^1) to zero. To facilitate the estimation, we also normalize y in units of 10,000 dollars, k_i in units of 1,000, and q_1 and q_2 in units of 100 dollars. Accordingly, we multiply $Wear_1$ and $Wear_2$ by 100 to keep the total amount of reimbursement unchanged in the budget constraint.

Notice that bundle 3 and bundle 5 each contains two vehicles of the same type, while bundle 4 consists of one car and one SUV. When the retail gas price increases, all gas prices per mile are affected in bundle-specific ways because MPG depends both on vehicle age and type (car or SUV). As revealed by Table 1, MPG is more type-specific than bundle-specific. Thus, we expect that the gas price parameters of car bundles 1 and 3 are quite close to one another, as are those of SUV bundles 2 and 5. For a household with one car and one SUV (bundle 4), however, we wish to allow more substitution. In our estimation, we assign one parameter α_{C1} to the gas price of the only car in bundle 1 and first car in bundle 3 (and α_{C2} to the second car of bundle 3). We assign one parameter α_{S1} to the only SUV in bundle 2 and first SUV of bundle 5 (and α_{S2} to the second SUV of bundle 5). Then we assign two gas price parameters to bundle 4: $\alpha_{p1}^4 (= \alpha_{CAR}^4)$ for the car and $\alpha_{p2}^4 (= \alpha_{SUV}^4)$ for the SUV. Results from the sequential estimation are discussed in subsection A, while those from the simultaneous estimation are in subsection B.

A. The Sequential Estimation

We follow the procedure suggested by Dubin and Mcfadden (1984), but at the first stage we estimate a nested logit structure instead of a multinomial logit model. The traditional ML method is employed. The RF method is adopted at the second stage because the correction terms derived by Dubin and Mcfadden are inappropriate for the GEV error structure. In the second stage we estimate four continuous demand equations jointly (only two equations for the one-vehicle bundles), using an objective function similar to equation (12) except that the last term is removed. We constrain parameters to be constant across bundles except those for gas prices and constant terms. The estimation results are reported in the first two columns of Table 7, under "sequential estimation".

For the discrete choice model in the first column of Table 7, the estimates of α_{C1} and α_{S1} are more significant than those of α_{C2} and α_{S2}. The estimates of $\alpha_{p1}^{4}(=\alpha_{CAR}^{4})$ and $\alpha_{p2}^{4}(=\alpha_{SUV}^{4})$ are both significant at the 0.05 level. All of them are negative as expected. Except for α_{q1}, all the other estimated parameters of key variables are significant at the 0.05 level. The parameter λ_n $(n = 1,2)$ measures the degree of independence of the errors of alternatives in nest n. In our model, the estimates of λ_1 and λ_2 are 0.204 and 0.398, respectively, both significant at the 0.05 level.[23]

Since all the estimates of α_{p1} and α_{p2} are negative, equations (13a) indicate that the marginal effects of gas prices per mile are negative. As consistent with our expectation, an increase in gas price reduces household utility. The marginal effects of reimbursement prices are positive, because of negative estimates of coefficients on q, which again is expected. A higher reimbursement price means more money back to the household for accepting a given vehicle age or level of *Wear*. Since estimates of β and β_1 are both negative and significant, equations (14) indicate that the marginal effect of capital cost is negative while that of income is positive.

Elasticities of discrete choices with respect to key variables are reported in Table 8. Each entry is not an elasticity with respect to each price in the model, as it might be difficult to interpret a number such as the change in the probability of holding two cars for a change in the price p_1 for gas *only* in the first car, and not p_2 or for other bundles. Rather, we want to know the simultaneous effect on *all* choices for a change in the price of gasoline. The first row of Table 8 shows that a 1% higher price of gas would decrease most the probability of holding bundle 4 with a car and an SUV (by 0.521%) while increasing the share holding one car (0.042%), one SUV (0.037%), or two cars (0.154%).

