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THE IMPACT OF DEMOGRAPHICS, BUILT ENVIRONMENT ATTRIBUTES, VEHICLE CHARACTERISTICS, AND GASOLINE PRICES ON HOUSEHOLD VEHICLE HOLDINGS AND USE

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ABSTRACT

In this paper, we formulate and estimate a nested model structure that includes a multiple discrete-continuous extreme value (MDCEV) component to analyze the choice of vehicle type/vintage and usage in the upper level and a multinomial logit (MNL) component to analyze the choice of vehicle make/model in the lower nest. Data for the analysis is drawn from the 2000 San Francisco Bay Area Travel Survey. The model results indicate the important effects of household demographics, household location characteristics, built environment attributes, household head characteristics, and vehicle attributes on household vehicle holdings and use. The model developed in the paper is applied to predict the impact of land use and fuel cost changes on vehicle holdings and usage of the households. Such predictions can inform the design of proactive land-use, economic, and transportation policies to influence household vehicle holdings and usage in a way that reduces the negative impacts of automobile dependency such as traffic congestion, fuel consumption and air pollution.

Keywords: MDCEV model, gasoline prices, built environment, household vehicle holdings and use, vehicle make/model choice.

1. INTRODUCTION

The dependence of U.S. households on the automobile to pursue daily activity-travel patterns has been the subject of increasing research study in recent years because of the far-reaching impacts of this dependence at multiple societal levels. At the household level, automobile dependency increases the transportation expenses of the household (CES, 2004); at a community level, automobile dependency contributes to social stratification and inequity among segments of the population (Litman, 2002; Engwicht, 1993; Untermann and Mouden, 1989; Carlson *et al.,* 1995; Litman, 2005); at a regional level, automobile dependency significantly impacts traffic congestion, environment, health, economic development, infrastructure, land-use and energy consumption (see Schrank and Lomax, 2005; EPA, 1999; Litman and Laube, 2002; Jeff *et al.,* 1997; Schipper, 2004).

One of the most widely used indicators of household automobile dependency is the extent of household vehicle holdings and use (*i.e.*, mileage traveled). In this context, the 2001 NHTS data shows that about 92% of American households owned at least one motor vehicle in 2001 (compared to about 80% in the early 1970s; see Pucher and Renne, 2003). Household vehicle miles of travel also increased 300% between 1977 and 2001 (relative to a population increase of 30% during the same period; see Polzin and Chu, 2004). In addition, there is an increasing diversity in the body type of vehicles held by households. The NHTS data shows that about 57% of the personal-use vehicles are cars or station wagons, while 21% are vans or Sports Utility Vehicles (SUV) and 19% are pickup trucks. The increasing holdings and usage of motorized personal vehicles, combined with the shift from small cars to larger vehicles, has a significant impact on traffic congestion, pollution, and energy consumption.

In addition to the overall impacts of vehicle holdings and use on regional quality of life, vehicle holdings and use also plays an important role in travel demand forecasting and transportation policy analysis. <u>From a travel demand forecasting perspective</u>, household vehicle holdings has been found to impact almost all aspects of daily activity-travel patterns, including the number of out-of-home activity episodes that individuals participate in, the location of out-of-home participations, and the travel mode and time-of-day of out-of-home activity participations (see, for example, Bhat and Lockwood, 2004; Pucher and Renne, 2003; Bhat and Castelar, 2002). Besides, households' vehicle holdings and residential location choice are also very intricately linked (see Pagliara and Preston, 2003, Bhat and Guo, 2007). Thus, it is of interest to forecast the impacts of demographic changes in the population (such as aging and rising immigrant population) and vehicle acquisition/maintenance costs (for example, rising fuel prices), among other things, on vehicle holdings and use. From a transportation policy standpoint, a good understanding of the determinants of vehicle holdings and usage (such as the impact of the built environment and acquisition/maintenance costs) can inform the design of proactive land-use, economic, and transportation policies to influence household vehicle holdings and usage in a way that reduces traffic congestion and air quality problems (Feng *et al.*, 2004)

Clearly, it is important to accurately predict the vehicle holdings of households as well as the vehicle miles of travel by vehicle type, to support critical transportation infrastructure and air quality planning decisions. Not surprisingly, therefore, there is a substantial literature in this area, as we discuss next.

2. OVERVIEW OF THE LITERATURE AND THE CURRENT STUDY

We present an overview of the literature by examining three broad issues related to vehicle holdings and use modeling: (1) The dimensions used to characterize household vehicle holdings and use, (2) The determinants of vehicle holdings and usage decisions considered in the analysis, and (3) The model structure employed.

2.1 Dimensions Used to Characterize Vehicle Holdings and Use

Several dimensions can be used to characterize household vehicle holdings and usage, including the number of vehicles owned by the household, type of each vehicle owned, number of miles traveled using each vehicle, age of each vehicle, fuel type of each vehicle, and make/model of each vehicle. The most commonly used dimensions of analysis in the existing literature include (1) The number of vehicles owned by the household with or without vehicle use decisions (see Burns and Golob,1976, Lerman and Ben-Akiva, 1976, Golob and Burns, 1978, Train, 1980, Kain and Fauth, 1977, Bhat and Pulugurta, 1998, Dargay and Vythoulkas, 1999, and Hanly and Dargay, 2000), and (2) The type of vehicle most recently purchased or most driven by the household. The vehicle type may be characterized by body type (such as sedan, coupe, pick up truck, sports utility vehicle, van, *etc*; see Lave and Train, 1979, Kitamura *et al.,* 2000, and Choo and Mokhtarian, 2004), make/model (Mannering and Mahmassani, 1985), fuel type (Brownstone and Train, 1999, Brownstone *et al.*, 2000, Hensher and Greene, 2001), body type and vintage (Mohammadian and Miller, 2003a), and make/model and vehicle acquisition type (Mannering *et al.,* 2002). Some studies have extended the analysis from the choice of the most recently purchased vehicle to choice of all the vehicles owned by the household and/or the usage of these vehicles.[1] A few other studies have examined the vehicle holdings of the household in terms of their vehicle transaction process (*i.e.*, whether to add a vehicle to the current fleet, or replace/dispose a vehicle from the current fleet; see Mohammadian and Miller, 2003b).

The discussion above indicates that, while there have been several studies focusing on different dimensions of vehicle holdings and use, each individual study has either confined its alternatives to a single vehicle in a household or examined household vehicle holdings along a relatively narrow set of dimensions. This can be attributed to the computational difficulties in model estimation associated with focusing on the entire fleet of vehicles and/or using several dimensions to characterize vehicle type.

2.2 Determinants of Vehicle Holdings and Usage Decisions

There are several factors that influence household vehicle holdings and usage decisions, including household and individual demographic characteristics, vehicle attributes, fuel costs, travel costs, and the built environment characteristics (land-use and urban form attributes) of the residential neighborhood. Most earlier studies have focused on only a few of these potential determinants. For instance, some studies exclusively examine the impact of household and individual demographic characteristics such as household income, household size, number of children in the household, and employment of individuals in the household (see, for example, Bhat and Pulugurta, 1998). Some other studies have identified the impact of vehicle attributes such as purchase price, operating cost, fuel efficiency, vehicle performance and external dimensions, in addition to demographic characteristics (see, for example, Lave and Train, 1979, Golob *et al.*, 1997, Mohammadian and Miller, 2003a, Manski and Sherman, 1980, Mannering and Winston, 1985). A more recent study has identified the impact of the driver's personality and

[1] These studies include the joint choice of vehicle ownership level and vehicle body type (Hensher and Plastrier, 1985), vehicle body type and vintage (Berkovec and Rust, 1985), vehicle fuel type choice (Brownstone *et al.,* 1996), vehicle body type, vintage and vehicle ownership level (Berkovec, 1985), joint choice of vehicle body type and usage (Golob *et al.*, 1997; Feng *et al.,* 2004), vehicle make/model and vintage (Manski and Sherman, 1980; Mannering and Winston, 1985), vehicle ownership level, vehicle body type and usage (Train and Lohrer, 1982; Train, 1986), number of vehicles owned and usage (Golob and Wissen, 1989; Jong, 1990), and vehicle body type and usage (Bhat and Sen, 2006).

travel perceptions on vehicle type choice (Choo and Mokhtarian, 2004), while another recent study recognized the impact of the built environment on vehicle ownership levels (Bhat and Guo, 2007). Both these studies also controlled for demographic characteristics.

The above studies have contributed in important ways to our understanding of vehicle holdings and usage decision. However, they have not jointly and comprehensively considered an exhaustive set of potential determinants of vehicle holdings and usage.

2.3 Modeling Methodology

Several types of discrete and discrete-continuous choice models have been used in the literature to model vehicle holdings and usage. Most of these studies use standard discrete choice models (multinomial logit, nested logit or mixed logit) for vehicle ownership and/or vehicle type and a continuous linear regression model for the vehicle use dimension (if this second dimension is included in the analysis). These conventional discrete or discrete-continuous models analyze situations in which the decision-maker can choose only one alternative from a set of mutually exclusive alternatives. This is not representative of the choice situation of multiple-vehicle households, where households own and use multiple types of vehicles simultaneously to satisfy various functional needs of the household. The analysis of such choice situations requires models that recognize the multiple discreteness in the mix of vehicles owned by the household.

