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Incorporating pro-environmental preferences toward green automobile technologies through a Bayesian Hybrid Choice Model

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Abstract

In this paper we develop, implement and apply an MCMC Gibbs sampler for Bayesian estimation of a Hybrid Choice Model (HCM), using stated data on both vehicle purchase decisions and environmental concerns. Our study has two main contributions. The first is the feasibility of the Bayesian estimator we derive. Whereas classical estimation of HCMs is fairly complex, we show that the Bayesian approach for HCMs is methodologically easier to implement than simulated maximum likelihood because the inclusion of latent variables translates into adding independent ordinary regressions; we also find that, using the Bayesian estimates, forecasting and deriving confidence intervals for willingness to pay measures is straightforward. The second is the capacity of HCMs to adapt to practical situations. Our empirical results coincide with a priori expectations, namely that environmentally-conscious consumers are willing to pay more for low-emission vehicles. The model outperforms standard discrete choice models because it not only incorporates pro-environmental preferences but also provides tools to build a profile of environmentally-conscious consumers.

Keywords: hybrid choice model; latent variables; pro-environmental preferences; discrete choice; Gibbs sampling

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1 Introduction

Hybrid choice models (HCMs) incorporate latent explanatory variables into the utility function of a discrete choice model. In the present paper we study a Bayesian approach to simultaneous estimation of an HCM; our novel estimation procedure is tested empirically to explain environmental preferences in a private vehicle choice context. In this section we motivate our study through literature review on vehicle purchase decisions and environmental preferences.

1.1 Car purchase decisions and environmental preferences

New car purchasing is an example of discrete choice. Effectively, economic-preference models of discrete choice aim to explain the process of individual choice among a mutually exclusive, exhaustive and finite group of alternatives (Ben-Akiva and Lerman, 1985). According to consumer theory the decision process reflects rational preferences set by a utility-maximization behavior. In the case of standard consumption theory, the utility function representing the preference relation depends on the continuous quantities composing the consumption set. However, when the nature of a specific good is discrete, the preference relation is assumed to depend on a group of attributes (Lancaster, 1966) combined according to individual tastes. In the context of private vehicle purchase decisions, each vehicle is described by a group of attributes, such as make and model, purchase price, performance, reliability, durability, comfort, style, and safety. According to individual preferences, each consumer selects the alternative that has the highest level of satisfaction. Then, the market demand for private vehicles is determined by the market share of each alternative, which is constructed as the proportion of consumers choosing each particular alternative. In discrete choice modeling, the most common approach is based on random utility theory (McFadden, 1974), which introduces the concept of individual choice behavior being intrinsically probabilistic. Whereas the Random Utility Maximization (RUM) framework recognizes the existence of a systematic component of individual behavior, RUM also takes into account the incapacity of the analyst to observe all the variables that have an influence on the decision (incomplete information that implies the presence of uncertainty; Manski, 1977). Different RUM discrete choice models can be derived based on various assumptions on the distribution of the random term. The probabilistic nature of the choice behavior implied by the RUM framework leads to individual probabilities of each consumer selecting each available alternative.

Modeling the private vehicle purchase decision using RUM discrete choice models has a long tradition (for example Lave and Train, 1979; Beggs and Cardell, 1980; Manski and Sherman, 1980; Train et al., 1986; McCarthy, 1996). In these applications, the alternatives are different types of private vehicles, such as choice between car and SUV. Each alternative is described using attributes such as purchase cost, fuel economies, vehicle size and age of the vehicle. More recently – owing to the interest in studying sustainable solutions to the environmental problems created by personal transportation – this kind of model has been used to analyze choice among different automobile technologies, namely the use of alternative fuels (Bunch et al., 1993; Brownstone and Train, 1999; Brownstone et al., 2000; Ewing and Sarigöllü, 2000; Horne et al., 2005). In this context, the baseline is the use of standard attributes such as purchase price, operating costs (including both maintenance and fuel costs), and power (comprising motor power, performance, top speed, and acceleration). However, to characterize vehicles with alternative technologies or fuel types we must introduce new sets of attributes that take into account special features or requirements for the new alternatives (Bunch et al., 1993; Brownstone et al., 2000; Dagsvik et al., 2002; Horne et al., 2005; Achtnicht et al., 2008; Dagsvik and Liu, 2009). These attributes include variables such as *service station availability* (stations selling the proper fuel – relevant in the case of new fuels), *driving range* (some new technologies such as electric cars suffer from a limited driving range between refueling), whether or not the vehicle would be granted certain priorities (such as *express lane access*), and *greenhouse gas emissions* GHG (CO_2 concentrations play a key role in global warming; and hence a reduction on this variable – which is in fact the leading objective of climate policies – determines how 'green' the new technology is). However, it is hard to maintain that these characteristics alone permit a full representation of consumer behavior allowing us to understand demand for 'green' (low-emission) personal vehicles. For instance using *greenhouse gas emissions*, environmental concerns are represented only by emission reductions without any consideration to other dimensions such as eco-friendly habits (cf. Johansson et al., 2006).