Given vehicle age, a higher reimbursement price for *Wear* of a particular bundle (q) means more money back to the household and thus higher probability of choosing that bundle. Again, however, it is difficult to interpret a change in the price q_1 for the first car but not q_2 for the second car of a two-car bundle. In the second row, we therefore show the effects of a 1% higher q for *all* cars in all bundles. This 1% higher reimbursement

[23] If $\lambda_n\ \forall n$ are within the range of zero to one, then "the model is consistent with utility maximization for all possible values of the explanatory variables" (Train, 2003, p.85). Since our λ are significantly less than one, the errors within each nest are correlated, evidence in favor of nesting rather than MNL.

price (subsidy to *Wear*) increases the probabilities of holding all SUV bundles, and decreases the shares in bundles with just cars. Since Table 5 above shows that emissions per mile (EPM) are higher for SUV's than for cars, a potential policy implication is that emissions might be cut by placing a tax on age or subsidizing the purchase of newer vehicles – either of which would reduce the q price received for holding a vehicle with more *Wear*.[24] But that effect is a somewhat indirect way to shift households into cars. The next row shows that a tax on the age only of cars would decrease the reimbursement for wear on cars, q_{car}, and switch households out of cars and into bundles 2 and 5 with one or two SUV's. Conversely, the next row shows that a tax on the age only of SUV's (or subsidy to purchase of newer SUV) means lower q_{suv}, which induces a switch into bundles 1 and 3 with only cars.

The income elasticities in the next row of Table 8 are positive and large for bundles 4 and 5, so more income makes households more likely to own two-vehicle bundles that include at least one SUV (and therefore less likely to hold other bundles). This result is consistent with the casual observation that high-income Americans seem to own an SUV.

We next look at an increase in the capital cost of *all* vehicles. As one might expect from the income elasticities, the higher k induces a large reduction in the share of households holding the two-vehicle bundles 4 and 5 that include an SUV, but the calculated elasticities are even larger than expected and probably larger than reasonable. As households shift out of those two-vehicle bundles, they increase the shares holding other bundles. While it does not make sense to increase the capital cost only for the first car of a two-car household, it might make sense to increase the capital cost only of cars relative to SUV's or vice versa (to represent a vehicle-type tax). The next row of Table 8 shows that if the increase in capital cost pertains only to cars, then it decreases the shares of all three bundles that have cars. If it pertains only to SUV's, however, then it has large effects that decrease the shares of all three bundles with SUV's. Such a policy could clearly reduce emissions (given the EPM in Table 5).

For the sequential model, returning to Table 7, we use the discrete choices from the first column to estimate the continuous demands shown in the second column. All coefficient estimates are significant at the 0.01 level (except one, for "Metro"). Just as in

[24] Table 5 also shows that EPM rise with age, so a tax on age would seem to reduce emissions two ways: by inducing a switch from SUV's to cars (Table 8), and by inducing purchase of newer vehicles (Table 9 below).

the first column, we find negative coefficients on prices, income, and capital cost. A glance down the second column indicates that some estimated coefficients are similar to the corresponding estimate in the first column, but some are quite different. Yet the parameters in the second column are the same parameters as in the first column, even from the same model, as the continuous demands are supposed to be consistent with a particular indirect utility function. For example, the estimated coefficient on income is –0.469 in the first column and –0.013 in the second column. Both have small errors, and so they are significantly different from each other, even though they are the same parameter of the same model. Similarly, the estimated coefficient on k from the discrete choice model is –0.844, whereas the estimate from the continuous demand model is –2.107. Their confidence intervals do not overlap. Many price coefficients also differ significantly in magnitude. Coefficients of most demographic variables even differ in sign.

Elasticities from these continuous demands are presented in the top half of Table 9. These are "short run" elasticities, in the sense that car choices are fixed and only continuous choices may change (Goldberg, 1998). In the first row, all elasticities for VMT_1 with respect to gasoline price are negative, as expected, for all bundles. Most are small, but one is larger than reasonable: this 1% increase in gas price results in 3% fewer miles for the two-car family. We should remember, however, that the point here is not to pin down the best possible estimate of each elasticity. Rather, we wish to compare signs and magnitudes of estimates from the sequential model and the simultaneous model.