Models that recognize multiple-discreteness have been developed recently in several fields (see Bhat, 2008 for a review). Among these, Bhat (2005) introduced a simple and parsimonious econometric approach to handle multiple discreteness. Bhat's model, labeled the multiple discrete-continuous extreme value (MDCEV) model, is analytically tractable in the probability expressions and is practical even for situations with a large number of discrete consumption alternatives. In fact, the MDCEV model represents the multinomial logit (MNL) form-equivalent for multiple discrete-continuous choice analysis and collapses exactly to the MNL in the case that each (and every) decision-maker chooses only one alternative.

The MDCEV and other multiple discrete-continuous model do not, however, accommodate a choice situation characterized by the joint choice of (1) multiple alternatives from a set of mutually exclusive alternatives, and (2) a single alternative from a set of mutually exclusive alternatives. Such a choice situation better characterizes the decision-making process of a multiple vehicle household. For instance, a household might choose to own multiple vehicle types such as an SUV, a Sedan and a Coupe from a set of mutually exclusive vehicle types because they serve different functional needs of individuals of the household. But within each of the vehicle types, the household chooses a single make/model from a vast array of alternative makes/models.

2.4 The Current Study

In this paper, we contribute to the vast literature in the area of vehicle holdings and use in many ways. First, we use several dimensions to characterize vehicle holdings and use. In particular, we model number of vehicles owned as well as the following attributes for each of the vehicles owned: (1) vehicle body type, (2) vehicle age (*i.e.*, vintage), (3) vehicle make and model, and (4) vehicle usage. Second, we incorporate a comprehensive set of determinants of vehicle holdings and usage decisions, including household demographics, individual characteristics, vehicle attributes, fuel cost, and built environment characteristics. Finally, we use a utility-theoretic formulation to analyze the many dimensions of vehicle holdings and use. Specifically, we use a multinomial logit structure to analyze the choice of a single make and model within each vehicle type/vintage chosen, and nest this MNL structure within an MDCEV formulation to analyze the simultaneous choice of multiple vehicle types/vintages and usage decisions. Such a joint MDCEV-MNL model has been proposed and applied by Bhat *et al.* (2006) for time-use decisions. In this current paper, we customize this earlier framework to vehicle holdings and use decisions, as well as extend the framework to include random coefficients/error components in the MDCEV component and MNL component. The resulting model is very flexible, and is able to accommodate general patterns of perfect and imperfect substitution among alternatives.[2]

The rest of this paper is structured as follows. The next section discusses the model structure of the mixed MDCEV-MNL model. Section 3 identifies the data sources, describes the sample formation process and provides relevant sample characteristics. Section 4 discusses the

[2] However, the modeling approach adopted here corresponds to a static vehicle body type/vintage/make/model holdings and use model, which ignores inter-relationships between vehicle holdings and use across time. Thus, the application of the static approach at two closely-spaced time points can lead to the unrealistic situation of a household holding very different vehicle portfolios between the two time points. But, the static approach may be reasonable over longer periods of time, as indicated by de Jong *et al.* (2004). An alternative formulation is to use a dynamic transactions approach (see de Jong, 1996, Bunch *et al.*, 1996, Mohammadian and Miller, 2003b), which is appealing. But this approach requires a "significant ongoing commitment to collecting panel data" (Bunch, 2000). Also, the theoretical linkage between usage and vehicle type is at best tenuous in dynamic models to date.

variables considered in model estimation and presents the empirical results. The final section summarizes the paper and discusses future extensions.

3. RANDOM UTILITY MODEL STRUCTURE

Let there be K different vehicle type/vintage combinations (for example, old Sedan, new Sedan, old SUV, new SUV, *etc.*) that a household can potentially choose from (for ease in presentation, we will use the term "vehicle type" to refer to vehicle type/vintage combinations). It is important to note that the K vehicle types are imperfect substitutes of each other in that they serve different functional needs of the household. Let m_k be the annual mileage of use for vehicle type k (k = 1, 2,…, K). Also, let the different vehicle types be defined such that households own no more than one vehicle of each type. If a household owns a particular vehicle type, this vehicle type may be one of several makes/models. That is, within a given vehicle type, a household chooses one make/model from several possible alternatives. Let the index for vehicle make/model be l, and let N_k be the set of makes/models within vehicle type k, and let W_{lk} be the utility perceived by the household for make/model l of vehicle type k. From the analyst's perspective, the household is assumed to maximize the following random utility function:

$$\tilde{U} = \sum_{k=1}^{K} \left\{ \left[\exp\left(\sum_{l \in N_k} \delta_{lk} W_{lk} \right) \right] \left(m_k + 1 \right)^{\alpha_k} \right\} \tag{1}$$

subject to $\sum_{k=1}^{K} m_k = M$, $m_k \geq 0$ and $\sum_{l \in N_k} \delta_{lk} = 1 \; \forall \, k$, where δ_{lk} is a dummy variable that takes a value of 1 if the l^{th} make/model is chosen in vehicle type k (note that only one make/model can be chosen within a vehicle type), α_k is a satiation factor that controls the use of each vehicle type k (see Bhat and Sen, 2006), and M is the exogenous total household annual mileage across all the k vehicle types (one of the "vehicle types" is assumed to be the non-motorized mode and hence the total household motorized annual mileage is endogenous to the formulation).[3] Since the household is maximizing $\tilde{U}$, and can choose only one make/model within vehicle type k, the implication is that the household will consider the make/model that provides maximum utility

[3] We do not distinguish between different non-motorized modes (bicycling and walking) in the current analysis, because the focus is on motorized travel.

within each vehicle type k in the process of maximizing $\tilde{U}$ (given the functional form of $\tilde{U}$). Thus, the household's utility maximizing problem of Equation (1) can be re-written as:

$$\tilde{U} = \sum_{k=1}^{K} \left\{ \left[\exp\left(\max_{l \in N_k} \{W_{lk}\} \right) \right] (m_k + 1)^{\alpha_k} \right\} \tag{2}$$

subject to $\sum_{k=1}^{K} m_k = M$, $m_k \geq 0 \; \forall \; k$.

The analyst can solve for optimal usage (m_k^*) by forming the Lagrangian and applying the Kuhn-Tucker conditions. Designating vehicle type 1 as a vehicle type to which the household allocates some non-zero amount of usage (note that the household should use at least one of the K vehicle types, given that the household will travel during the year), and using algebraic manipulations, the Kuhn-Tucker conditions may be written as (see, Bhat, 2008):

$$\left. \begin{array}{l} H_k = H_1 \text{ if } \mathrm{m}_k^* > 0 \\ H_k < H_1 \text{ if } \mathrm{m}_k^* = 0 \end{array} \right\} \; (k = 2, 3, ...K), \tag{3}$$

where

$$H_k = \max_{l \in N_k} \{W_{lk}\} + \ln \alpha_k + (\alpha_k - 1) \ln(m_k^* + 1), k \geq 1 \tag{4}$$

The satiation parameter, α_k, needs to be bounded between 0 and 1. To enforce this condition, we parameterize α_k as $1/[1 + \exp(-\delta_k)]$. Further, to allow the satiation parameters to vary across households, we write $\delta_k = \tau_k' y_k$, where y_k is a vector of household characteristics impacting satiation for the k^{th} alternative, and τ_k is a corresponding vector of parameter.

3.1 Econometric Model

The assumptions about the W_{lk} terms complete the econometric specification. Consider the following functional form for W_{lk}:

$$W_{lk} = \beta' x_k + \gamma' z_{lk} + \varepsilon_{lk} \tag{5}$$

In the above expression, $\beta' x_k$ is the overall observed utility component of vehicle type *k*, z_{lk} is an exogenous variable vector influencing the utility of vehicle make/model *l* of vehicle type *k*, γ is a corresponding coefficient vector to be estimated, and ε_{lk} is an unobserved error component associated with make/model *l* of vehicle type *k*. We assume that the ε_{lk} terms are identically distributed standard type I extreme value. Also, the error terms of the make/models belonging to the same vehicle type *k* may share common unobserved components (for example, a household may have a high overall preference for all SUV makes/models due to a preference for sitting high up when driving, ease in getting in/out, and projecting a social perception of being luxury-minded). This generates correlation across the error terms ε_{lk} belonging to the same *k*. Let this correlation be determined by a dissimilarity parameter θ_k. Then, we can write the distribution function for $(\varepsilon_{1k}, \varepsilon_{2k}, ..., \varepsilon_{Lk})$ as:

$$F(\varepsilon_{1k}, \varepsilon_{2k}, ..., \varepsilon_{Lk}) = \exp\left\{-\left[e^{-\varepsilon_{1k}/\theta_k} + e^{-\varepsilon_{2k}/\theta_k} + ...e^{-\varepsilon_{Lk}/\theta}\right]^{\theta_k}\right\} \tag{6}$$

But there is no reason for any correlation in the ε_{lk} terms across different vehicle types, and so we assume $\operatorname{cov}(\varepsilon_{lk}, \varepsilon_{l'k'}) = 0$ if $k \neq k'$.

