A DISCRETE-CONTINUOUS MODEL OF HOUSEHOLDS' VEHICLE CHOICE AND USAGE, WITH AN APPLICATION TO THE EFFECTS OF RESIDENTIAL DENSITY

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Abstract

This paper develops a new method to solve multivariate discrete-continuous problems and applies the model to measure how much residential density influences households' vehicle fuel efficiency and usage choices. Traditional discrete-continuous modelling of vehicle holding choice and vehicle usage becomes unwieldy with large numbers of vehicles and vehicle categories. I propose a more flexible method of modelling vehicle holdings in terms of number of vehicles in each category, with a Bayesian multivariate ordinal response system. I also combine the multivariate ordered equations with tobit equations to jointly estimate vehicle type/usage demand in a reduced form, offering a simpler alternative to the traditional discrete/continuous analysis. Using the 2001 National Household Travel Survey data, I find that increasing residential density reduces households' truck holdings and utilization in a statistically significant but economically insignificant way. The results are broadly consistent with those from a model derived from random utility maximization. The method used to estimate the system can be applied to other discrete-continuous problems.

Keywords: multivariate ordered probit; multivariate tobit; discrete/continuous; residential density; vehicle choice; fuel economy

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1 Introduction

Policies aimed at reducing gasoline consumption of automobiles can target either vehicle usage, measured by total miles driven, or vehicle fuel efficiency, the inverse of gallons per mile. Empirical studies have found that elements of urban spatial structure, particularly higher residential density, are associated with lower private vehicle utilization (Cervero and Kockelman 1991, Dunphy and Fisher 1996, and Golob and Brownstone 2005 etc.). However, whether or not density induces a compositional shift of households' automobile holdings towards more fuel efficient vehicles has not been widely studied. This paper develops a Bayesian Multivariate Ordered Probit & Tobit (BMOPT) model to estimate a joint system of vehicle fuel efficiency choice and vehicle utilization in response to varying residential density.

Motivation for a possible causal relationship between density and vehicle type choice comes from the observation that high density areas tend to have smaller parking spaces, narrower streets and more severe traffic. These conditions all work in favor of choosing smaller, easier-to-maneuver and more fuel efficient vehicles. Since a driver's cost of manoeuvering in the streets and searching for a parking space in dense areas is increasing in vehicle size, an incentive to choose smaller vehicles exists. Therefore, we would expect urban sprawl, which leads to low densities, to deter consumers from choosing fuel efficient vehicles. Indeed, results from Golob and Brownstone (2005) reveal that annual fuel consumption per vehicle declines a bit more sharply with increasing housing density than does annual miles driven, generating a positive relationship between fuel efficiency and density. The relationship is further explored in this paper.

The BMOPT model combines a multivariate ordered probit model describing vehicle type choice with a multivariate tobit model describing vehicle usage, both at a disaggregate level. All the equations are linked by an unrestricted covariance matrix. Several features of the framework merit discussion.

Vehicle choice decisions are modelled as ordered for each vehicle type that I specify (for example, the ordered choice for trucks would be zero truck, one truck, or two or more trucks). The traditional method of studying vehicle holdings decision utilizes a nested logit framework with the following decision tree: total number of vehicles a household owns in the upper level, and possible combinations of vehicle types, given the total number, in the lower level (Train 1984, Berkovec and Rust 1985, Mannering and Winston 1985, Goldberg 1998, Feng, Fullerton and Gan 2005, West 2005). When more vehicles are owned by the households, or vehicles are classified into finer categories, the possible vehicle combinations proliferate. For example, if vehicles are classified into five categories there will be 15 vehicle combinations in a two-vehicle household, 35 combinations in a three-vehicle household, 70 combinations in a four-vehicle household, and so on. This proliferation in vehicle compositions as vehicle number increases makes nested logit models hard to implement for households with more than two vehicles. As a result, most of these studies only concentrate on one-vehicle and two-vehicle households. This restriction results in a loss of useful data.

Since vehicle holdings composition is fully represented by number of each vehicle type, I propose to use 'number of each type of vehicle', instead of 'total number' of all vehicles, to model households' vehicle holdings decision. Because the number of each vehicle type is ordered and the choices of each vehicle type within one household are interrelated, I utilize a multivariate ordered probit model with a correlated covariance matrix. This structure makes vehicle type choice models less restrictive to number of vehicle holdings within a household. In the 2001 National Household Travel Survey (NHTS) California data set, one-vehicle and two-vehicle households comprise 67.5 percent of the total households surveyed; households with no vehicles comprise 5 percent. To be able to add the remaining 27.5 percent of households, which own 48 percent of the total vehicles in the sample, will make the estimation results dependent upon the whole vehicle stock and allow policy analysis for the entire population.

I adopt a reduced-form approach for joint discrete-continuous estimation. Two types of discrete-continuous models, deriving from random utility maximization, are currently implemented in the literature. The first one follows the methodology developed in Dubin and McFadden (1984) and Hannemann (1985), where a conditional indirect utility function, giving the maximum utility achievable, provides the basis for deriving the continuous demand and the discrete choice. Because the indirect utility function derived from Roy's identity is often in a non-linear form, the procedure involves an approximation in estimation: researchers either make additional assumptions to produce a linear equation (Dubin and McFadden 1984) or use a linear approximation (Train 1987, Goldberg 1998, West 2004).

The second type of utility-based econometric model is developed by Bhat (2006), who proposes a multiple discrete-continuous extreme value (MDCEV) model. In the model's application to vehicle choice and usage (Bhat and Sen, 2006), 'miles driven' by each type of vehicle is a choice variable in the upper level and make/model choices are captured by a multinomial logit component in the lower level. By embedding vehicle usage into type choice, modelling discrete-continuous choices becomes much simpler. The model offers an elegant and practical method for handling multiple choices of a large number of discrete consumption alternatives. Two drawbacks of the model are as follows. First, subject to the utility function specification, total vehicle utilizations in terms of miles travelled (including non-motorized modes of transportation) are fixed for each household. Considering that the walking/biking miles are negligible compared to the vehicle miles in California, fixing the total travel miles is de facto fixing the total vehicle utilization. While the model might capture substitution effects between different types of vehicle utilization, this restriction rules out the potential vehicle utilization reduction which we would expect to occur, or at least test, in response to particular policies. Second, vehicles must be finely classified such that households own no more than one vehicle of each type. Multiple choices of one particular vehicle type, say two subcompacts, are not allowed. Such fine classification requires additional data to describe vehicle characteristics and is often not necessary for some research purposes.

The model I propose plays a complementary role to the models derived from utility maximization mentioned above. A reduced-form analysis escapes the complexity of behavioral models and its functional and parametric assumptions, to embrace another set of functional form assumptions for the estimation equations. Though less attached to economic theory, it has advantages in terms of estimation and data fitting. A similar reduced-form exercise is carried out in Srinivasan and Bhat (2006), analyzing daily time-investment activity decisions of couples. This paper differs from the aforementioned study in three main aspects, in addition to the different application. First, correlations across the continuous equations are accommodated in this paper. This allows me to model automobile usages that are interrelated within a household, and gain efficiency in the model estimation. Second, the discrete choices in this paper are ordered, instead of binary, adding an additional layer of complexity to the computation. Third, a Bayesian method is used for the model estimation. The method is free from direct evaluation of multiple integrals and the use of asymptotic approximations. It produces exact finite sample inferences.

The BMOPT model is estimated using data augmentation and Bayesian Markov Chain Monte Carlo methods. To compare the results from the proposed reduced-form model to those from a utility-based model, Bhat's MDCEV model is also applied using maximum likelihood estimation. The results from the two models are broadly consistent in terms of truck usage. Higher density is found to discourage additional truck choice and also to discourage truck usage.