Consumers' preferences for green vehicles must be understood first in a context where the new technologies often have a low market share (or even a zero market penetration in the case of the introduction of a new alternative) and hence the role of knowledge, experience and information is critical. Second, demand for low-emission vehicles is a decision-making process guided by *environmental preferences*, among other dimensions, such as desires for energy independence and for advanced technologies. Flamm (2009) finds that households with environmental knowledge and attitudes own fewer and more fuel-efficient vehicles; these households actually show an eco-friendly travel behavior because they drive their vehicles less. Environmentally-conscious consumers are aware of the dangers of climate change and oil dependency; their concerns about the role of transportation in global warming lead to a consequent change in their purchasing and travel behavior, and they are willing to pay more for sustainable solutions (low-emission vehicles) despite potential drawbacks (such as a reduced refueling availability). Although environmentally-conscious consumers should be more likely to choose vehicles that are good for the environment, current demand models have a hard time representing this likelihood. The key is then how to incorporate the consumers' environmental concerns into an economic model for private vehicle purchase decisions.

According to cognitive psychology, preferences and behavior (toward green technologies in the case of environmental psychology) are affected by perceptions and attitudes. On the one hand, *perception variables* measure the individual cognitive capacity to represent the attributes of different alternatives. Perceptions are relevant because the choice process depends on how attribute levels are perceived according to the individual beliefs of a specific consumer. On the other hand, *attitude variables* measure the evaluation of favor or disfavor assigned by the individual to the features of different alternatives. Attitudes influence behavioral intentions (e.g. to adopt a new technology), are related to individual heterogeneity (*taste variations*), reflect individual tastes, needs, values, goals, and capabilities that develop over time, and are affected by knowledge, experience and external factors, such as the socioeconomic characteristics of the decision-maker (Ajzen, 2001); for a discussion related to transportation see Walker (2001).

Attitudinal research (i.e. psychometric studies, mostly focused on factor analysis) for green vehicles has mainly been centered on public acceptance of hydrogen and fuel cell technologies using attitudinal/perceptual surveys (Dinse, 2000; Lossen et al., 2003; O'Garra et al., 2007). Consumers reveal highly positive attitudes toward green vehicles, although knowledge of the new technologies is low (for a more comprehensive review of the attitudinal approach see Roche et al., 2009). Roche et al. also review the economic preference approach as well as the semiotic approach applied by Heffner et al. (2007). An important problem with the attitudinal approach (if used independently from economic models of choice) is that it does not necessarily explain economic choice behavior, and in some cases the attitudes being measured are not even directly related to actual purchase intentions (for instance, Dinse, 2000; Lossen et al., 2003, measured general attitudes and knowledge toward hydrogen vehicles, as a concept for technological development not as a choice). In fact as noted by Gould and Golob (1998), economic preference surveys usually provide lower acceptance levels for new technologies than those predicted by attitudes alone.

In sum, there are two important modeling tools to analyze the low-emission vehicle market, namely economic-preference models (discrete choice models) and attitudinal models (structural equation models, mainly factor analysis). The problem is that even though both econometricians and psychometricians have the same fundamental interests in modeling behavior, there is a significant gap between practical models of economic decision-making and cognitive models with an in-depth understanding of agent behavior (Kahneman, 2003). From the perspective of behavioral theory, standard RUM discrete choice models represent the decision process as an obscure black box, where attitudes, perceptions and knowledge are neglected. In addition, attitudinal models alone tell us little about how perceptions affect economic choice behavior. As McFadden (2000) points out, the key to understanding choice together with the cognitive decision process itself comes through incorporating attitudinal and perceptual data into conventional economic models of decision making, i.e. integrating both approaches into one. Some effort to achieve this goal has been made in the literature, such as the work of Choo and Mokhtarian (2004) where the authors incorporate attitudes, personality and lifestyle in a discrete choice model of vehicle types. In previous studies, however, attitudes are incorporated as factor scores in a two-step procedure that produces both inconsistent and inefficient estimators. Hybrid Choice Models (HCMs) appear as a solution to this problem.