The maximization property of the type-I extreme value distribution can now be invoked to write H_k in Equation (4) as:

$$\begin{aligned} H_k &= \max_{l \in N_k}\{\beta' x_k + \gamma' z_{lk} + \varepsilon_{lk}\} + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \\ &= \beta' x_k + \max_{l \in N_k}\{\gamma' z_{lk} + \varepsilon_{lk}\} + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \\ &= \beta' x_k + \theta_k \ln \sum_{l \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right) + \lambda_k + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1), \end{aligned} \tag{7}$$

where λ_k is a standard type I extreme value random term. Also, since $\operatorname{cov}(\varepsilon_{lk}, \varepsilon_{l'k'}) = 0$ if $k \neq k'$, $\operatorname{cov}(\lambda_k, \lambda_{k'}) = 0$. Then, following the derivation of the Multiple Discrete Continuous Extreme Value (MDCEV) model in Bhat (2005), the probability that the household uses the first *Q* of *K* vehicle types ($Q \geq 1$) for annual mileages $m_1^*, m_2^*, ..., m_Q^*$ may be written as:

$$P(m_1^*, m_2^*, ...m_Q^*, 0, 0, 0, ..., 0) = \left[\prod_{k=1}^{Q} r_k\right]\left[\sum_{k=1}^{Q} \frac{1}{r_k}\right]\left[\frac{\prod_{k=1}^{Q} e^{V_k}}{\left(\sum_{h=1}^{K} e^{V_h}\right)^Q}\right](Q-1)!, \tag{8}$$

where

$r_k = \left(\dfrac{1-\alpha_k}{m_k^* + 1}\right)$ and

$$V_k = \beta' x_k + \theta_k \ln \sum_{l \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right) + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \tag{9}$$

The conditional probability that vehicle make/model l will be used for an annual mileage $m_k^* (l \in N_k)$, given that $m_k^* > 0$, is given by:

$$P(l \mid m_k^* > 0;\ l \in N_k) = P\left[\gamma' z_{lk} + \varepsilon_{lk} > \gamma' z_{l'k} + \varepsilon_{l'k}\ \forall\, l' \neq l\right] \tag{10}$$

Based on the multivariate type-I extreme value distribution function for the ε_{lk} terms (l = 1, 2, …, L) as assumed in Equation (6), the above probability expression can be computed as (see Appendix A for the derivation):

$$P(l \mid m_k^* > 0;\ l \in N_k) = \frac{\exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right)}{\sum_{l' \in N_k} \exp\left(\frac{\gamma' z_{l'k}}{\theta_k}\right)} \tag{11}$$

Next, the unconditional probability that the household uses vehicle make/model a of vehicle type 1 for annual mileage m_{1a}^*, make/model b of vehicle type 2 for m_{2b}^*, … make/model q of vehicle type Q for m_{Qq}^* may be written as:

$$\begin{aligned} &P(m_{1a}^*, m_{2b}^*, m_{3c}^*, \ldots m_{Qq}^*, 0, 0, 0, \ldots 0) \\ &= P(m_1^*, m_2^*, \ldots m_Q^*, 0, 0, \ldots 0) \times P(a \mid m_1^* > 0) \times P(b \mid m_2^* > 0) \ldots P(q \mid m_Q^* > 0) \end{aligned} \tag{12}$$

It is important to note that the parameters γ and θ_k appear in both the MDCEV probability expression (Equation 6) as well as the standard discrete choice probability expression for the choice of make/model (Equation 8). This creates the jointness in the multiple discrete and single discrete choices. The θ_k values are dissimilarity parameters indicating the level of correlation among the vehicle makes/models within vehicle type k. When $\theta_k = 1$ for all k, the MDCEV-MNL model collapses to an MDCEV model with a fixed satiation parameter α_k for all make/model alternatives within vehicle type k.

3.2 Mixed MDCEV-MNL Model

The model developed thus far does not incorporate error correlation and/or random components in either the MDCEV vehicle type component or in the MNL make/model component. These can be accommodated by considering the β vector in the baseline preference of the MDCEV component and the γ vector characterizing the parameters in the MNL models as being draws from multivariate normal distributions $\boldsymbol{\phi}(\beta)$ and $\boldsymbol{\phi}(\gamma)$. The unconditional probability of vehicle holdings and usage may then be written as:

$$P(m_{1a}^{*}, m_{2b}^{*}, m_{3c}^{*}, \ldots m_{Qq}^{*}, 0, 0, 0, \ldots 0)$$
$$= \int_{\beta}\int_{\gamma} \Big\{ P(m_{1}^{*}, m_{2}^{*}, \ldots m_{Q}^{*}, 0, 0, \ldots 0) \times P(a \mid m_{1}^{*} > 0) \times P(b \mid m_{2}^{*} > 0) \tag{13}$$
$$\ldots \times P(q \mid m_{Q}^{*} > 0) \mid (\beta, \gamma) \Big\} \boldsymbol{\phi}(\beta) \boldsymbol{\phi}(\gamma) \, \mathrm{d}\beta \, \mathrm{d}\gamma$$

The likelihood function above can be estimated using the maximum simulated likelihood approach. We use Halton draws in the current research (see Bhat, 2003). The parameters to be estimated in the model structure include the moment parameters characterizing the β and the γ multivariate distributions, the τ_k vector for each alternative *k* (embedded in the scalar α_k within V_k), and the θ_k scalars for each alternative *k*. We estimate the parameters of the mixed MDCEV-MNL model jointly. However, as in the familiar nested logit model, one can first estimate the vehicle make/model MNL models for each vehicle body type/vintage and then estimate the MDCEV model after constructing logsum terms. However, this two-stage procedure can be quite inefficient. Besides, one has to anyway estimate 20 MNL models (one for each vehicle body type/vintage) simultaneously in the first step to maintain parameter restrictions on variables across "nests". When undertaking all this, one may as well estimate all parameters jointly.

4. DATA SOURCES AND SAMPLE FORMATION

4.1 Data Sources

The primary data source used for this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS). This survey was designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission. The survey collected information on vehicle fleet mix of over 15,000 households in the Bay Area for a two-day period (see MORPACE International Inc., 2002 for details on survey, sampling, and administration procedures). The information collected on household vehicle ownership included the make/model of all the vehicles owned by the household, the year of possession of the vehicles, odometer reading on the day of their possession, the year of manufacture of each vehicle, and the odometer reading of each vehicle on the two days of the survey. Furthermore, data on individual and household demographics, and activity travel characteristics, were collected.

In addition to the 2000 BATS data, several other secondary sources were used to generate the dataset in the current analysis. Specifically, data on purchase price (for new and used vehicles), engine size (in liters) and cylinders, engine horse power, vehicle weight, wheelbase, length, width, height, front/rear head room and leg room space, seating capacity, luggage volume, passenger volume and standard payload (for pickup trucks only) were obtained for each vehicle make/model from *Consumer Guide* (Consumer Guide, 2005). Data on annual fuel cost, fuel type (gasoline, diesel), type of drive wheels (front-wheel, rear-wheel and all-wheel), and annual greenhouse gas emissions (in tons) were obtained from the *EPA Fuel Economy Guide* (EPA, 2005). Residential location variables and built environment attributes were constructed from land use/demographic coverage data, a GIS layer of bicycle facilities, and the Census 2000 Tiger files (the first two datasets were obtained from the Metropolitan Transportation Commission of the San Francisco Bay area).

4.2 Sample Formation

The BATS survey data is available in four files: (1) vehicle file (2) person file (3) activity file and (4) household file. The first step in the sample formation process was to categorize the vehicles in the vehicle file into one of 20 vehicle classes, based upon vehicle type and vintage. In addition to providing a good characterization of vehicle type/vintage, the classification scheme adopted was also based on ensuring that no household owned more than 1 vehicle of each vehicle type/vintage.[4] This ensures that the model provides a comprehensive characterization of all dimensions corresponding to vehicle holdings and usage. The ten vehicle types used were (1) Coupe (2) Subcompact Sedan (3) Compact Sedan (4) Mid-size Sedan (5) Large Sedan (6) Hatchback/Station Wagon (which we will refer to as Station Wagons for brevity) (7) Sports Utility Vehicle (SUV) (8) Pickup Truck (9) Minivan and (10) Van. The two categories for vintage of each of these vehicle types were (1) New vehicles (2) Old Vehicles. A vehicle was

[4] The formulation here requires that households own no more than one vehicle of each type. In the empirical analysis in the current paper that uses data from the San Francisco region, we achieve this by defining vehicle types based on a combination of vehicle body type and vintage. This leads to 20 vehicle types in our empirical analysis (though within each vehicle type, we further model the choice of make and model). In other empirical settings, the definition of vehicle types may need to be modified, and may result in fewer or more vehicle types. But the advantage of our formulation is that any increase in the number of vehicle types does not have much impact on model complexity or estimation time.

defined as 'new' if the age of the vehicle (survey year minus the year of manufacture) was less than or equal to 5 years, and 'old' if the age of the vehicle was more than 5 years.

Within each of the 20 vehicle type/vintage classes, there are a large number of makes/models. For practical reasons, we collapsed the makes/models into commonly held distinct makes/models and grouped the other makes/models into a single "other" make/model category.[5] Figure 1 indicates the broad classification of vehicles into vehicle type/vintage categories and make/model subcategories. After classifying the vehicles, the vehicle dataset was populated with information on vehicle attributes obtained from secondary data sources. For those vehicle makes/models which belonged to the 'other' category, an average value of the vehicle attributes of all the vehicle makes/models which belonged to that vehicle type/vintage category was used. The annual mileage[6] for each vehicle was then computed.

The person file data was next screened to obtain information on the socio-demographic characteristics of the household head, including age, ethnicity, gender, and employment status.[7] Subsequently, the activity file was used to obtain information on the usage of non-motorized forms of transportation by the household members. The duration spent in walking and biking on the two days of the survey were aggregated across all the household members and projected to an annual level. Based upon the average rate of walking (3.5 miles/hour) and biking (15 miles/hour), the annual usage (miles) of non-motorized forms of transportation of a household was obtained.