Since the research goal here is to find out households' preference for vehicle types in terms of fuel efficiency, I classify vehicles into two types - cars and trucks, in the BMOPT model. Car is defined as automobile, car, or station wagon; truck refers to van, sports utility vehicle, or pickup truck. Due to Corporate Average Fuel Economy (CAFE) standards enacted in 1975, passenger cars and light trucks are regulated under two different fuel economy requirements. For example, model year 1996 to 2004 cars must meet the 27.5 miles per gallon CAFE standard and light trucks must meet the 20.7 miles per gallon standard. Under the standards, the actual average fuel economy for model year 2000 passenger cars is 28.5 mpg and that for light trucks is 21.3 mpg. These large differences between fuel economy and weight of passenger cars and trucks make me believe that by categorizing vehicles into cars and trucks, I can capture the fuel efficiency choice a household actually makes. To demonstrate that the model can handle more classifications, and to check whether the choice pattern with respect to residential density retains for finer classification of vehicles, subclassification of vehicles into small-size cars, large-size cars, small-size trucks, and large-size trucks are also implemented in section 2.5.

The MDCEV model requires the vehicles to be finely classified, but the estimation results can be grouped into category of cars and trucks to be comparable to the results from the BMOPT model.

2 The BMOPT model

The data analysis is complicated in two aspects. First, vehicle choices within one household are interdependent. Instead of estimating each choice equation independently and using the univariate ordered probit model, a bivariate ordered probit model is adopted with an unrestricted correlation. In addition, vehicle usages are interdependent themselves and with vehicle choices. I add equations for annual miles driven by cars and trucks to the two bivariate ordered probit equations. Second, the observations on average annual miles driven by cars and trucks are censored. About 56.7 percent of the households in the sample don't hold trucks, and 10.3 percent don't hold cars, with whom we observe zero miles driven on trucks and cars respectively. In a censored regression model where a large proportion of dependent variables are zero, the OLS estimates fail to account for the qualitative difference between zero observations and continuous observations, and are biased (Greene, 1997). Tobit models (Tobin 1958, Amemiya 1984) have been widely used to model censored, correlated, bivariate data, and will be adopted in the analysis here.

2.1 The likelihood function

Let two latent continuous variables y_1^* and y_2^* represent the preference levels for holding cars and trucks, let latent variables y_3^* and y_4^* represent uncensored average annual miles driven by cars and trucks. Indexing household by i, $i = 1, ...N$, the system for discrete-continuous choice of the vehicles can be written as:

$$y_{1i}^* = \mathbf{w}_i'\beta_{11} + \ln(d_i)'\beta_{12} + \epsilon_{1i} \quad (1)$$

$$y_{2i}^* = \mathbf{w}_i'\beta_{21} + \ln(d_i)'\beta_{22} + \epsilon_{2i} \quad (2)$$

$$y_{3i}^* = \mathbf{w}_i'\beta_{31} + \ln(d_i)'\beta_{32} + \epsilon_{3i} \quad (3)$$

$$y_{4i}^* = \mathbf{w}_i'\beta_{41} + \ln(d_i)'\beta_{42} + \epsilon_{4i} \quad (4)$$

where $\mathbf{w}_i$ is a vector of characteristics for household i; d_i is an indicator of residential density; The observed ordinal variables y_1 and y_2, the number of cars and trucks held, take on values determined by the interval in which y_i^* lies. For $j = 1, 2$, $y_j = 0$, if $y_j^* \leq \alpha_1$, $y_j = 1$, if $\alpha_1 < y_j^* \leq \alpha_2$, $y_j = 2$ or more, if $y_i^* > \alpha_2$. Average annual miles driven by cars y_3 is observed only when a household holds at least one car; that is,

$$y_3 = y_3^*, \text{ if } y_1 = 1 \text{ or } 2 \quad (5)$$

$$= 0, \text{ if } y_1 = 0 \quad (6)$$

The same logic applies to miles driven by trucks y_4:

$$y_4 = y_4^*, \text{ if } y_2 = 1 \text{ or } 2 \quad (7)$$

$$= 0, \text{ if } y_2 = 0 \quad (8)$$

Here the lowest and highest cut points of the ordered probit equations, α_1 and α_2, are set to be $\alpha_1 = \Phi^{-1}(1/3)$ and $\alpha_2 = -\Phi^{-1}(1/3)$ (where Φ stands for normal cumulative density function); while the variances of the ordered equations are no longer restricted to 1's. This differs from the common practice of estimating ordered probit models with the variance constrained to be 1, and with only one of the cut-points constrained (usually at zero). As Nandrum and Chen (1996) has proved using a re-paramerization, constraining the lowest and highest thresholds is equivalent to constraining one cut point and the variance for identification purposes in estimating an ordered probit model. The advantage of the former is that the covariance matrix can be totally unrestricted in a multivariate case, making sampling much easier. Such approach has also been adopted in Webb and Forster (2006). Since there are only two cut points in my case, the only parameters to be estimated are the coefficients and the covariance matrix. I have experimented fixing the two cut-points to be other numbers. Since the covariance matrix changes accordingly, the inference remains the same after standardization.

The whole system can then be written into a SUR (seemingly unrelated regression) form:

$$\mathbf{y}_i^* = \mathbf{x}_i\beta + \epsilon_i \tag{9}$$

The error structure is a multivariate normal with zero means and unrestricted covariance matrix:

$$\epsilon_{\mathbf{i}} \sim^{i.i.d.} N(\mathbf{0}, \mathbf{\Sigma}) \tag{10}$$

The likelihood function is given as the following,

$$\begin{aligned}
& L(\beta, \Sigma; y_1, y_2, y_3, y_4) \\
\propto & \prod_{i \ni y_{1i}=0, y_{2i}=0} f(y_{1i}^* < \alpha_1, y_{2i}^* < \alpha_1) \\
\times & \prod_{i \ni y_{1i}=0, y_{2i}=1} f(y_{1i}^* < \alpha_1, \alpha_1 < y_{2i}^* < \alpha_2, y_{4i} = y_{4i}^*) \\
\times & \prod_{i \ni y_{1i}=0, y_{2i}=2} f(y_{1i}^* < \alpha_1, y_{2i}^* > \alpha_2, y_{4i} = y_{4i}^*) \\
\times & \prod_{i \ni y_{1i}=1, y_{2i}=0} f(\alpha_1 < y_{1i}^* < \alpha_2, y_{2i}^* < \alpha_1, y_{3i} = y_{3i}^*) \\
\times & \prod_{i \ni y_{1i}=1, y_{2i}=1} f(\alpha_1 < y_{1i}^* < \alpha_2, \alpha_1 < y_{2i}^* < \alpha_2, y_{3i} = y_{3i}^*, y_{4i} = y_{4i}^*) \\
\times & \prod_{i \ni y_{1i}=1, y_{2i}=2} f(\alpha_1 < y_{1i}^* < \alpha_2, y_{2i}^* > \alpha_2, y_{3i} = y_{3i}^*, y_{4i} = y_{4i}^*) \\
\times & \prod_{i \ni y_{1i}=2, y_{2i}=0} f(y_{1i}^* > \alpha_2, y_{2i}^* < \alpha_1, y_{3i} = y_{3i}^*) \\
\times & \prod_{i \ni y_{1i}=2, y_{2i}=1} f(y_{1i}^* > \alpha_2, \alpha_1 < y_{2i}^* < \alpha_2, y_{3i} = y_{3i}^*, y_{4i} = y_{4i}^*) \\
\times & \prod_{i \ni y_{1i}=2, y_{2i}=2} f(y_{1i}^* > \alpha_2, y_{2i}^* > \alpha_2, y_{3i} = y_{3i}^*, y_{4i} = y_{4i}^*)
\end{aligned}$$