The next row of Table 9 shows the effects of a 1% increase in q, the reimbursement the price of *Wear*. These elasticities are all positive, as expected: a higher reimbursement price for *Wear* means higher cost of depreciation from holding a new vehicle, which induces households to buy an older vehicle. Again, however, these estimates seem larger than reasonable. Next, due to the symmetric specification of demand functions, income and capital cost elasticities are the same for demands of both *VMT* and *Wear* and for the second vehicle (if it exists). Income elasticities are positive as expected, but small. The capital cost elasticities are negative as expected, but unreasonably large.

The specific form for utility in equation (4) means a specific form for demands in equations (5), where $\ln(VMT)$ and $\ln(Wear)$ both depend on $\alpha^i_p p_i - \alpha_q q_i$. In other words, the parameter that determines the important effect of gas price on miles (α^i_p) also necessarily drives the less-important effect of the gas price on choice of *Wear*.

Similarly, the own-price effect of q on $Wear$ also drives the cross-price effect of q on VMT. We note this fact, but we do not mean to emphasize these cross-price elasticities.

B. The Simultaneous Estimation

Next, the model is estimated by the simultaneous estimation procedure proposed in Section I.C. The advantage of this procedure is to enable us to capture the interactive effects between discrete and continuous choices. It is like a two-way process, connected by the same parameters and random error term η appearing in both functions. In contrast, the sequential procedure is analogous to a one-way process where the bundle choice affects continuous demands (and not vice versa). The simultaneous estimates are reported in the last column of Table 7.

All of the estimated coefficients on key variables have expected signs, and all but two are significantly different from zero. Yet for many parameters, the estimate differs from *both* estimates obtained by sequential estimation. In some cases, the estimate is not even between the two estimates from the sequential model. For bundle 4 with a car and SUV, for example, the gas price coefficient for the SUV (α_{SUV}^{4}) is either -1.062 or -1.328 in the sequential model, but it is -0.662 in the simultaneous model. For the income coefficient (β), the simultaneous estimate in column 3 is closer to the discrete model's estimate in column 1 than to the continuous model's estimate in column 2. For the capital cost coefficient (β_I), however, the simultaneous estimate (–0.405) is significantly smaller than either that of the logit model (–0.844) or the continuous demand model (–2.107). The estimates of coefficients on demographic variables vary with the estimation method, not only in magnitude but also in sign.

Bundle choice elasticities are presented in the lower part of Table 8. With a 1% higher gas price, households holding bundle 4 (Car, SUV) seem to shift into bundle 3 (Car, Car), with little change in other shares. Households sell the SUV for a second car instead. This change is driven by the high price of driving an SUV with low fuel efficiency.[25] The elasticities with respect to reimbursement prices have similar signs to those above, for the sequential model, but are smaller in magnitude – as might seem more reasonable.

[25] This reasoning is confirmed by the choice elasticities with respect to p_1 and p_2 separately. For bundle 4, a 1% higher price per mile in the car reduces the probability of choosing that bundle by 0.31%, while a 1% higher price per mile in the SUV (p_2) reduces the probability of choosing that bundle by 0.67%. Thus, the gas consumption of the SUV has twice as much impact as that of the car.

The choice elasticities with respect to income are negative for car-only bundles 1 and 3, but most positive for bundle 4. When income increases, households are most likely to switch to a bundle with a car and an SUV. This result is consistent with the logit model in the top half of the table, but the size is more reasonable (income elasticity of 0.667 instead of 2.327). In the next row, the choice elasticity with respect to capital cost is most negative for bundle 4, and large (but not as large as for the logit model). Households who face higher capital costs for all vehicles switch their second vehicle from an SUV to a car (from bundle 4 to 3). It is possible, however, that capital costs could rise only for cars or only for SUV's, because of market conditions, production costs, or government regulation. The last row shows that such a policy could reduce emission rates by raising SUV costs and shifting families into cars. The 1% higher cost of an SUV means 18.9% less of bundle 4, which seems too large, but it means that the share falls from 14.45% of all households (Table 6) to 11.72% of all households.