After preparing the data from the vehicle, person and activity files, as discussed above, the resulting dataset was appended to the household file. The built environment variables were also added at this stage based on household location. The final sample comprised 8107 records that represented households that own at least one vehicle.[8]

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[5] A vehicle make/model was defined as not being "commonly held" if less than 1% of the vehicles in the vehicle type/vintage category were of that make/model.

[6] Annual Mileage = (mileage recorded by odometer on second survey day – miles on possession) / (survey year – year of possession). The mileage as computed here is clearly not as accurate as collecting odometer readings at multiple points in time, as done in the 2001 National Household Travel Survey (NHTS).

[7] The household head was defined as the employed individual in one-worker household. If all the adults in a household were unemployed, or if more than 1 adult was employed, the oldest member was defined as the household head.

[8] Our framework enables the modeling of the decision to not own vehicles too. Such households will exclusively use non-motorized forms of personal mode of travel. However, due to the very small percentage of households in the sample owning no vehicles (<5%), and the substantial presence of missing information on the potential determinants of vehicle holdings and use in these households, the final sample included only households that own one or more vehicles.

4.3 Descriptive Statistics

The distribution of the number of vehicles owned by households is as follows: one vehicle (55%), two vehicles (36%), three vehicles (8%) and four or more vehicles (1%). Table 1 shows the descriptive statistics of usage of different vehicle types/vintages owned by households. The second and the third columns of the table indicate the frequency (percentage) of the households owning each vehicle type/vintage category and the annual usage of the vehicle by the households owning that vehicle type/vintage, respectively. Several insights may be drawn from the statistics in these two columns. First, a high fraction of the households own old midsize sedans (19% of the households), old pickup trucks (15% of the households) and old compact sedans (14% of the households). Also, these vehicle types/vintages have a high annual usage rate (as observed in the third column of Table 1). This suggests a high baseline utility preference and low satiation for old midsize sedans, old pickup trucks and old compact sedans. Second, other most commonly owned vehicle types/vintages include old coupes (13% of the households) and new midsize sedans (12% of the households). Interestingly, these two vehicle types/vintages are also amongst the motorized vehicles with the least annual mileage. This indicates a high baseline preference, and a high satiation in the use of old coupes and new midsize sedans. Third, a small percentage of households own vehicle types/vintages with very high annual usage such as new van, new and old minivan, old SUV and old subcompact sedans. This reflects a low baseline preference and low satiation for these vehicle types/vintages. Fourth, new vans and old vans have the lowest baseline preference, and the new large sedan category has a high satiation effect (*i.e.* lowest annual usage) amongst all motorized vehicle types/vintages. Fifth, only 3% of the households use non-motorized forms of transportation (as observed in the last row of Table 1). Also, as expected, the non-motorized form of transportation has the least annual miles amongst all the vehicle types/vintages.

The last two columns in Table 1 indicate the split between one-vehicle households (*i.e.*, households that own and use one vehicle type or a corner solution) and multiple vehicle households (*i.e.*, households that own and use multiple vehicle types or interior solutions) for each vehicle type/vintage category. Thus, the number for new coupe indicates that, of the 389 households that own a new coupe, 132 (34%) own a new coupe only and 257 (66%) own new coupe along with one or more vehicle types/vintages. The statistics for one-vehicle households (as observed in the fourth column) show that old and new subcompact sedans, and old and new compact sedans, are the most commonly owned vehicles by such households, while new vans are the least commonly owned vehicle type/vintage. The results further indicate that households owning and using new vans, new minivans, new pickup trucks and old pickup trucks are most likely two and more vehicle households. Additionally, households always use the non-motorized form of transportation in combination with motorized vehicle types/vintages (as observed in the last row in Table 1).

5. EMPIRICAL ANALYSIS

5.1. Variable Specification

Several different types of variables were considered as determinants of vehicle type/vintage, make/model and usage decisions of the household. These included household demographics, residential location attributes, built environment variables, characteristics of the household head, and vehicle attributes of the household

The household demographic variables considered in the specification include household income, presence of children, household size, number of employed individuals, and presence of senior adults in the household. The residential location variables included population density of the zone of residence of the household, zonal employment density, and the zone type of the residential area (central business district (CBD), urban, suburban, or rural). The built environment variables corresponding to a household's residential neighborhood included land-use structure variables and local transportation network measures. The land-use structure variables included the percentages and absolute values of acreage in residential, commercial/industrial, and other land-use categories, fractions and numbers of single family and multi-family dwelling units, and fractions and number of households living in single family and multi-family dwelling units. The local transportation network measures included bikeway density (miles of bicycle facility per unit area), street block density (number of street blocks per unit area), highway density (miles of highway per unit area), and local road density (miles of local road per unit area). All the built environment variables are computed at the zonal level as well as for 0.25 mile, 1 mile, and 5 mile radii around the residence of each household.[9]

[9] An implicit assumption in using the built environment variables as exogenous determinants of vehicle holdings and use decisions is that residential location choice and vehicle-related decisions are not jointly made. Bhat and Guo

The characteristics of the household head included age, gender and ethnicity. Finally, the vehicle attributes considered included the purchase price, fuel cost, internal dimensions, vehicle performance indicators, type of drive wheels, type of vehicle makes, fuel emissions and type of fuel required by the vehicle.

5.2. Empirical Results

This section presents the empirical results of the joint MDCEV-MNL model for examining the vehicle type/vintage, make/model and usage decisions of the household. The model was estimated at different numbers of Halton draws per observation. However, there was literally no change in the estimation results beyond 50 Halton draws per observation (this is related to the large number of observations available for estimation). In our estimations, we used 100 Halton draws per observation.

The effects of the exogenous variables at the multiple discrete-continuous level (vehicle type/vintage) are presented first (Section 5.2.1), followed by effects of exogenous variables at the single discrete choice level (Section 5.2.2). This is followed by satiation effects (Section 5.2.3) and logsum parameters effects (Section 5.2.4). Section 5.2.5 presents the overall likelihood-based measures of fit.

5.2.1 MDCEV Model

The final specification results of the MDCEV component of the vehicle holdings and usage model are presented in Table 2 (the results corresponding to any given variable span two pages, because there are 21 vehicle type/vintage categories; each column of Table 2 represents one vehicle type/vintage). The vehicle type/vintage category of "new coupe" serves as the base category for all variables (and, thus, this vehicle type/vintage does not appear in the table as a column). In addition, a "–" entry corresponding to a variable for any vehicle type/vintage category implies that the category also constitutes the base category for the variable. Finally, some parameter estimates may be identical across multiple vehicle type/vintage categories. This is because we did not find statistically different effects of the corresponding variables on the

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(2007) propose a framework to accommodate such residential sorting effects. However, this issue is beyond the scope of the current paper.

baseline preferences for the multiple vehicle type/vintage categories, and so combined the effects for statistical efficiency.

5.2.1.1 Household Demographics

<u>*Household Income*</u> The household income effects indicate that medium and high income households have a high preference, relative to low income households, for new SUVs (see, Kitamura *et al.,* 2000 and Choo and Mokhtarian, 2004 for similar results), and a low preference for old vans (see the positive coefficients in the "new SUV" column and the negative coefficients in the "old van" column corresponding to the medium and high annual income rows of the table). Medium (high) income households also have a higher (lower) baseline preference for old pickup truck, old minivan, and old station wagons relative to low income households. Overall, the high income households have a lower baseline preference for older vehicles relative to low/middle income households, consistent with the ownership and usage of new vehicles by high income households (see the negative coefficients corresponding to the old vintage categories in the row for the high income dummy variable). Interestingly, high income households are also less likely than low and middle income households to undertake activities using non-motorized forms of transportation (see last column of the table corresponding to the high annual income row of the table.

<u>*Presence of Children in the Household*</u> The results show that households with very small children (less than or equal to 4 years of age) are more likely to use compact sedans, mid-size sedans, and SUVs than other households. In addition, the coefficients under the columns "new minivan" and "old minivan" for "presence of children less than or equal to 4 years" and "presence of children between 5 and 15 years" suggest that households with children prefer minivans, presumably due to the spacious, affordable, and family oriented nature of minivans.

Also, the results show that households with children between 16 and 17 years of age are unlikely to own/use old vans. This result is intuitive, since 16 or 17 years old adolescents are eligible to drive and are more likely to prefer owning/using vehicles types that are sporty and stylish.

Presence of Senior Adults in the Household Households with senior adults are more likely to own and use compact, mid-size, and large sedans relative to coupes and subcompact sedans. This is perhaps due to the preference for vehicles that are easy to get in and out of. Households with senior adults are also more likely to own old station wagons and old vans, as well as travel more by non-motorized forms of transportation compared to other households.

Household Size The household size coefficients are positive for the vehicle types corresponding to mid-size sedans, large sedans, station wagons, SUVs, pickup trucks, minivans and vans. This suggests a preference for bigger vehicles (to carry more people) rather than the smaller vehicle types of coupes, subcompact sedans, and compact sedans. It is also interesting to note that households with more members, in general, prefer older vehicle types than newer vehicle types. This may be because of less discretionary income of such households, leading them to invest in more affordable vehicles that meet their functional needs.

Number of Employed Individuals in the Household Households with more number of employed members have a high baseline preference for new vehicle types such as subcompact sedans and compact sedans, and an overall low baseline preference for large sedans and minivans. These results clearly indicate that households with several employed members prefer vehicle types that are new and compact rather than vehicle types that are old and have high seating capacity. Also, the results show that these households use non-motorized forms of transportation (such as walking and biking) less than other households.