Due to the discrete nature of the system, the likelihood function involves integrals of multivariate normal densities, which can be approximated by the GHK algorithm. The simulated likelihood function can then be maximized to obtain parameter estimates. This simulated maximum likelihood approach, however, incurs high computational cost and ignores the simulation error. The computational cost of direct evaluating the multiple integrals can be avoided in a Bayesian approach with data augmentation (Albert and Chib 1993, Chib and Greenberg 1998). By "augmentation", we mean the unobservable latent dependent variables y_j^* are added as additional parameters, which in turn aids estimation. As Rossi and Allenby (2003) point out, "To a Bayesian, all unobservable quantities can be considered the object of inference regardless of whether they are called parameters or latent variables"(PP.309). Additional benefit of using Bayesian method is that, unlike the classical method, it doesn't require a large sample to insure the adequacy of asymptotic approximations. Because Bayesian method uses the rules of probability and adheres to the likelihood principle, the estimators have finite sample properties and are consistent and asymptotically efficient under mild conditions.

2.2 Estimation method

I use Gibbs sampler algorithm to simulate draws from the conditional distributions for the unknown parameters and latent variables y_j^*. These draws from the Markov chain can later be used to run policy simulations, enabling finite sample inferences. Each iteration of the Gibbs sampler cycles through β, $\mathbf{\Sigma}$ and $\mathbf{y_i^*}$. At iteration t, each vector of parameters is sampled from the conditional distribution given all the other parameters:

$$\beta^{(t)} \quad \text{from} \quad \pi(\beta|\mathbf{\Sigma}^{(t-1)}, \mathbf{y_i^*}^{(t-1)},) \tag{11}$$

$$\mathbf{\Sigma}^{(t)} \quad \text{from} \quad \pi(\mathbf{\Sigma}|\beta^{(t)}, \mathbf{y_i^*}^{(t-1)}) \tag{12}$$

$$\mathbf{y_i^*}^{(t)} \quad \text{from} \quad \pi(\mathbf{y_i^*}|\beta^{(t)}, \mathbf{\Sigma}^{(t)}, \mathbf{y_i}) \tag{13}$$

It can be shown that the sequence of iterations $\beta^{(t)}, \mathbf{\Sigma}^{(t)}, \mathbf{y_i^*}^{(t)}$ converges to the joint posterior distribution of $(\beta, \mathbf{\Sigma}, \mathbf{y_i^*})$.

There are two advantages of the Bayesian approach. First, it provides exact finite sample inference and hence is free from the use of asymptotic approximations. Second, with augmented latent variables, it avoids evaluation of the multivariate normal distributions and reduces computational costs.

Assume a normal prior for $\beta \sim N(\beta_0, V_0)$, an Inverse-Wishart for $\mathbf{\Sigma} \sim IW(\nu, Q)$. To make the priors relatively noninformative, I set the variance of the normal prior to be large and prior degree of freedom of the Wishart to be small. Specifically, I set β_0 to be a vector of ones, and V_0 to be a diagonal matrix with 100 on the diagonal, ν to be 10, and Q an identity matrix. I check the effect of the prior by increasing the prior variance of β to reflect the noninformativeness of the prior. Since results obtained from the noninformative priors are virtually the same with the relatively noninformative prior mentioned above, I conclude data information is predominant. Figure 1 and Figure 2 show the prior and posterior density of $\beta_{density}$. Note that the prior distribution is so flat that almost all the information in the posterior is from the data.

Given a sample of N observations on the four dependent variables $y_{ij}, i = 1, ..., N, j = 1, ..., 4$ and a prior density $f(\beta, \Sigma)$, the full conditionals for β and Σ have familiar closed forms:

$$\beta|\mathbf{y_i^*}, \Sigma \sim \mathscr{N}(\bar{\beta}, \bar{V}) \tag{14}$$

$$\Sigma|\mathbf{y_i^*}, \beta \sim \mathscr{IW}(\nu + N, \sum_{i=1}^{N}(\mathbf{y_i^*} - \mathbf{x_i}\beta)'(\mathbf{y_i^*} - \mathbf{x_i}\beta) + Q) \tag{15}$$

where $\bar{V} = (V_0^{-1} + \sum_{i=1}^{N} \mathbf{x_i'}\Sigma^{-1}\mathbf{x_i})^{-1}$ and $\bar{\beta} = \bar{V}(V_0^{-1}\beta_0 + \sum_{i=1}^{N} \mathbf{x_i'}\Sigma^{-1}\mathbf{y_i^*})$.

Sampling from the full conditional of latent variables $\mathbf{y_i^*}$ requires a bit more computation, but is equally straightforward. The truncated multivariate normal distributed $f(\mathbf{y_i^*}|\beta, \Sigma)$ can be drawn from a series of full conditional distributions of each component of $\mathbf{y_i^*}$ given all the others (McCulloch and Rossi 1994): $f(y_{1i}^*|y_{2i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma)$, $f(y_{2i}^*|y_{1i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma)$, $f(y_{3i}^*|y_{1i}^*, y_{2i}^*, y_{3i}^*, \beta, \Sigma)$,

$f(y^*_{4i}|y^*_{1i}, y^*_{2i}, y^*_{3i}, \beta, \Sigma)$, where

$$\begin{aligned}
y^*_{1i}|y^*_{2i}, y^*_{3i}, y^*_{4i}, \beta, \Sigma &\sim N(\mu_{1|\neg 1}, \sigma_{1|\neg 1}) I(\alpha_{y_{1i}} < y^*_{1i} < \alpha_{y_{1i+1}}) \\
y^*_{2i}|y^*_{1i}, y^*_{3i}, y^*_{4i}, \beta, \Sigma &\sim N(\mu_{2|\neg 2}, \Sigma_{2|\neg 2}) I(\alpha_{y_{2i}} < y^*_{2i} < \alpha_{y_{2i+1}}) \\
y^*_{3i}|y_{3i} = 0, y^*_{1i}, y^*_{2i}, y^*_{4i}, \beta, \Sigma &\sim N(\mu_{3|\neg 3}, \Sigma_{3|\neg 3}) I(y^*_{3i} < 0) \\
y^*_{4i}|y_{4i} = 0, y^*_{1i}, y^*_{2i}, y^*_{3i}, \beta, \Sigma &\sim N(\mu_{4|\neg 4}, \Sigma_{4|\neg 4}) I(y^*_{4i} < 0)
\end{aligned}$$

y_{1i} and y_{2i} take on values of 0, 1, or 2, $\alpha_0 = -\infty$, $\alpha_1 = \Phi^{-1}(1/3)$, $\alpha_2 = -\Phi^{-1}(1/3)$, $\alpha_3 = \infty$, $\mu_{j|\neg j}$ stands for the mean of equation j conditional on the joint distribution of the equations other than j ($\neg j$). The conditional means ($\mu_{j|\neg j}$) and the covariance matrix of the distributions above are calculated according to Poirier (1995, P. 122) (Detailed derivation of the conditional posterior distributions is given in Appendix A).

Latent miles driven are used for households without cars or trucks to draw marginal inference about how much a household would have driven had it held a car or truck. Regard y^*_3 and y^*_4 as latent willingness to drive by cars and trucks, the two variables can be negative, which stands for how far away people are from taking up driving. Because their levels of dis-utility (or costs) for driving differs, some households may purchase new cars and have additional driving whilst others still remain the same vehicle holdings and the same annual miles driven, when density decreases or income increases to a certain level. I hence draw latent miles driven from a truncated normal distribution below zero to reflect the heterogeneity of those households who don't hold either one of the vehicles.