1.2 Hybrid Choice Modeling

Hybrid Choice Models are discrete choice models with improved explanatory power that integrate standard discrete choice and latent variable models, taking into account the impact of attitudes and perceptions on the decision process (McFadden, 1986; Ben-Akiva et al., 2002a). Specifically, HCMs expand on discrete choice models by considering the following important extensions (Walker and Ben-Akiva, 2002, see Figure 1): heterogeneity through flexible error structures (such as the use of mixed logit), the combination of revealed (RP) and stated preference (SP) data, the presence of latent market segments (variation in tastes) through a latent class model, and the integration of explanatory latent (unobserved) constructs according to an *Integrated Choice and Latent Variable* (ICLV) model (Bolduc et al., 2005). It is the ICLV model inside the HCM conceptual framework which permits the inclusion of attitudes, opinions and perceptions as psychometric latent variables in such a way that consumer behavior is better understood while the model gains in predictive power (Ashok et al., 2002; Ben-Akiva et al., 2002b). Although research on the inclusion of attitudes into discrete choice models started in the late 1970s (Koppelman and Hauser, 1978; Prashker, 1979), we recognize a reemergence of the model after the seminal work of Ben-Akiva et al. (2002a) with a new trend focused on simultaneous estimation. Methodologically, the modeling challenge arises in the ICLV model and the consideration of flexible disturbances.

Figure 1: Hybrid Choice Model

In this paper we analyze stated choices made by Canadian consumers when faced with green personal vehicle alternatives (Horne et al., 2005). We seek to implement both theoretically and empirically a Bayesian approach to an HCM of personal vehicle choice (cf. Bolduc et al., 2008, where using the same data we analyzed classical estimation of HCMs). Specifically, we construct an HCM setting where we take perceptual indicator variables about transport policies and problems, and then define an environment-related latent variable which enters directly into the choice process. This paper expands on our previous research (Bolduc et al., 2008; Bolduc and Alvarez-Daziano, 2010) by introducing Bayesian methods to analyze the data, not only for estimation of parameters and willingness to pay measures but also for forecasting policy scenarios.

The rest of the paper is organized as follows. In section 2, we present the empirical data on private vehicle choice and we define an environmental concern latent variable related to transportation. Section 3 describes both the hybrid personal vehicle setting and the technical details of Bayesian estimation of this model. In section 4, we present the results of each partial model that configures the HCM setting. Then the estimated HCM is applied to forecast the impact of different policies. In section 5, we present the main conclusions of our work, identifying guidelines for future research.

2 Personal vehicle choice data

We use data from a survey conducted in 2002 by the EMRG (Energy and Materials Research Group, Simon Fraser University) of stated personal vehicle choices made by Canadian consumers when faced with technological innovations. Full details regarding the survey, including the design of the questionnaire, the process of conducting the survey, and analysis of the collected data can be found in Horne (2003).

Survey participants were first contacted in a telephone interview used to personalize a detailed questionnaire that was then mailed to them. The mailed questionnaire had 5 different parts:

- *Part 1:* Transportation options, requirements and habits;
- *Part 2:* Personal vehicle choice (stated preference experiment);
- *Part 3:* Transportation mode preferences;
- *Part 4:* Views on transportation issues; and
- *Part 5:* Additional information (gender, education, income).

SP questions in Part 2 considered four vehicle types:

1. *Standard gasoline vehicle* (SGV): operating on gasoline or diesel,
2. *Alternative fuel vehicle* (AFV): natural-gas vehicle,
3. *Hybrid vehicle* (HEV): gasoline-electric, and
4. *Hydrogen fuel cell vehicle* (HFC).

For each of these alternative vehicle types, the attributes were defined as:

- *Purchase price*: capital cost associated with the purchase of a new car [CAD2002/10000],
- *Fuel cost*: monthly operating costs [CAD2002/100-month],
- *Fuel availability*: proportion of stations selling the proper fuel [ratio],
- *Express lane access*: whether or not the vehicle would be granted express lane access,
- *Emissions data*: emissions compared to a standard gasoline vehicle [ratio], and
- *Power*: horsepower of engine compared to current vehicle [ratio].