5.2.1.2 Household Location Characteristics

The household location attribute effects indicate that households in suburban zones are, in general, less likely to own and use old vehicles relative to households in urban zones. Suburban and rural households are also more likely to own pickup trucks relative to urban households (see the positive coefficients corresponding to the new pickup and old pickup truck columns corresponding to the suburban and rural rows of Table 2). This latter result, consistent with Cao *et al.* (2006), is presumably because of the rugged terrains of suburban/rural areas and the occupational/family needs of suburban/rural households. This impact is further emphasized by the negative effect of employment density on the holding and use of new pickup trucks.

5.2.1.3 Built Environment Characteristics of the Residential Neighborhood

The built environment characteristics of the household neighborhood indicate that households located in highly residential areas are less likely to prefer large vehicle types such as pickup trucks and vans, irrespective of the age of the vehicle. A similar result is observed for households located in neighborhoods with high commercial/industrial acres. These results are intuitive, because neighborhoods with dense residential or commercial areas have space constraints for parking and maneuvering, leading to a preference for compact vehicles. Also, the results indicate the low baseline preference of households located in a neighborhood with high multi-family dwelling units for large sedans. This result is not immediately intuitive and needs additional exploration in future studies.

The results further indicate that households located in a neighborhood with high bike lane density have a high baseline preference for non-motorized modes of transportation, presumably because such neighborhoods encourage walking and bicycling. Also, households located in a neighborhood with high street block density are more likely to prefer smaller vehicle types (such as subcompact and compact sedans), and older vehicles, relative to new vehicles.

5.2.1.4 Household Head Characteristics

The impacts of the household head characteristics suggest that older households (*i.e.*, households whose heads are greater than 30 years) are generally more likely to own vehicles of an older vintage compared to younger households (*i.e.,* households whose heads are less than or equal to 30 years of age). This can be inferred from the negative signs on the age-related dummy variables for the new vehicle types, and the positive signs on the age-related dummy variables for the old vehicle types, in Table 2. In addition, older households are more likely to own minivans and old vans, and travel by non-motorized forms of transportation.

The "male" variable effects point to a higher baseline preference for older and larger vehicles if the male is the oldest member (or only adult) in the household relative to households with the female being the oldest member (or only adult). Finally, the ethnicity variables are also highly significant, with Asians more likely to own sedans and new minivans, and less likely to own pickup trucks, compared to other ethnicities. These and other ethnicity effects, may reflect overall cultural differences in preferences, and need to be examined more extensively in future studies.

5.2.1.5 Baseline Preference Constants

The baseline preference constants do not have any substantive interpretation, and are included to accommodate generic differences in preference across the vehicle types/vintages and the range of independent variables used in the model.

5.2.1.6 Random Error Components/Coefficients

Several different specifications for random error components and random coefficients were attempted in the MDCEV component of the joint model. The preferred specification included two error components as follows: (1) Coupes (standard deviation of 0.394 with a t-statistic of 2.08) and (2) Old vehicles (standard deviation of 0.517 with a t-statistic of 7.73). The error component corresponding to coupes provides evidence that households preferring old coupes due to unobserved factors (such as, for example, an inclination for sporty, small vehicles) also prefer new coupes. Similarly, there may be tangible unobserved factors, such as a generic dislike for the "old" label, that may decrease the utility of all old vehicles.

5.2.2 MNL Model for Vehicle Make/Model Choice

Table 3 provides the results for the Multinomial Logit (MNL) model for the choice of vehicle make/model, conditional on the choice of a vehicle type/vintage category. All the variables are introduced with generic parameters, with the coefficients of the variables held to be the same value across all the MNL logit models for the different vehicle type/vintage categories.

5.2.2.1 Cost Variables

The effects of the cost variables are intuitive: Households, on average, prefer vehicle makes and models that are less expensive to purchase and operate. As expected, households with high incomes are less sensitive to cost variables than are households with low incomes (see, Lave and Train, 1979, Mannering and Winston, 1985, for similar results). Also, the standard deviation of the random coefficient corresponding to purchase price/income is highly statistically significant, indicating the presence of unobserved heterogeneity across households to purchase price. A comparison of the mean and standard deviation of this coefficient shows that less than 1% of the households positively value purchase price. However, we found no unobserved heterogeneity to fuel cost. Finally, it is interesting to note the lower sensitivity to fuel cost relative to purchase price. This is understandable, since the purchase price constitutes a large investment at one point in time, while the annual fuel cost is incurred over multiple gas station trips.

5.2.2.2 Internal Dimensions

Households with 2 or less members are less likely, compared to households with more than 2 members, to prefer vehicle makes/models with high seat capacity. This is intuitive because of the need to be able to carry more individuals. Also, households prefer vehicle makes/models with high luggage volume and high standard payload capacity (the latter is applicable to pickup trucks only).

5.2.2.3 Vehicle Performance Indicators

The performance of the vehicle make/model was captured by using the engine horse power to vehicle weight ratio and engine size. Table 3 shows that households have a strong preference for vehicle makes/models with powerful and efficient engines.

5.2.2.4 Type of Drive Wheels and Vehicle Make

Households in the San Francisco Bay area are less likely to prefer vehicle makes/models with all-wheel-drive than vehicles with rear-wheel drive. Further, households prefer makes/models associated with Ford, Honda, Toyota, Cadillac, Volkswagen and Dodge relative to makes/models of other car manufacturers.

5.2.2.5 Fuel Emissions and Type

Households are less likely to use vehicle makes/models with high amounts of greenhouse gas emissions, perhaps because of the detrimental environmental and health impacts of harmful tailpipe emissions. Further, the results indicate that households are less likely to prefer vehicle makes/models that require premium gasoline compared to vehicle makes/models that can operate on regular or premium gasoline.

5.2.2.6 Trade-off Analysis

A trade-off analysis was conducted to assess the household's willingness to pay for vehicle attribute features relative to purchase price. The average household income of \$82,240 in the sample was used in the trade-off analysis. The results indicate that households significantly value additional units of luggage volume and vehicle performance. Specifically, average income households are willing to pay an additional purchase price of \$109 for an additional cubic of luggage volume and \$164 for one additional Horsepower of engine performance for a vehicle with an average weight of 3185 pounds. Additionally, the results indicate that households are also willing to pay \$2039 for a reduction in the green house gas emissions of 1 ton per year, indicating environmental consciousness and sensitivity.

5.2.3 Satiation Effects

The satiation parameter, α_k, for each vehicle type *k* is parameterized as $1/[1+\exp(-\delta_k)]$, where $\delta_k = \tau_k' y_k$, where y_k is a vector of household characteristics impacting satiation for the k^{th} vehicle type/vintage alternative. This parameterization allows α_k to vary across households and still be bounded between 0 and 1.

The estimated values of α_k and the t-statistics with respect to the null hypothesis of α_k=1 (note that standard discrete choice models assume α_k=1) are presented in Table 4. The table indicates the following results. First, all the satiation parameters are very significantly different from 1, thereby rejecting the linear utility structure employed in standard discrete choice models. That is, there are clear satiation effects in vehicle holdings and usage decisions. Second, as expected, middle and high income households are more likely to get satiated with the increasing use of any vehicle type/vintage compared to low income households. That is, middle and high income households are more likely to own and use multiple types/vintages of vehicles. Third, low income households are least likely to get satiated with the increasing use of old subcompact sedans, new and old compact sedans, and old midsize sedans, presumably because these vehicle type/vintage categories efficiently satisfy the functional needs of such households. Finally, the satiation effect is highest for non-motorized mode of transportation compared to all vehicle type/vintage categories. This is to be expected since the annual miles of walking and bicycling is very small relative to the use of motorized vehicles.

5.2.4 Logsum Parameters

The logsum parameters (*i.e.* θ_k parameters) create jointness between the single discrete choice component and the MDCEV components of the MDCEV-MNL model. There are two logsum parameters: (1) The logsum parameter for the makes/models corresponding to the old SUV, old minivan, new minivan, old van, and new van vehicle type/vintage categories is estimated to be 0.5354 (the t-statistic for the test that the parameter is different from 1 is 4.61), (2) The logsum parameter for the rest of the vehicle type/vintages is estimated to be 0.8378 (the t-statistic for the test that the parameter is different from 1 is 1.05). The logsum parameters indicate the presence of common unobserved attributes that affect the utilities of all makes/models corresponding to a given vehicle type/vintage category.

5.2.5 Overall Likelihood-based Measures of fit

The log-likelihood value at convergence of the final joint model is -87215. The corresponding value for the model with only the constants in the MDCEV and single discrete choice components, the satiation parameters, and unit logsum parameters is -90264. The likelihood ratio test for testing the presence of exogenous variable effects, satiation effects, and logsum effects is 6098, which is substantially larger than the critical chi-square value with 192 degrees of freedom at any reasonable level of significance. This clearly indicates the value of the model estimated in this paper to predict vehicle holdings and usage.

5.3 Model Application

The model estimated in this paper can be used to determine the change in the holdings and usage of vehicle types due to changes in independent variables. To do so at the mean parameter value on purchase price, we compute the logsum variable from the MNL models and predict vehicle holdings and usage by maximizing the systematic part of the random utility expression of Equation (1) (after including the computed logsum variable) under the constraint that $\sum_k m_k = M$.