2.3 Data

The study uses data from 2001 National Household Travel Survey (NHTS), a cross-section survey of a total of 69,817 households nationwide. Importantly for the research purposes, it contains detailed information on households' demographics, various measures of land use density, and vehicle properties including year, make, model, and estimates of annual miles travelled. To be comparable to the results from Golob and Brownstone (2005), I focus on the California sub-sample. We can compare the results based on a regional data (California) to the national data to see if the consumer behavior changes across regions. The original California sample included 2,583 households. I eliminate observations missing important information such as income, highest education within the family, and vehicle characteristics etc. The sample retained and used in the analysis contains 2,299 households.

Explanatory variables include density, other neighborhood characteristics, and household demographic characteristics. Density is measured by housing units per square mile at the census block level and jobs per square mile at the tract level. To capture local transit networks and non-motorized facilities, indicator of whether or not the MSA has rail, dummies for selected MSAs, and the number of bicycles in the households are used. Demographic variables include total household annual income, the highest education level achieved within a household, number of adults, number of children, children's ages, home ownership, and zone type of the residence area. The definitions and sample statistics of the explanatory variables used in the analysis are presented in Table 1. The average density in California is 2,566 housing units per square mile at census block level. The minimum density value assigned is 25 and the maximum is 6,000 housing units per square mile. In the four largest MSAs of the California state, Los Angeles-Riverside-Orange County has the highest density with 3,016 housing units per square mile on average, immediately followed by San Francisco-Oakland-San Jose with 2,905 housing units. The density drops to 2,563 in San Diego and further down to 2,113 in Sacramento. Sample statistics of the dependent variables are presented in Table 2. The average number of car holdings for a California household is 1.1 and the average number of trucks is 0.72. The variation in vehicle holdings is high, with some households having a total of 6 cars and some none. The average annual miles driven by cars is 11,541, a little bit lower than the 13,198 average annual miles driven by trucks. The utilization is also marked with high variance.

2.4 Estimation results

In the Gibbs Sampler, I take 10 000 iterations and burn in the first 1000 to mitigate start up effects and use the remaining draws to get posterior inferences. MCMC convergence diagnoses, such as autocorrelation within the parameter chain, numerical standard errors (Raftery-Lewis diagnostic, Geweke diagnostic), all indicate a high degree of accuracy with this number of iterations.

The density coefficient for the car choice equation is positive but with a large standard deviation, indicating insignificance; while the density coefficient in the truck choice equation is significantly negative. Since the coefficients of the order probit equations do not have meanings in themselves, I calculated the changes in probabilities of truck holdings when residential density increases by 10, 25 and 50 percent for each household. The probabilities are calculated for each household for each draw in the MCMC chain excluding the first 1,000 draws. This way, the distribution of the probability changes can be obtained. Table 3 lists the mean and standard deviation of the probability changes in number of cars and trucks in response to density. When density increases by half, the probability of not holding trucks increases by 1.19 percent, and the probabilities of holding one truck and two trucks decrease by .74 percent and .45 percent respectively. Clearly, when density increases, only a limited portion of people opt not to choose trucks. The probability of holding more than one car increases, though in a less significant way. The positive sign can be explained as a substitution effect between cars and trucks when households move from low density areas to high density areas. When trucks are too costly, in terms of parking search and maneuvering, to hold in high density areas, households might substitute cars for trucks.

I plot the changes in probabilities of choosing of trucks against the residential density in Figure 3, holding the household characteristics (x) fixed at the mean. The choice of trucks responds sharply to an increasing in density in areas populated with less than 500 housing units per square mile, then the curve flattens out.

In terms of vehicle utilization, miles driven by cars are less responsive to density changes than miles driven by trucks. For example, the average utilization of trucks per household will decrease by 308.6 miles annually when density increases by 25 percent. Figure 5 shows how much vehicle utilization changes with respect to density for a representative household whose characteristics are fixed at the mean of the sample. As we can see, the truck utilization reduces to zero at around 3,200 housing units per square mile,

Table 5 presents the error correlation matrix of the four equations. These correlations allow me to gauge whether the association between the errors are important enough to be taken into consideration. The errors from number of cars held and number of trucks held exhibit a high negative correlation of -.44. The correlation between miles driven by cars and miles driven by trucks is also large at -.32. This indicates a substitution effect between cars and trucks, not only type-wise but also usage-wise. Across vehicle choice and vehicle usage, I find the error of choice of cars is positively associated with utilization of cars and negatively associated with utilization of trucks, and the inverse applies to choice of trucks as well. Hence I conclude a joint estimation of the whole system is expected to gain substantial efficiency.

2.5 Subclassification of vehicles

To demonstrate that finer vehicle type classifications can be accommodated by the proposed model, I subclassify cars and trucks into two types respectively according to their size: small-size cars, large-size cars, small-size trucks, and large-size trucks. The enhanced system consists of eight equations, four for the ordered choice of the four types of vehicles and four for the vehicle usages. The estimation procedure remains the same regardless. Table 6 displays marginal effects of increasing density by 25 percent on the probabilities of choosing different type of vehicles and their usage.

The results are consistent with what we have obtained previously. When density increases by 25 percent, people tend to switch from trucks to cars, and from large-size truck to small-size trucks within the truck category. More specifically, the probability of holding zero large-size trucks increases by .73 percentage point, in which .54 percentage point is due to the reduced choice of one large-size truck and .19 percentage point is due to the reduced choice of two or more large-size trucks. In the meanwhile, the annual usage of large-size cars and all trucks decrease, with the utilization of small-size cars increases. Like the car/truck classification, the marginal effects of density are more precisely estimated for trucks than cars.

Finer classifications can continue but only to a manageable number of classifications depending on the size of the data set. This leads to a limitation in this exercise: the model can not handle hundreds of vehicle make/model/body type/vintage combinations as estimated by models such as MDCEV devopled by Bhat (2006). For some research focuses where fine vehicle classification is essential, we have to use models such as MDCEV; for others, the model structure proposed is a simple alternative.

3 The MDCEV Model

In the MDCEV model as proposed by Bhat (2006), households' utility stems from choosing make/model l of class k, which contains a total of N_k number of make/model. There are altogether K classes of vehicles to choose from, and the actual number of classes of vehicles a household owns is denoted as Q. The utility function of a typical household is then formed as

$$U = \sum_{k=1}^{K} \exp(\max_{l \in N_k}\{W_k + Y_{kl} + \eta_{kl}\})(m_k + 1)^{s_k} \tag{16}$$

where W_k depends on household characteristics $\mathbf{x}$ that relates to the choice of class k and equals to $\mathbf{x}'\beta_k$, Y_{kl} depends on vehicle properties of a certain make/model l within class k, $\mathbf{z}_{kl}$, and equals to $\mathbf{z}'_{kl}\gamma$, and m_k denotes miles driven by a vehicle of class k. s_k is considered as a non-satiation factor, and is constrained between 0 and 1. For simplicity, household subscript i is omitted.

Households maximize their utility by choosing miles driven m_k for each class and one make/model l from class k for which $m_k > 0$, under the constraint that total miles driven is fixed at M ($\sum_{k=1}^{K} m_k = M$). The stochastic term η_{kl} is assumed to be generalized extreme value distributed.