Continuous demand elasticities from simultaneous estimation are listed in the bottom half of Table 9. The first row shows that *all* gas-price elasticities have the expected negative effect on *VMT*, and all are small, but at least they are consistent across bundles and probably more reasonable than for the sequential model above (where the elasticity was -3.2 for the two-car bundle and less than one for all other bundles). Next, a lower reimbursement price increases demand for newer cars (*Wear*). If the desired cars were available, a 10% lower q reduces average desired *Wear* by about 1.2% to 1.4%. These numbers are two orders of magnitude smaller than for the sequential model.[26] One percent more income would increase driving miles by about one percent for all bundles (in contrast to the sequential model where income elasticities were all near zero). Capital costs have negative effects on *VMT*, as for the sequential case, but the elasticities from simultaneous estimation are more reasonable (magnitudes are 1.4 to 3.3, instead of 7.3 to 17.0).

In the simultaneously estimated model, the coefficients are affected by all discrete and continuous choices. The model imposes more constraints on the estimates. Thus, if those constrained estimates are plugged into the likelihood function for either part of the sequential procedure, then the likelihood is not as high as for that *portion* of the sequential

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[26] Table 6 says that the average *Wear* is 0.75, and this *Wear* corresponds to 6.2 years of age. A 1.2% decrease in *Wear* is equivalent to a decrease of one month of age. The sequential model says that the same tax on age (10% lower q) would induce all drivers to want a car with 85% less wear on it.

procedure. However, the sequentially estimated model yields two sets of estimates for the same parameters. The finding that these estimates are not consistent with each other raises a question about whether that behavioral model is correctly specified.

IV. Conclusion

This paper focuses on the incentive effects of price changes that might be associated with policies to reduce vehicle emissions. We provide a model of household behavior that incorporates both the discrete choice of vehicle type, with different fuel efficiencies and emission rates, and continuous demands for miles driven. Because emissions depend on each year of vehicle age, we also model vehicle age as a continuous choice. To model the effect of prices on the choice of vehicle age, we establish a choice of "concept vehicle" that is separate from the choice of "*Wear*". Using hedonic price regression, we quantify the price of *Wear*. Then, after the discrete choice among concept vehicles, both *VMT* and *Wear* become continuous variables that enter utility.

Yearly household data are obtained from the CEX of 1996 – 2000, supplemented with fuel efficiency estimates from the CARB, and gas prices from the ACCRA cost of living indexes. First, like many others, we follow the sequential procedure suggested by Dubin and McFadden (1984). This procedure generates two different sets of estimates for the same set of parameters, which we argue is inconsistent with maintained hypotheses about the utility function and utility maximization. We then propose and implement a simultaneous method for consistent estimation of both discrete and continuous choices in one step. Results from the simultaneous estimation differ significantly both in signs and magnitudes from both sets of estimates obtained by sequential estimation.

We find that a higher price of gasoline would shift households out of the Car-SUV pair and into vehicle bundles that include only cars. It also would reduce miles driven. Both of these changes reduce emissions. A tax on vehicle age or subsidy to buying a newer car would induce shifts to newer vehicles with less "*Wear*", and would also shift families from SUV bundles to car bundles. Both of these changes also reduce emissions. Similarly, a tax on SUV bundles would induce such shifts. The size of these shifts is important information for environmental policy. Rather than pin down the exact size of the important parameters, however, this paper points to important problems with existing methods and suggests an alternative approach with more internal consistency.

Table 1. Vehicle Bundle Descriptions and Statistics

Bundle	# of Vehicles	First Vehicle	Second Vehicle	# of Households	MPG of First Vehicle	MPG of Second Vehicle
1	1	Car	--	3471	21.37	--
2	1	SUV	--	742	16.76	--
3	2	Car	Car	1187	21.89	21.56
4	2	Car	SUV	1306	21.51	16.52
5	2	SUV	SUV	253	17.04	16.50
6	0	--	--	2077	--	--

Note: The number of households is from the consumer expenditure survey (CEX), and miles per gallon (MPG) is calculated from CARB data described below.