In this paper, we demonstrate the application of the model by studying the effect of an increase in bike lane density, an increase in the street block density, and an increase in the vehicle fuel cost. Specifically, we increase the length of bikeways within a 0.25 mile radius of household's residences by 25%, increase the number of street blocks within 1 mile radius of household's residences by 25%, and increase the fuel cost by 25%. These changes are applied to each household in the sample. To examine the impact of these changes, we computed the predicted aggregate vehicle holdings and use patterns before and after the changes, and obtained a percentage change from the baseline estimates. The effect of the changes on aggregate vehicle holdings and use patterns is measured along two dimensions: (1) Percentage change in the number of households owning a particular vehicle type, and (2) Net percentage change in the annual miles of usage of each vehicle type. The vehicle types/vintages have been regrouped into six categories to better understand the implication of these changes. They are (1) Compact cars including new and old coupes, subcompact sedans, compact sedans and station wagons (2) new and old Midsize and large sedans (3) new and old SUVs (4) new and old Pickup trucks (5) new and old Minivans and Vans, and (6) Non-motorized modes of transportation. Table 5 presents the results for a 25% increase in the bike lane density, a 25% increase in the street block density, and a 25% increase in fuel cost. A "–" entry in the table indicates changes less than 0.2% along both the dimensions of holdings and usage. Also, note that we have provided 95% confidence bands around the point estimates in Table 5. These bands were computed using bootstrap draws.

The results from Table 5 indicate that an increase in bike lane density results in a marginal decrease in the holdings as well as usage of all motorized vehicle types, though some of these changes are not statistically significant at the 5% level. Further, as expected, the results indicate a statistically significant increase in the use, and intensity of use, of non-motorized modes of transportation.

An increase in street block density results in a statistically significant increase in the holdings of compact cars and a significant decrease in the holdings of pickup trucks. Further, the results indicate a high positive increase in the usage of compact cars and a marginal decrease in the use of other motorized vehicle types. The overall significant increase in the holdings and usage of compact cars indicates that increasing street block density encourages the use of small vehicles which are easy to maneuver. As expected, the holdings and usage of non-compact cars decrease with increasing number of street blocks. Additionally, the results show a statistically significant decrease in the use of non-motorized modes of transportation. This result is intuitive, because additional traffic contributed by the increase in the number of street blocks leads to safety concerns and hinders the use of non-motorized modes of transportation (see, Stinson and Bhat, 2005 for similar results).

Finally, an increase in the fuel cost leads to a statistically insignificant increase in the holdings of compact cars and a statistically significant decreases in the holdings of minivans and vans.[10] This result reflects the shift in the ownership of vehicles from larger vehicles to smaller, fuel efficient, vehicles. The percentage change in overall usage shows a statistically significant decrease in the use of compact cars, and statistically insignificant decrease in the use of all other motorized vehicle types. Additionally, as expected, the results indicate that an increase in fuel cost results in a significant increase in the use, and intensity of use, of non-motorized modes of transportation. Overall, however, the results reflect the rather small elasticity of vehicle holdings and use to fuel cost.

6. CONCLUSION

In this paper, we formulate and estimate a nested model structure that includes a multiple discrete-continuous extreme value (MDCEV) component to analyze the choice of vehicle type/vintage and usage in the upper level and a multinomial logit (MNL) component to analyze the choice of vehicle make/model in the lower level. The model accommodates heteroscedasticity and/or error correlation in both the multiple discrete-continuous component and the single discrete choice component of the joint model using a mixing distribution. The joint model also incorporates random coefficients in one or both components of the joint model. Data for the analysis is drawn from the 2000 San Francisco Bay Survey. The empirical results provide important insights into the determinants of vehicle holdings and usage decisions of households. Some important findings from the analysis are presented below.

The demographic variable effects show that high income households have a lower baseline preference for older vehicles relative to low/middle income households, as expected. A similar result is observed for households with more number of employed members. It is also interesting to note that both high income households and households with more number of employed members are less likely to use non-motorized forms of transportation compared to other households.

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[10] The scenario corresponding to an increase in fuel cost implied an increase in average fuel cost from \$2.55 per gallon to about \$3.19 per gallon.

The household location attributes and built environment characteristics of the household residential neighborhood indicate that households located in urban areas or in high residential or commercial/industrial neighborhoods are less likely to own/use large vehicle types such as pickup trucks and vans compared to other households. Also, households located in residential neighborhood with high bike lane density are more likely to use non-motorized modes of transportation, while those located in neighborhoods with high street block density are more likely to prefer compact vehicles.

In addition to the household demographic characteristics, the residential location attributes, and the built environment characteristics, the household head characteristics also impact the vehicle holdings and usage decisions. Households with older household heads are generally more likely to own vehicles of an older vintage compared to younger households. The preferences for vehicle holdings and use also vary depending upon the gender and ethnicity of the household head.

Finally, the empirical results give us valuable insights into the effect of vehicle attributes, fuel cost and fuel emissions on vehicle make/model holdings and usage decisions. Households prefer vehicle makes/models which are less expensive to purchase and operate, which have high luggage volume and seating capacity, high engine performance and low greenhouse gas emissions, amongst other things.

The aforementioned variable impacts on vehicle holdings and usage predictions can inform the design of proactive land-use, economic, and transportation policies to influence household vehicle holdings and usage in a way that reduces the negative impacts of automobile dependency such as traffic congestion, fuel consumption and air pollution.

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Appendix A

From Equation (6) and (10) of the text, and for alternative $l = 1$,

$$P(l=1\,|\,m_k^* > 0;\ l \in N_k) = P\left[\varepsilon_{2k} < \gamma' z_{1k} - \gamma' z_{2k} + \varepsilon_{1k},\, \varepsilon_{3k} < \gamma' z_{1k} - \gamma' z_{3k} + \varepsilon_{1k}, \ldots, \varepsilon_{Lk} < \gamma' z_{1k} - \gamma' z_{Lk} + \varepsilon_{1k}\right]$$

$$= \int_{\varepsilon_{1k}=-\infty}^{\infty} \frac{\partial F}{\partial \varepsilon_{1k}} \left(\varepsilon_{1k}, \gamma' z_{1k} - \gamma' z_{2k} + \varepsilon_{1k}, \gamma' z_{1k} - \gamma' z_{3k} + \varepsilon_{1k}, \ldots, \gamma' z_{1k} - \gamma' z_{Lk} + \varepsilon_{1k}\right) d\varepsilon_{1k}$$

$$= \int_{\varepsilon_{1k}=-\infty}^{\infty} \left(\exp\left\{-\left[e^{-\varepsilon_{1k}/\theta_k} + e^{-(\gamma' z_{1k} - \gamma' z_{2k} + \varepsilon_{1k})/\theta_k} + e^{-(\gamma' z_{1k} - \gamma' z_{3k} + \varepsilon_{1k})/\theta_k} + \ldots + e^{-(\gamma' z_{1k} - \gamma' z_{Lk} + \varepsilon_{1k})/\theta_k}\right]^{\theta_k}\right\}\right) \times$$
$$\left[e^{-\varepsilon_{1k}/\theta_k} + e^{-(\gamma' z_{1k} - \gamma' z_{2k} + \varepsilon_{1k})/\theta_k} + e^{-(\gamma' z_{1k} - \gamma' z_{3k} + \varepsilon_{1k})/\theta_k} + \ldots + e^{-(\gamma' z_{1k} - \gamma' z_{Lk} + \varepsilon_{1k})/\theta_k}\right]^{\theta_k - 1} e^{-\varepsilon_{1k}/\theta_k} d\varepsilon_{1k}$$

$$= \int_{\varepsilon_{1k}=-\infty}^{\infty} \left(\exp\left\{-\left(e^{-\varepsilon_{1k}}\right) C^{\theta_k}\right\}\right)\left\{e^{-\varepsilon_{1k}/\theta_k} C\right\}^{\theta_k - 1} e^{-\varepsilon_{1k}/\theta_k} d\varepsilon_{1k}$$

where $C = 1 + e^{-\gamma' z_{1k} - \gamma' z_{2k}} + e^{-\gamma' z_{1k} - \gamma' z_{3k}} + \ldots + e^{-\gamma' z_{1k} - \gamma' z_{Lk}}$

$$= \int_{\varepsilon_{1k}=-\infty}^{\infty} \left(\exp\left\{-\left(e^{-\varepsilon_{1k}}\right) C^{\theta_k}\right\}\right) C^{\theta_k - 1} e^{-\varepsilon_{1k}} d\varepsilon_{1k}$$

$$= \frac{1}{C} = \frac{\exp\left(\dfrac{\gamma' z_{1k}}{\theta_k}\right)}{\sum_{l' \in N_k} \exp\left(\dfrac{\gamma' z_{l'k}}{\theta_k}\right)}$$ as in Equation (11).