Applying the Kuhn-Tucker conditions, we have,

$$H_k = H_1, \quad \text{if} \quad m_k^* > 0$$

$$H_k < H_1, \quad \text{if} \quad m_k^* = 0$$

where

$$H_k = \mathbf{x}'\beta_k + \theta_k \text{ln} \sum_{l \in N_k} \exp(\frac{\mathbf{z}'_{kl}\gamma}{\theta}) + lns_k + (s_k - 1)ln(m_k^* + 1) + \varepsilon_k \tag{17}$$

The probability that the first Q of the K vehicles being chosen, $P(m_1^*, m_2^*, ..., m_Q^*, 0, ..., 0)$, is then derived from the above Kuhn-Tucker conditions (c.f. Bhat 2005).

3.1 Likelihood function

The probability function for each household i can be written as

$$P_i(\mathbf{x}, \mathbf{z}; \beta, \tau, \gamma, \theta) \sim \underbrace{\prod_{k=1}^{Q} r_k \sum_{k=1}^{Q} \frac{1}{r_k} \frac{\prod_{k=1}^{Q} e^{V_k}}{(\sum_{h=1}^{K} e^{V_h})^Q} (Q-1)!}_{P(m_1^*, m_2^*, ..., m_Q^*, 0, ..., 0)} \quad \prod_{\substack{l \in N_k \\ (m_k^* > 0)}} \underbrace{\frac{\exp(\frac{\mathbf{z}'_{kl}\gamma}{\theta})}{\sum_{g \in N_k} \exp(\frac{\mathbf{z}'_{kg}\gamma}{\theta})}}_{P(l | m_k^* > 0, l \in N_k)} \tag{18, 19}$$

where

$$r_k = (\frac{1 - s_k}{m_k^* + 1}) \tag{20}$$

$$V_k = \mathbf{x}'\beta_k + \theta_k \text{ln} \sum_{l \in N_k} \exp(\frac{\mathbf{z}'_{kl}\gamma}{\theta}) + \text{ln}\alpha_k + (s_k - 1)\text{ln}(m_k^* + 1) \tag{21}$$

The log likelihood function is then $L = \sum_i logP_i$. For identification purpose, we need to pick a baseline class K_1 so that its coefficients β_{k1} are set to zeros. *Compact* cars are used here as the baseline choice. The log likelihood is maximized using quasi-Newton (BFGS) algorithm.

3.2 Additional data used

Besides the California sub-sample of the 2001 National Household Travel Survey (NHTS) for household characteristics, Wards Automobile Yearbook is also used get vehicle properties, such as price, length, weight, and mile per gallon (mpg), down to the make/model level. Vehicle are classified into ten types: compact, compact luxury, sedan midsize, sedan fullsize, sedan luxury, SUV small, SUV midsize, SUV large, mini-van, and pickup trucks. Table 8 presents the vehicle classifications in the sample used. The second column lists how many make/model there are within each class and the third column counts how many vehicles within the sample belong to that particular class.

3.3 Empirical results

The smallest vehicle type, *compact car*, is chosen as the baseline type. The negative signs of the density coefficient for each of the remaining classes represents that the attractiveness of that class diminishes against *compact car* when density increases. As the estimation results show, *compact cars* are gaining edge over all but *SUV midsize*, in dense areas.

To draw policy implications of an increase in density, I substitute the estimated parameters into the utility function (Equation 16), and maximize the utility function, subject to $\sum_{k=1}^{K} m_k = M$ and $m_k \geq 0$ for $k = 1, ..., K$, with respect to m_k for each household. The matrix of optimal m_k's for all the households are obtained through numerical optimization with constraints. The optimization is done before and after a policy change to calculate the the policy effects.

To compare the results to those from the BMOPT model of the car/truck classification, I group the vehicles into cars and trucks from the original ten classifications, and obtain the changes in vehicle type choice and utilization with density increases by 10 percent, 25 percent and 50 percent respectively. The changes are presented in Table 10. Two observations are in order. First, the changes in truck miles from the MDCEV model are consistent with those in BMOPT model. For all density changes, the changes in truck miles from MDCEV remain within one standard deviation from the changes in truck miles from BMOPT model. Therefore, the association between higher density and lower truck utilization is well established. Second, under the requirement of the MDCEV model, total miles driven has to remain fixed. Therefore, we would see the decrease in the truck utilization is equal to the increase in car utilization.

This estimation of the MDCEV model shows that the results from the utility derived MDCEV are comparable to those from the reduced-form BMOPT model proposed. The advantages of BMOPT model in solving this type of problem, in which only broader classification of vehicles are necessary, are that it is conceptually and computationally easy; no addition information is need for finer classification of vehicles; no constraint is imposed on total miles driven by vehicles; and policy simulations are less costly.

4 Endogeneity

The estimates from the model are useful for policy implications if, beyond correlation, they also indicate causality. I argue that since the decision process for most of the people is to first choose where to live and then choose what kind of vehicles to own, reverse causality is unlikely. The other potential problem that might bias my estimates is the existence of unobserved factors that affect both vehicle choice and density choice. In other words, a person drives a truck not because she lives in a suburb, but because she enjoys larger spaces, which in turn influences her decision to live in the suburb and drive a truck. I control for part of this by using disaggregate data and detailed household characteristics. With this approach I hope to capture some of the factors that affect both residential density choice and vehicle type and usage choice.

To test and control for endogeneity, there is no clear way out for the MDCEV model. In the BMOPT model, we can either use appropriate instrumental variables, or estimate a simultaneous residential location and vehicle ownership and usage mode system with choice of residential density itself as a dependent variable and an endogenous component. In the latter case, we need additional exogenous covariates other than the explanatory variables used in the vehicle ownership and usage equations to identify the system and these variables are valid instrumental variables. Therefore, finding appropriate exogenous variables to act as IVs is the key to the problem.

However, it is difficult to find instrumental variables that are correlated with density but not with vehicle choice. In the extreme case, such variables may not be readily available. A possible solution is using 'average density for a tract's MSA as an instrument variable for the tract population density. This IV was used by Brueckner and Largey (2006) in their study. However, the data set I use has only six MSAs, a number too small to provide enough variability in the density to capture its influence. School quality might be another feasible instrument, since schools with good quality are usually located in low density suburban areas, while those with lower quality are located in high density downtown areas. However, school quality itself is a variable difficult to measure and hence hard to obtain.

More importantly, Golob and Brownstone (2006) dealt with the sample selection problem with a simultaneous equation system and did not find any evidence for endogeneity of density choice. This does not, of course, rule out the endogeneity issue in this paper. If the estimation results can be driven either by a casual relation between density and fuel efficiency or unobserved factors that determine both density and fuel efficiency choice, the results from this analysis provide an upper bound on the possible reductions in choice and usage of fuel inefficient vehicles. Since the reduction is negligibly small even if causality is assumed, we can conclude that changing density hardly effects vehicle choice and usage.

5 Conclusion

Two models, a reduced-form Bayesian Multivariate Probit and Tobit (BMOPT) model and the Multiple Discrete Continuous Extreme Value (MDCEV) model derived from utility maximization, are applied to model households' vehicle holdings and usage decisions in California.

The system of BMOPT is composed of a bivariate ordered probit model and a bivariate tobit model. The ordered probit is used to capture household decisions on number of vehicles in each category. Within this framework, vehicles are categorized into fuel efficient (cars) and fuel inefficient vehicles (trucks), which permits me to capture possible environmental and energy saving policy implications. Note that this model can be extended to incorporate a finer classification of vehicles, thereby suiting the needs of particular studies. By using 'number of vehicles' in each category instead of 'total number of vehicles', the analysis circumvents a usual difficulty faced by traditional modelling of vehicle holdings. In traditional modelling, with an increase in total number of vehicles, possible combinations of vehicle holdings proliferate. Hence the estimation becomes cumbersome when there are households with more than two vehicles. With the method employed in this paper, however, handling multiple-vehicle households becomes simple and flexible.