Table 2. Variable Definitions

Variable	Definition
y	Household's yearly expenditure
k	Total capital cost of a vehicle bundle
p_1	Gas price per mile of the first vehicle
p_2	Gas price per mile of the second vehicle
q_1	Unit price of *Wear* of the first vehicle
q_2	Unit price of *Wear* of the second vehicle
VMT_1	Miles driven in the first vehicle
VMT_2	Miles driven in the second vehicle
$Wear_1$	Continuous variable to measure the wear of the first vehicle
$Wear_2$	Continuous variable to measure the wear of the second vehicle
Famsize	Number of members in a household
Earnr	Number of income earners in a household
Kids	Number of children less than 18 in a household
Drivers	Number of household members 16 years old and over
Metro	A dummy variable: one if the household resides inside a Metropolitan Statistical Area (MSA), and zero otherwise
Pop4	A dummy variable: one if the household lives in an area with a population of more than 4 million, and zero otherwise
Urban	A dummy variable: one if the household lives in an urban area, and zero otherwise.
Age	Age of household head
White	A dummy variable: one if the household head is white, and zero otherwise
Male	A dummy variable: one if the head is male, zero otherwise
Educ	A dummy variable: one if the head has education higher than high school, zero otherwise
Northwest	A dummy variable: one if in the Northwest, zero otherwise
Midwest	A dummy variable: one if in the Midwest, zero otherwise
South	A dummy variable: one if in the South, zero otherwise
West	A dummy variable: one if in the West, zero otherwise

Table 3. Summary of Household Statistics by Vehicle Bundles

Characteristics	Bundle					
	1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
# of Households	3471	742	1187	1306	253	2077
Household size	1.92	2.30	2.65	2.94	3.44	1.98
% with kids	23.88	33.56	33.53	44.03	62.45	26.05
# of kids	0.44	0.73	0.56	0.89	1.42	0.55
# > 15 years old	1.52	1.63	2.12	2.12	2.13	1.48
# of workers	0.85	1.08	1.43	1.49	1.58	0.70
% heads male	40.07	63.07	65.54	71.82	77.47	33.22
Age of head	55.23	48.22	51.79	49.44	45.24	55.66
% heads white	82.05	87.60	83.32	89.05	92.89	67.89
% heads educ > high school	52.18	52.29	66.13	57.04	57.31	34.33
% in area with pop.> 4 million	28.38	19.41	30.41	22.74	18.58	38.61
Expenditures	22751.02	24574.29	35439.56	33799.41	34246.25	17795.34
Total gas cost	647.97	920.13	1102.97	1279.14	1397.83	--

Table 4. Hedonic Price Regressions

Dependent Variable: *cmv*	Cars		SUVs	
	Coefficient	Standard Error	Coefficient	Standard Error
a_0	-8283.42	814.083	-6169.23	1109.01
cyl (a_1)	1566.41	119.320	1148.71	163.710
tran (a_2)	868.518	456.643	1445.71	528.592
import (a_3)	1946.22	336.294	1413.43	587.268
b	15619.4	713.644	17902.4	879.598
R^2	0.467		0.518	
# of obs.	793		510	

Table 5: Estimation of Miles Per Gallon (MPG) and Emissions Per Mile (EPM)

Independent Variable	Dependent Variable			
	MPG		EPM	
	Coefficent	Standard Error	Coefficient	Standard Error
Constant	24.021	(0.496)	-0.597	0.663
Cyl6	-4.395	(0.483)	1.103	0.645
Cyl8	-7.948	(0.581)	3.548	0.777
Age	-0.419	(0.049)	0.285	0.065
Age^2	0.006	(0.002)	0.003	0.002
Car	4.262	(0.410)	-0.589	0.548
Cyl6 × Car	-1.439	(0.560)	-0.661	0.749
Cyl8 × Car	-1.149	(0.655)	-2.819	0.875
R^2	0.7598		0.4095	
F-value	299.997		65.775	
# of obs.	672		672	