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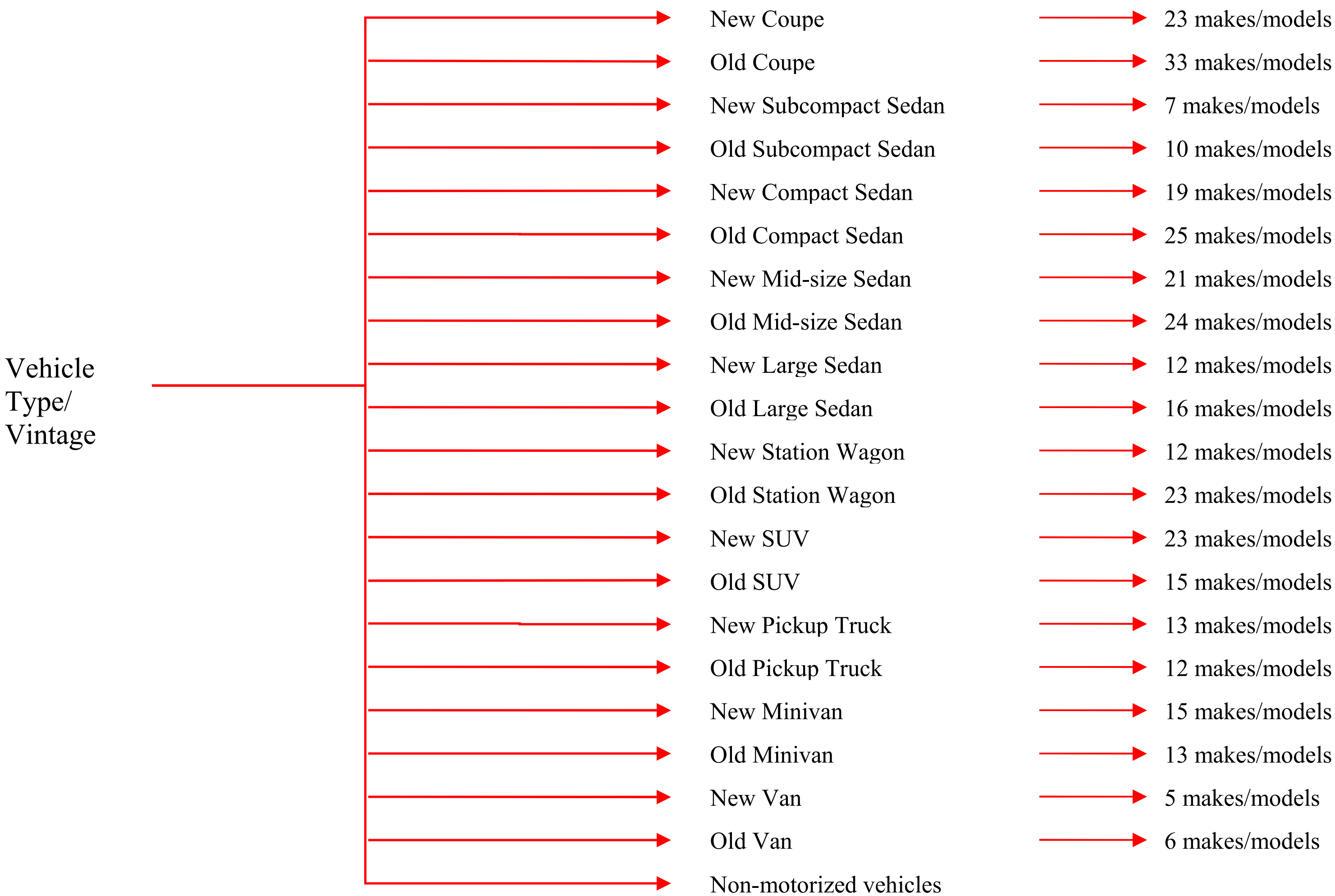

Figure 1. Classification of vehicle type/vintage

Table 1. Descriptive Statistics of Vehicle Type/Vintage Holdings

Vehicle type/vintage	Total number (%) of households owning/using	Annual Mileage	No. of households who own (%)	
			Only Vehicle type/vintage (one-vehicle households)	Vehicle type/vintage and other Vehicle type/vintages (2+ vehicle households)
New Coupe	389 (5%)	7763	132 (34%)	257 (66%)
Old Coupe	1024 (13%)	7766	374 (37%)	650 (63%)
New Subcompact Sedan	292 (4%)	7838	127 (43%)	165 (57%)
Old Subcompact Sedan	513 (6%)	9570	238 (46%)	275 (54%)
New Compact Sedan	767 (9%)	8321	342 (45%)	425 (55%)
Old Compact Sedan	1175 (14%)	9614	495 (42%)	680 (58%)
New Midsize Sedan	987 (12%)	7688	361 (37%)	626 (63%)
Old Midsize Sedan	1543 (19%)	9342	636 (41%)	907 (59%)
New Large Sedan	250 (3%)	7418	71 (28%)	179 (72%)
Old Large Sedan	377 (5%)	8339	151 (40%)	226 (60%)
New Station Wagon	242 (3%)	7869	80 (33%)	162 (67%)
Old Station Wagon	728 (9%)	8248	254 (35%)	474 (65%)
New SUV	707 (9%)	8920	245 (35%)	462 (65%)
Old SUV	711 (9%)	9813	213 (30%)	498 (70%)
New Pickup Truck	578 (7%)	8887	153 (26%)	425 (74%)
Old Pickup Truck	1198 (15%)	8679	301 (25%)	897 (75%)
New Minivan	459 (6%)	9156	115 (25%)	344 (75%)
Old Minivan	480 (6%)	9890	130 (27%)	350 (73%)
New Van	39 (1%)	10640	8 (21%)	31 (79%)
Old Van	122 (2%)	8203	33 (27%)	89 (73%)
Non-Motorized mode of transportation	201 (3%)	2695	-	201 (100%)

Table 2. MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Demographics										
Annual household income dummy variables										
Medium annual income (35K-90K)	-	-	-	-	-	-	-	-	-	-
High annual income (>90K)	-0.378 (-6.03)	-	-0.378 (-6.03)	-0.438 (-5.60)	-0.378 (-6.03)	-	-0.378 (-6.03)	-	-0.378 (-6.03)	-
Presence of children in the household										
Presence of children < = 4 yrs	-	-	0.334 (4.68)	0.392 (5.04)	0.334 (4.68)	0.392 (5.04)	0.334 (4.68)	-	-	-
Presence of children b/w 5 and 15 yrs	-	-	-	-	0.244 (4.27)	-	0.244 (4.27)	-	-	-
Presence of children 16 and 17 yrs	-	-	-	-	-	-	-	-	-	-
Presence of senior adults (> 65 years) in the household	-	-	-	0.423 (6.09)	0.574 (9.18)	0.423 (6.09)	0.574 (9.18)	1.172 (11.78)	1.172 (11.78)	-
Household size	-	-	-	-	-	0.074 (2.84)	0.139 (7.33)	0.494 (13.29)	0.139 (7.33)	0.074 (2.84)
Number of employed individuals in the household	-	0.161 (4.43)	-	0.161 (4.43)	-	-	-	-0.419 (-8.89)	-0.193 (-4.36)	-

Table 2 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Demographics										
Annual household income dummy variables										
Medium annual income (35K-90K)	0.159 (1.96)	0.662 (2.63)	-	-	0.223 (3.79)	-	0.223 (3.79)	-	-0.633 (-2.24)	-
High annual income (>90K)	-0.378 (-6.03)	0.663 (2.56)	-0.378 (-6.03)	-0.438 (-5.60)	-0.378 (-6.03)	-	-0.378 (-6.03)	-	-1.452 (-4.13)	-0.378 (-6.03)
Presence of children in the household										
Presence of children < = 4 yrs	-	0.392 (5.04)	0.334 (4.68)	-	-	0.392 (5.04)	-	-	-0.924 (-2.24)	-
Presence of children b/w 5 and 15 yrs	-	-	-	-	-	0.809 (6.93)	0.656 (5.17)	-	-	-
Presence of children 16 and 17 yrs	-	-	-	-	-	-	-	-	-0.618 (-1.53)	-
Presence of senior adults (> 65 years) in the household	0.423 (6.09)	-	-	-	-	-	-	-	0.574 (9.18)	0.574 (9.18)
Household size	0.139 (7.33)	0.074 (2.84)	0.139 (7.33)	-	0.139 (7.33)	0.494 (13.29)	0.563 (12.87)	0.494 (13.29)	0.563 (12.87)	0.494 (13.29)
Number of employed individuals in the household	-	-	-	0.161 (4.43)	-	-0.419 (-8.89)	-0.193 (-4.36)	-	-	-0.419 (-8.89)

Table 2 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Location Attributes										
Zonal dummy variables (urban is base)										
Suburban	-	-	-0.257 (-4.68)	-	-0.257 (-4.68)	-	-	0.281 (2.45)	-	-
Rural	-	-	-	-	-	-	-	-	-	-0.678 (-1.72)
Employment Density	-	-	-	-	-	-	-	-	-	-
Built Environment Characteristics of the Residential Neighborhood										
Land Use Structure Variables										
Residential Acres within 1 mile radius	-	-	-	-	-	-	-	-	-	-
Commercial / Industrial Acres within 1 mile radius	-	-	-	-	-	-0.268 (-2.73)	-0.268 (-2.73)	-	-	-0.268 (-2.73)
Number of Households in Multi-family Dwelling Units within 1 mile radius (in 10,000's)	-	-	-	-	-	-	-	-0.464 (-4.43)	-0.464 (-4.43)	-
Local Transportation Network Measures										
Bike Lane Density (Total miles of bikeway within 0.25 mile radius)	-	-	-	-	-	-	-	-	-	-
Street Block Density (Number of Street Blocks within 1 mile radius)	-	0.678 (3.95)	0.998 (3.99)	0.678 (3.95)	0.998 (3.99)	-	-	-	-	0.678 (3.95)