The multivariate tobit captures household decisions on miles driven, conditional on each category. Traditional discrete-continuous models were built upon utility maximization theory, but approximations (in estimation) dampen the elegance of the theoretical derivation. By combining the multivariate ordered probit and tobit model and assuming an unrestricted covariance matrix, I can more 'cleanly' estimate a reduced-form discrete/continuous system. Using data augmentation and Bayesian Markov Chain Monte Carlo methods, the estimation is straightforward.

The BMOPT model and the MDCEV model both have their pros and cons. The BMOPT model is easy to implement, convenient to get inferences and hence draw policy implications, able to handle a large total number of vehicles, but it will become computation intensive with increasing vehicle categories because the number of equations to be estimated increases proportionally with number of categories. The MDCEV is consistent with random utility maximization, and able to accommodate hundreds of vehicle classifications, but one big restriction is that the total utilization of vehicles are assumed to be fixed no matter how the policy changes. This assumption is questionable and rules out the potential vehicle utilization reduction which we would expect to occur, or at least test, in response to particular policies. In addition, finer classification of vehicles to a degree that no one type of vehicle can be chosen twice for a household is a must for the model implementation.

In sum, an efficient estimation technique along with the recent and detailed 2001 NHTS data enables me to obtain a small but statistically significant effect of density on households' vehicle choice. I conclude that increasing residential density within feasible ranges will have a very small impact on household vehicle holdings and vehicle fuel usage.

Appendix A. Gibbs sampler

Given the priors:

$$\beta \sim \mathscr{N}(\beta_0, V_0) \text{ and } \Sigma \sim \mathscr{IW}(\nu, Q)$$

The posterior distribution of the unknown parameters are:

$$\begin{aligned}
f(\beta, \Sigma, \mathbf{y}^*|\mathbf{y}) &\propto f(\mathbf{y}, \mathbf{y}^*|\beta, \Sigma) f(\beta, \Sigma) = \prod_{i=1}^{T} f(y_i|y_i^*, \beta, \Sigma) f(y_i^*|\beta, \Sigma) f(\beta, \Sigma) \\
&\propto \prod_{i=1}^{T} |\Sigma^{-1}|^{1/2} \exp(-\frac{1}{2}(y_i^* - x_i\beta)'\Sigma^{-1}(y_i^* - x_i\beta)) I_{j=1,2}(\alpha_{y_{ij}} < y_{ij}^* \leq \alpha_{y_{ij}+1}) \\
&\times \exp(-\frac{1}{2}(\beta - \beta_0)' V_0^{-1}(\beta - \beta_0) \times |\Sigma^{-1}|^{(\nu+k+1)/2} \exp(-\frac{1}{2} tr \Sigma^{-1} Q)
\end{aligned}$$

Given the joint posterior distribution, the conditional posterior distributions are:

$$\begin{aligned}
f(\beta|y_i, y_i^*, \Sigma) &\propto \exp(-\frac{1}{2}[\sum_{i=1}^{T}(y_i^* - x_i\beta)'\Sigma^{-1}(y_i^* - x_i\beta) + (\beta - \beta_0)' V_0^{-1}(\beta - \beta_0)]) \\
&\propto \exp(-\frac{1}{2}(\beta - \bar{\beta})' \bar{V}^{-1}(\beta - \bar{\beta}))
\end{aligned}$$

where

$$\begin{aligned}
\bar{V} &= (V_0^{-1} + \sum_{i=1}^{T} x_i' \Sigma^{-1} x_i)^{-1} \\
\bar{\beta} &= \bar{V}(V_0^{-1}\beta_0 + \sum_{i=1}^{T} x_i' \Sigma^{-1} y_i^*)
\end{aligned}$$

Hence,

$$\beta|y_i, y_i^*, \Sigma \sim \mathscr{N}(\bar{\beta}, \bar{V})$$

$$
\begin{aligned}
f(\Sigma|y_i, y_i^*, \beta) &\propto |\Sigma^{-1}|^{T/2} \exp(-\frac{1}{2} tr(\Sigma^{-1} \sum_{-1}^{T} (y_i^* - x_i\beta)'(y_i^* - x_i\beta))) \\
&\times |\Sigma^{-1}|^{(\nu+k+1)/2} \exp(-\frac{1}{2} tr\Sigma^{-1} Q) \\
&\propto |\Sigma^{-1}|^{(\nu+T+k+1)/2} \exp(-\frac{1}{2} tr\Sigma^{-1} (\sum_{i=1}^{T} (y_i^* - x_i\beta)'(y_i^* - x_i\beta) + Q))
\end{aligned}
$$

Therefore,

$$
\Sigma|y_i, y_i^*, \beta \sim \mathscr{IW}(\nu + T, \sum_{i=1}^{T} (y_i^* - x_i\beta)'(y_i^* - x_i\beta) + Q)
$$

$$
\begin{aligned}
f(\mathbf{y_i^*}|y_i, \beta, \Sigma) \sim\ & f(y_{1i}^*|y_{2i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma) \cdot f(y_{2i}^*|y_{1i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma) \cdot \\
& f(y_{3i}^*|y_{1i}^*, y_{2i}^*, y_{3i}^*, \beta, \Sigma) \cdot f(y_{4i}^*|y_{1i}^*, y_{2i}^*, y_{3i}^*, \beta, \Sigma)
\end{aligned}
$$

where

$$
\begin{aligned}
y_{1i}^*|y_{2i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma &\sim N(\mu_{1|\neg 1}, \sigma_{1|\neg 1}) I(\alpha_{y_{1i}} < y_{1i}^* < \alpha_{y_{1i+1}}) \\
y_{2i}^*|y_{1i}^*, y_{3i}^*, y_{4i}^*, \beta, \Sigma &\sim N(\mu_{2|\neg 2}, \Sigma_{2|\neg 2}) I(\alpha_{y_{2i}} < y_{2i}^* < \alpha_{y_{2i+1}}) \\
y_{3i}^*|y_{3i} = 0, y_{1i}^*, y_{2i}^*, y_{4i}^*, \beta, \Sigma &\sim N(\mu_{3|\neg 3}, \Sigma_{3|\neg 3}) I(y_{3i}^* < 0) \\
y_{4i}^*|y_{4i} = 0, y_{1i}^*, y_{2i}^*, y_{3i}^*, \beta, \Sigma &\sim N(\mu_{4|\neg 4}, \Sigma_{4|\neg 4}) I(y_{4i}^* < 0)
\end{aligned}
$$

I follow Poirier (1995) to obtain the conditional mean and variance for partitioned matrix. Generally, for $Z = [Z_1' \ Z_2']' \sim N(\mu, \Sigma)$ where Z is a $N \times 1$ random vector, Z_1 is a $m \times 1$ vector, and Z_2 is $(N - m) \times 1$ with

$$
\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}' & \Sigma_{22} \end{bmatrix}
$$

The conditional distribution of Z_1 given Z_2 is $Z_1|Z_2 \sim N(\mu_{1|2}, \Sigma_{1|2})$, where

$$
\begin{aligned}
\mu_{1|2} &= \mu_1 + \Sigma_{11}\Sigma_{12}^{-1}(Z_2 - \mu_2) \\
\Sigma_{1|2} &= \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}'
\end{aligned}
$$

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Tables

Table 1: Descriptive Statistics

Variable (observation: 2,299)	Mean	(Std.)
Residential density	2566	(1886)
Number of bikes	.96	(1.26)
Total number of people	2.69	(1.45)
Number of adults	1.99	(0.80)
If the highest education achieved is high school	31%	
If the highest education achieved is bachelor's degree or higher	46.2 %	
If the youngest child is under 6	16.9%	
If the youngest child is between 6 and 15	18.1%	
If the youngest child is between 15 and 21	5.8%	
If no children or youngest child more than 21 years old	59.2%	
If MSA has rail	65.1 %	
If household resides in urban area at census tract level	93%	
If household resided in rural area at census tract level	7%	
If household resides in Los Angeles MSA	42%	
If household resides in San Francisco MSA	23.1%	
If household resides in San Diego MSA	8.7%	
If household resides in Sacramento MSA	7.9%	
If household resides in other MSAs	18.3 %	
If annual household income is less than 20k	15%	
If annual household income is between 20k and 30k	10.7%	
If annual household income is between 30k and 50k	21%	
If annual household income is between 50k and 75k	18.8%	
If annual household income is between 75k and 100k	12.8%	
If annual household income is greater than 100k	21.7%	
If the household owns home	69.1%	

Note: Residential density is measured in housing units per square mile, coded into six ranges using midpoints.