Table 6. Mean Values of Key Variables Involved in Estimation

Variable	Bundle 1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
% of Households	38.4	8.2	13.1	14.5	2.8	22.0
VMT_1	11799.	12977.	15272.	10514.	16151.	--
VMT_2	--	--	5579.	10769.	5358.	--
Price of Gas 1 (p_1)	0.058	0.074	0.056	0.057	0.072	--
Price of Gas 2 (p_2)	--	--	0.057	0.075	0.075	--
Vintage1	8.62	8.24	7.62	7.90	6.87	--
Vintage2	--	--	9.03	8.50	8.78	--
$Wear_1$	0.76	0.73	0.72	0.73	0.68	--
$Wear_2$	--	--	0.77	0.73	0.75	--
Price of $Wear_1$ (q_1)	15619.	17902.	15619.	15619.	17902.	--
Price of $Wear_2$ (q_2)	--	--	15619.	17902.	17902.	--
Expenditure (y)	22751.	24574.	35440.	33799.	34246.	17795.
Capital Cost (k)	17243.	20087.	34335.	37481.	40355.	--
Capital Cost 1	17243.	20087.	17224.	17273.	20204.	--
Capital Cost 2	--	--	17112.	20207.	20151.	--

Table 7. Estimation Results

Parameters	Sequential Estimation: Nested Logit	Sequential Estimation: Continuous Demands	Simultaneous Estimation
p_{11}, p_{31} (α_{C1})	-0.513*	-0.417**	-0.433**
	(0.264)	(0.067)	(0.073)
p_{32} (α_{C2})	-0.512	-57.163**	-0.045**
	(0.417)	(2.181)	(0.008)
p_{21}, p_{51} (α_{S1})	-0.497*	-0.129**	-0.526**
	(0.277)	(0.046)	(0.106)
p_{52} (α_{S2})	-0.496	-12.149**	-0.013
	(0.420)	(5.833)	(0.138)
p_{41} (α^4_{CAR})	-0.363**	-0.389**	-0.399**
	(0.176)	(0.071)	(0.062)
p_{42} (α^4_{SUV})	-1.062**	-1.328**	-0.662**
	(0.291)	(0.274)	(0.104)
q_1 (α_{q1})	-0.006	-0.271**	-0.004**
	(0.016)	(0.050)	(0.001)
q_2 (α_{q2})	-0.004**	-0.229**	-0.219E-36
	(0.002)	(0.052)	(0.562E-36)
y (β)	-0.469**	-0.013**	-0.420**
	(0.013)	(0.004)	(0.379E-03)
k (β_1)	-0.844**	-2.107**	-0.405**
	(0.022)	(0.457)	(0.021)
Choice specific:			
Constant 2 (α^2_0)	0.305**		0.113**
	(0.091)		(0.024)
Constant 3 (α^3_0)	1.703**		1.282**
	(0.096)		(0.081)
Constant 4 (α^4_0)	1.687**		1.490**
	(0.103)		(0.098)
Constant 5 (α^5_0)	1.793**		1.757**
	(0.129)		(0.108)
Constant 6 (α^6_0)	-0.953**		-1.480**
	(0.090)		(0.068)
Demand-Specific:			
Constant 1 (α_{V1})		8.858**	0.302**
		(0.031)	(0.081)
Constant 2 (α_{V2})		6.579**	0.805**
		(0.032)	(0.086)
Constant 3 (α_{W1})		4.200**	2.580**
		(0.073)	(0.255)
Constant 4 (α_{W2})		4.307**	5.114**