Table 2 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Location Attributes										
Zonal dummy variables (urban is base)										
Suburban	-0.257 (-4.68)	-	-	0.281 (2.45)	0.166 (2.01)	-	-	-	-	0.166 (2.01)
Rural	-	-	-	0.349 (1.77)	0.232 (1.59)	-	-	-	-	-
Employment Density	-	-	-	-0.003 (-2.39)	-	-	-	-	-	-
Built Environment Characteristics of the Residential Neighborhood										
Land Use Structure Variables										
Residential Acres within 1 mile radius	-	-	-	-0.408 (-6.79)	-0.408 (-6.79)	-	-	-0.364 (-2.09)	-0.364 (-2.09)	-
Commercial / Industrial Acres within 1 mile radius	-0.268 (-2.73)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-	-	-
Number of Households in Multi-family Dwelling Units within 1 mile radius (in 10,000's)	-	-	-	-	-	-	-	-	-	-
Local Transportation Network Measures										
Bike Lane Density (Total miles of bikeway within 0.25 mile radius)	-	-	-	-	-	-	-	-	-	1.559 (3.27)
Street Block Density (Number of Street Blocks within 1 mile radius)	0.998 (3.99)	-	-	-	-	-	-	-	-	-

Table 2 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Head Characteristics										
Age (age < = 30 yrs is base)										
Age between 31 and 45 yrs	-	-0.586 (-5.99)	-	-0.586 (-5.99)	-	-	0.211 (3.32)	-	-	-0.586 (-5.99)
Age greater than 45 yrs of age	0.245 (4.48)	-1.031 (-7.22)	-	-0.602 (-5.86)	-	-	0.644 (8.70)	0.909 (6.19)	0.644 (8.70)	-0.602 (-5.86)
Male	0.288 (4.88)	-0.267 (-3.76)	-	-0.271 (-3.81)	-	-	-	0.445 (6.08)	-	-
Ethnicity (Caucasian is base)										
African-American	-	-	-	-	-	-	-	-	0.807 (3.05)	-
Hispanic	-	-	-	-	-	-	-	-	0.545 (2.21)	-
Asian	-	0.641 (7.69)	0.462 (5.49)	0.641 (7.69)	0.462 (5.49)	0.641 (7.69)	0.462 (5.49)	-	-	-0.989 (-4.33)
Other	-	0.414 (2.39)	0.354 (2.83)	-	-	-	-	-	0.354 (2.83)	-
Baseline Preference Constants	0.368 (2.88)	0.508 (2.82)	0.528 (3.90)	0.945 (6.28)	0.747 (5.57)	0.800 (6.62)	0.356 (2.51)	-1.958 (-8.04)	-0.435 (-2.55)	0.445 (2.22)

Table 2 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Head Characteristics										
Age (age < = 30 yrs is base)										
Age between 31 and 45 yrs	-	-	-	-	0.211 (3.32)	0.628 (3.73)	0.211 (1.79)	-	0.211 (1.79)	0.211 (3.32)
Age greater than 45 yrs of age	0.245 (4.48)	-	-	-	0.245 (4.48)	0.909 (6.19)	0.644 (8.70)	-	0.644 (8.70)	0.644 (8.70)
Male	-	-	0.288 (4.88)	0.445 (6.08)	0.489 (7.00)	0.445 (6.08)	-	-	0.489 (7.00)	-
Ethnicity (Caucasian is base)										
African-American	-	-	-0.619 (-1.80)	-0.679 (-1.77)	-	-	-	-	-	-
Hispanic	-	-	-	-	-	-	-	-	-1.777 (-1.63)	-
Asian	-	-	-	-0.989 (-4.33)	-0.597 (-3.81)	0.641 (7.69)	-	-	-0.597 (-3.81)	-
Other	0.354 (2.83)	-	-	-	-	0.414 (2.39)	-	1.082 (1.99)	-	-
Baseline Preference Constants	0.043 (0.27)	0.104 (0.35)	1.539 (4.94)	0.536 (2.83)	0.763 (4.23)	-0.962 (-2.89)	-0.627 (-1.96)	-2.284 (-5.79)	-1.225 (-2.91)	1.431 (1.96)

Table 3. Multinomial Logit Model Results for Vehicle Make/Model Choice

Variable	Parameter	t-stat
Cost Variables		
Purchase Price (in $)/Income (in $/yr) [x 10]		
Mean Effect	-0.173	-5.71
Standard Deviation	0.064	4.44
Fuel Cost (in $/yr) /Income (in $/yr) [x 10]	-0.003	-1.61
Internal Vehicle Dimensions		
Seat Capacity * Household Size less than equal to 2 dummy variable	-0.075	-5.11
Luggage Volume (in 10s of cubic feet)	0.023	3.54
Standard Payload Capacity (for Pickup Trucks only) (in 1000 lbs)	0.196	5.13
Vehicle Performance Indicators		
Horsepower (in HP) /Vehicle Weight (in lbs) [in 10s]	1.102	4.89
Engine Size (in liters)	-0.045	-2.42
Type of Drive Wheels and Vehicle Makes		
Dummy variable for All-Wheel-Drive (base: rear-wheel-drive)	-0.214	-3.81
Dummy Variable for Vehicle Make - Chevy	-0.149	-1.25
Dummy Variable for Vehicle Make - Ford	0.716	5.37
Dummy Variable for Vehicle Make - Honda	1.444	5.37
Dummy Variable for Vehicle Make - Toyota	0.752	5.29
Dummy Variable for Vehicle Make - Cadillac	0.880	4.36
Dummy Variable for Vehicle Make - Volkswagen	0.374	2.55
Dummy Variable for Vehicle Make - Dodge	0.699	4.96
Fuel Emissions and Type		
Amount of Greenhouse Gas Emissions (in 10s of tons/yr)	-0.429	-2.71
Dummy variable for Premium Fuel (base: regular fuel)	-0.552	-5.01

Table 4. Satiation Effects

Vehicle Type/Vintage	Parameter	t-statistic
New Coupe		
Low Income Households	0.9036	4.05
Medium Income Households	0.8196	3.45
High Income Households	0.7344	3.87
Old Coupe		
Low Income Households	0.8929	6.59
Medium Income Households	0.7794	5.68
High Income Households	0.7280	5.94
New Subcompact Sedan		
Low and Medium Income Households	0.9066	4.29
High Income Households	0.7413	3.98
Old Subcompact Sedan		
Low Income Households	0.9574	4.15
Medium Income Households	0.9050	3.78
High Income Households	0.8783	3.84
New Compact Sedan		
Low Income Households	0.9242	4.41
Medium Income Households	0.8553	3.52
High Income Households	0.7826	3.87
Old Compact Sedan		
Low Income Households	0.9361	5.95
Medium Income Households	0.8612	4.98
High Income Households	0.8246	5.09
New Midsize Sedan		
Low Income Households	0.8985	4.75
Medium Income Households	0.8110	3.81
High Income Households	0.7231	4.30
Old Midsize Sedan		
Low Income Households	0.9293	6.30
Medium Income Households	0.8478	5.21
High Income Households	0.8084	5.34
New Large Sedan		
Constant	0.7723	5.83

Table 4. Satiation Effects (continued)

Vehicle Type/Vintage	Parameter	t-statistic
Old Large Sedan		
Constant	0.8485	6.11
New Station Wagon		
Low and Medium Income Households	0.8893	4.40
High Income Households	0.7034	4.21
Old Station Wagon		
Low Income Households	0.9051	6.03
Medium Income Households	0.8018	5.28
High Income Households	0.7540	5.50
New SUV		
Constant	0.8167	9.25
Old SUV		
Constant	0.8338	8.48
New Pickup Truck		
Low Income Households	0.8741	4.70
Medium Income Households	0.7710	3.92
High Income Households	0.6720	4.53
Old Pickup Truck		
Low Income Households	0.8481	7.63
Medium Income Households	0.7029	6.63
High Income Households	0.6419	7.07
New Minivan		
Constant	0.7698	8.02
Old Minivan		
Constant	0.8100	7.32
New Van		
Constant	0.8009	2.18
Old Van		
Low and Medium Income Households	0.8280	3.50
High Income Households	0.6072	4.35
Non-motorized form of transportation		
Constant	0.2211	5.56

Table 5. Impact of Change in Built Environment Variables and Fuel Cost

Vehicle Type	Impact of a 25% increase in bike lane density		Impact of a 25% increase in street block density		Impact of a 25% increase in fuel cost	
	change in holdings of vehicle type	change in overall use of vehicle type	change in holdings of vehicle type	change in overall use of vehicle type	change in holdings of vehicle type	change in overall use of vehicle type
Compact Car	-	-2.2 (-3.0,-1.4)	8.5 (4.8, 12.2)	3.4 (1.7, 5.1)	1.3 (-3.1,5.7)	-0.9 (-1.1,-0.7)
Midsize and Large Sedan	-2.2 (-4.2,-0.2)	-2.1 (-3.5,-0.7)	-	-0.8 (-4.2, 2.6)	-	-0.6 (-1.3, 0.1)
SUV	-0.6 (-1.3, 0.1)	-0.4 (0.0,-0.8)	-	-	-	-
Pickup Truck	-1.4 (-1.4,-1.4)	-0.4 (-3.2,2.4)	-2.1 (-2.1,-2.1)	-1.7 (-5.1, 1.7)	-5.7 (-14.1, 2.5)	-2.3 (-5.7, 1.1)
Minivan and Van	-	-0.7 (-1.3,-0.2)	-	-0.6 (-0.1,-1.1)	-2.6 (-3.8,-1.4)	-
Non-motorized modes of transportation	7.4 (4.2, 10.6)	13.9 (11.2, 16.6)	-4.0 (-6.3,-1.7)	-3.3 (-4.3,-2.3)	1.5 (0.8, 2.2)	0.8 (0.4, 1.2)