Table 2: Dependent Variables

Variable	Mean	(std.)	Min	Max
number of cars held	1.1	(0.82)	0	6
number of trucks held	0.72	(0.79)	0	4
			25 quantile	75 quantile
average miles driven by cars	11541	(9949)	5927	14609
average miles driven by trucks	13198	(11945)	6803	16395

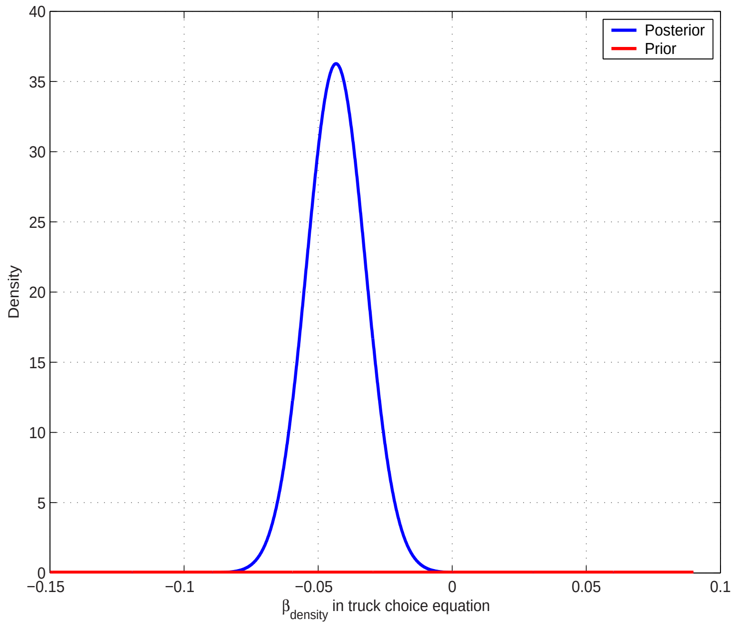

Figure 1: Prior and posterior density of $\beta_{density}$ in the truck choice equation

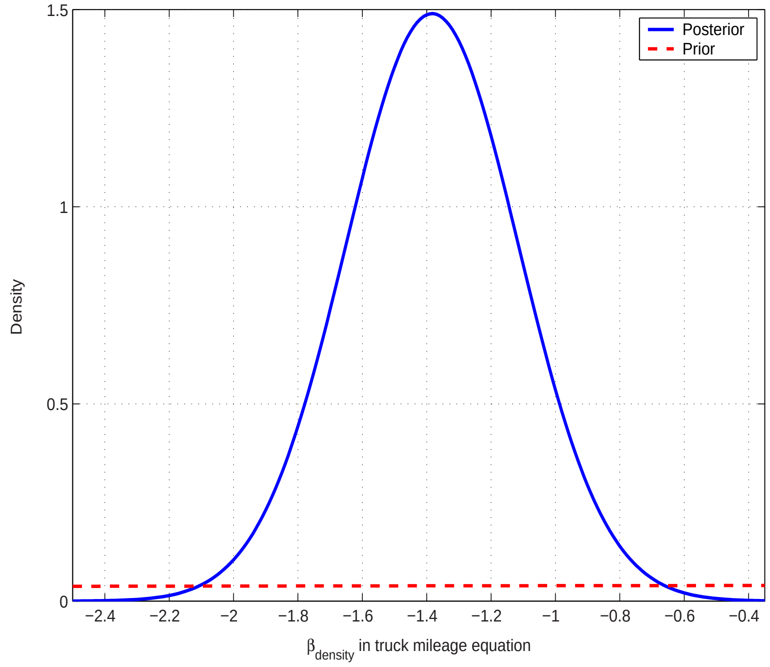

Figure 2: Prior and posterior density of $\beta_{density}$ in the truck mileage equation

The miles driven by trucks are in the unit of 1,000 miles.

Table 3: Changes in vehicle choice when density increases (BMOPT)

% changes in density	Probability changes for truck choice		
	ΔP(tnum=0)	ΔP(tnum=1)	ΔP(tnum≥2)
10 %	.0028	-.0017	-.0011
	(.0007)	(.0004)	(.0003)
25 %	.0066	-.004	-.0025
	(.0017)	(.001)	(.0006)
50 %	.0119	-.0074	-.0045
	(.0031)	(.0019)	(.0012)
% changes in density	Probability changes for car choice (in 10^{-3} unit)		
	ΔP(cnum=0)	ΔP(cnum=1)	ΔP(cnum≥2)
10 %	-.84	-.02	.86
	(.78)	(.04)	(.81)
25 %	-2	-.1	2
	(1.8)	(.1)	(1.9)
50 %	-3.6	-.1	3.7
	(3.3)	(.2)	(3.4)

Notes: posterior standard deviations are reported in parentheses

This table documents the changes in the probabilities of holding zero (P(tnum=0)), one (P(tnum=1)), and two or more (P(tnum≥2)) trucks, and zero (P(cnum=0)), one (P(cnum=1)), and two or more (P(cnum≥2)) cars, averaging across each household in the sample, when density increases by 10, 25, and 50 percent respectively.

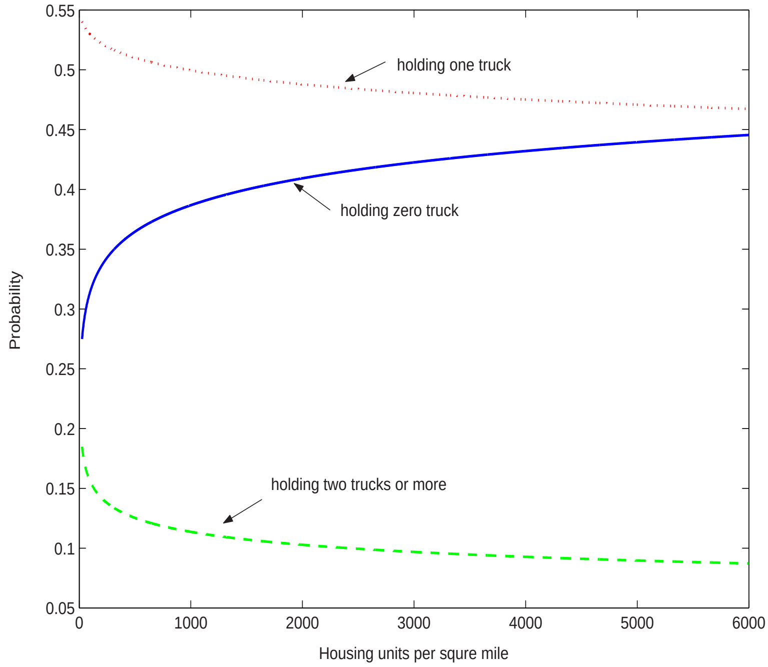

Figure 3: Changes in probabilistic choice of trucks in response to increasing density

This figure shows how the probabilities of trucks choice change when density increases, for a representative household with mean characteristics of the households in the sample. The probability of holding zero trucks decreases, and those of holding one or more trucks increase, with increasing residential density.