		(0.059)	(0.881)
Famsize	-0.020	0.072**	0.058**
	(0.025)	(0.009)	(0.001)
Earnr	0.003	0.067**	0.032**
	(0.010)	(0.004)	(0.423E-03)
Kids	0.028	-0.081**	-0.031**
	(0.025)	(0.009)	(0.001)
Drivers	-0.080**	-0.060**	-0.041**
	(0.023)	(0.009)	(0.001)
Metro	-0.006	0.012	0.012**
	(0.022)	(0.010)	(0.001)
Pop4	0.035**	0.013**	0.012**
	(0.017)	(0.006)	(0.001)
Urban	0.044	0.058**	0.105**
	(0.029)	(0.011)	(0.001)
Age	0.047**	-0.007**	0.004**
	(0.001)	(0.483E-03)	(0.203E-04)
White	0.897**	-0.135**	0.097**
	(0.024)	(0.011)	(0.001)
Male	0.699**	-0.109**	0.004**
	(0.022)	(0.008)	(0.001)
Educ	-0.031**	0.058**	0.036**
	(0.014)	(0.005)	(0.001)
Northwest	0.269**	-0.042**	0.046**
	(0.022)	(0.008)	(0.001)
Midwest	0.419**	-0.064**	0.059**
	(0.019)	(0.008)	(0.001)
South	0.718**	-0.150**	0.072**
	(0.022)	(0.009)	(0.001)
λ_1	0.204**		0.138**
	(0.107)		(0.010)
λ_2	0.398**		0.103**
	(0.067)		(0.004)
Log Likelihood	-8152.71	-47237.3	-0.231E+07

* indicates 0.10 significance level, and ** indicates 0.05 significance level.

Table 8. Elasticities of Discrete Choices for each Variable

Variable	Bundle					
	1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
Sequential: [a]						
p	0.042	0.037	0.154	-0.521	0.017	--
q	-0.134	0.270	-0.124	1.365	0.064	--
q_{car}	0.439	-2.674	0.524	0.525	-0.299	--
q_{suv}	-0.573	2.944	-0.648	0.840	0.364	--
y	-0.205	-0.616	-0.392	2.327	0.736	-0.767
k	1.248	4.620	2.499	-13.425	-4.617	--
k_{car}	-0.318	7.685	-3.149	-4.176	1.820	--
k_{suv}	1.566	-3.064	5.648	-9.249	-6.437	--
Simultaneous: [b]						
p	-0.003	-0.004	0.565	-0.653	0.023	--
q	0.099	-1.12E-04	0.069	0.176	-0.005	--
q_{car}	0.112	-0.064	0.087	0.192	-0.178	--
q_{suv}	-0.013	0.064	-0.018	-0.016	0.173	--
y	-0.139	0.051	-0.437	0.667	-0.006	0.046
k	0.135	-0.177	0.618	-7.698	-0.634	--
k_{car}	-0.489	0.566	-18.025	11.243	2.530	--
k_{suv}	0.624	-0.743	18.644	-18.941	-3.164	--

[a] Calculation based on estimates in column 1 of Table 7.

[b] Calculation based on estimates in column 3 of Table 7.

Table 9. Short-Run Elasticities of Continuous Demands

Variable	Bundle 1 (Car)	2(SUV)	3 (C,C)	4 (C,S)	5 (S,S)	Total Emissions [c]
Sequential: [a]						
p	-0.024	-0.009	-3.193	-0.118	-0.887	X
q	8.481	9.721	15.641	16.687	17.927	X
q_{car}	8.481	--	15.641	8.481	--	X
q_{suv}	--	9.721	--	8.206	17.927	X
y	0.029	0.032	0.046	0.044	0.044	X
k	-7.265	-8.463	-14.467	-15.792	-17.003	X
Simultaneous: [b]						
p	-0.024	-0.037	-0.026	-0.070	-0.038	X
q	0.122	0.140	0.122	0.122	0.140	X
q_{car}	0.122	--	0.122	0.122	--	X
q_{suv}	--	0.140	--	7.83E-36	0.140	X
y	0.955	1.032	1.488	1.419	1.438	X
k	-1.398	-1.629	-2.784	-3.039	-3.272	X

Each entry is the elasticity of VMT or $Wear$, in the first or second vehicle, with respect to each variable.

[a] Calculation based on estimates in column 2 of Table 7.

[b] Calculation based on estimates in column 3 of Table 7.

[c] The last column is the percent change in total emissions, $E = \sum \text{EPM} \times \text{miles}$, adding over all vehicles in all bundles, for a one percent change in each variable.

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