Table 4: Changes in vehicle miles when density increases (BMOPT)

	Δ car miles	Δtruck miles
10 %	18.7	-131.8
	(34.9)	(37)
25 %	43.9	-308.6
	(81.7)	(86.5)
50 %	79.7	-560.7
	(148.5)	(157.2)

Notes: posterior standard deviations are reported in parentheses

From this table, we find strong evidence that an increase in density has a consistently negative impact on average truck miles. However, the impact on average car miles is not as evident, as the probabilistic intervals for the changes in car miles are large.

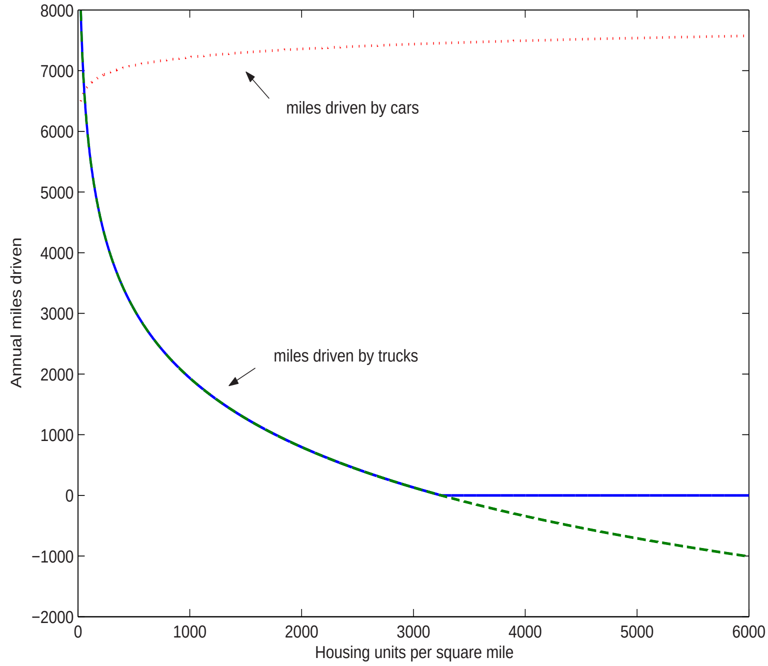

Figure 4: Changes in annual miles in response to density

Like Figure 3, this figure is plotted for a representative household with mean characteristics of the households in the sample. As we can see, the miles driven by cars remain relatively flat with increasing density, while the miles driven by trucks drops, and to a certain point (around 32000 housing units per square mile), to zero.

Table 5: Error Correlation Matrix (BMOPT)

	number of cars	number of trucks	average car mile	average truck mile
number of cars	1.00	-	-	-
number of trucks	-0.44	1.00	-	-
average car mile	0.48	-0.32	1.00	-
average truck mile	-0.32	0.59	-0.19	1.00

There is a negative error correlation between choice of cars and trucks, and between usage of cars and trucks, showing that the substitutive effect dominates the complementary effect of the two types. There is also a positive error correlation between car numbers and average car usage, same applies to truck as well.

Table 6: Changes in vehicle choice and usage when density is increased by 25 percent (subclassification, BMOPT)

equations		probability changes		
		Δ Pr(n = 0)	Δ Pr(n = 1)	Δ Pr(n ≥ 2)
Car	small-size	-.0024	.0016	.0008
		(.0026)	(.0017)	(.0009)
	large-size	-.0005	.0003	.0002
		(.0024)	(.0015)	(.0009)
truck	small-size	.0016	-.0012	-.0004
		(.0024)	(.0018)	(.0006)
	large-size	.0073	-.0054	-.0019
		(.0022)	(.0017)	(.0006)

		usage changes
Car	small miles	24.4
		(129.5)
	large miles	-88.9
		(120.4)
Truck	small miles	-201.2
		(145.6)
	large miles	-646.9
		(179.9)

Notes: posterior standard deviations are reported in parentheses

Table 7: Error Correlation Matrix (subclassification, BMOPT)

number of small cars	1.00	-	-	-	-	-	-	-
number of large cars	-0.35	1.00	-	-	-	-	-	-
number of small truck	-0.16	-0.20	1.00	-	-	-	-	-
number of large trucks	-0.21	-0.14	-0.18	1.00	-	-	-	-
miles driven by small cars	0.74	-0.33	-0.12	-0.17	1.00	-	-	-
miles driven by large cars	-0.26	0.75	-0.18	-0.15	-0.25	1.00	-	-
miles driven by small trucks	-0.15	-0.16	0.82	-0.22	-0.11	-0.13	1.00	-
miles driven by large trucks	-0.17	-0.12	-0.14	0.78	-0.15	-0.14	-0.19	1.00

Table 8: Classification of Vehicles

types	number of make/model	observations
compact	39	461
compact: luxury	46	275
sedan: midsize	28	532
sedan: fullsize	9	84
sedan: luxury	34	195
SUV: small	7	52
SUV: midsize	13	247
SUV: large	10	131
minivan	18	266
pickup trucks	23	429
Total	*227*	*2672*

Table 9: Coefficient estimates for vehicle properties

variables	Coefficient	Standard Error
M.P.G.	0.039***	(0.011)
Price	-0.020***	(0.005)
Chevrolet	0.071	(0.067)
Ford	1.406***	(0.223)
Honda	1.938***	(0.321)
Toyota	1.175***	(0.195)
Dodge	0.856***	(0.157)
Nissan	0.254***	(0.072)

In Table 8, vehicle types are derived according to the classifications in Consumer Report. In Table 9, purchase price of the vehicle (Price) is in the unit of $1,000. Six major makes of the vehicles are included as the explanatory variables to examine the brand effect. There are altogether 39 makes. The left out makes are Acura, Audi, BMW, Buick, Cadillac, Chrysler, GMC, Hyundai, Infiniti, Isuzu, Jaguar, Jeep, Kia, Land Rover, Lexus, Lincoln, Lotus, Mazda, Mercedes Benz, Mercury, Mini cooper, Mitsubish, Oldsmobile, Plymouth, Pontiac, Porsche, SAAB, Saturn, Scion, Subaru, Suzuki, Volkswagen, and Volvo.

Table 10: Changes in vehicle choice and usage when density increases (MDCEV)

when density	change in		% change in		% change in	
increases by	car miles	truck mile	car miles	truck mile	car holdings	truck holdings
10 %	136.7	-136.7	1.47	-2.01	-0.17	-1.81
25 %	343.7	-343.7	3.52	-4.81	-0.56	-3.72
50 %	603.1	-603.1	6.52	-8.91	-1.47	-8.2

Table 11: Comparison of truck usage changes between the MDCEV and BMOPT model

when density	MDCEV	BMOPT
increases by	Δtruck miles	Δtruck miles
10 %	-136.7	-131.8
	(70.1)	(37)
25 %	-343.7	-308.6
	(156.6)	(86.5)
50 %	-603.1	-560.7
	(366.0)	(157.2)

Due to the imposed restriction in the MDCEV model that the total usage of the vehicles is fixed for each household, the aggregate changes in car miles and truck miles add up to zero in Table 10. Table 11 presents the changes in truck miles under the MDCEV mode and the BMOPT model respectively. The results are broadly consistent. Note that the changes in miles are more accurately estimated in the BMOPT and in the MDCEV model.