The sampled individuals were randomly drawn from households living in Canadian urban centers with populations of more than 250,000 people. Respondents have an average household income approximately equal to $62,000 CAD, and a high level of education (75% of the sample attained undergraduate degrees or completed graduate school). The sample has a 59% proportion of females, and 59% of the sampled individuals are 41 years or older. Each participant needed to either have access to a vehicle, or commute to work. The respondents who met these criteria were asked to make up to four consecutive virtual choices while the vehicle attribute values were modified after each round according to randomized blocks of an individual-customized labeled SP experimental design (Horne et al., 2005, see Table 1). The sample has 866 completed surveys (of the total of 1150 individuals, 75% response rate). After a clean up where we retain only the individuals who answered the whole perceptual-attitudinal rating exercise, there remain 1877 usable observations (pseudo-individuals) for HCM estimation. This analytic sample consists mainly of workers (80%) who commute, mostly driving alone (68%).

	SGV	AFV	HEV	HFC
Purchase Price (PP)	100% PP 105% PP 110% PP 115% PP	105% PP 110% PP	105% PP 120% PP	110% PP 120% PP
Fuel Cost (FC)	100% FC 110% FC 120% FC 130% FC	110% FC 120% FC	75% SGV	110% FC 120% FC
Fuel Availability	100%	25% 75%	100%	25% 75%
Express lane access	No	No Yes	= AFV	No Yes
Emissions	Equal	10% less	25% less	100% less
Power	Equal	Equal 10% less	Equal 10% less	Equal 10% less

Table 1: Experimental attribute levels, Horne (2003)

According to our review of the literature, emission data is the standard way to describe choice behavior of environmentally-conscious consumers when using discrete choice models for vehicle purchase decisions. But in the EMRG survey the emission variable does not vary across choice situations in the SP design. This simplifying assumption was made to avoid an explosive number of choice situations (see discussion in Horne, 2003, a 2^{16-11} fractional factorial design was used – this problem could have been avoided using an efficient SP design). The consequence of this assumption is that the effects of environmental benefits related to emission reductions cannot be distinguished from the alternative specific constants of a discrete choice model. This is a major problem if we make the hypothesis that ecologically motivated consumers have a different purchase behavior. However, the introduction of a latent variable will help resolve this issue.

In fact, using this data we want to model the impact of environmental-related cognitive factors on the private vehicle purchase decision. The first step to address this issue through an HCM is to set the latent variables involved. Our hypothesis here is that the private vehicle purchase decision is affected not only by the attributes of the different vehicles but also by the environmental awareness of the consumer. Ultimately, an environmentally-conscious consumer should prefer a cleaner automobile technology associated with less environmental impact. In our model, this effect is taken into account by introducing the latent variable ***Environmental Concern*** (EC), related precisely to transportation and its environmental impact.

We continue the analysis focusing on two different relevant questions of the survey that translates into both transport policy support (5 levels from *strongly opposed* to *strongly supportive*) and transport problem evaluation (5 levels from *not a problem* to *major problem*), see Table 2.

Description of Manifest Variables	Response Level 1	2	3	4	5
Transport Policy Support: 1 = strongly opposed → 5 = strongly supportive					
Building new roads & expanding existing roads	5%	12%	16%	23%	43%
Discouraging automobile use with road tolls & gas taxes	44%	23%	12%	10%	11%
Making neighborhoods more attractive by using bike lanes & speed controls	1%	3%	20%	22%	54%
Reducing vehicle emissions with regular testing & emission standards	2%	3%	13%	22%	59%
Providing transit and HOVs dedicated traffic lanes & priority at intersections	3%	6%	23%	26%	42%
Improving transit service	1%	2%	15%	19%	63%
Reducing transport distances by promoting compact communities	12%	10%	35%	19%	25%
Reducing transport needs by encouraging compressed workweeks	1%	4%	23%	25%	47%
Transport Problem Evaluation: 1 = not a problem → 5 = major problem					
Traffic congestion that you experience while driving	7%	9%	22%	29%	32%
Traffic noise that you hear at home, work, or school	29%	18%	28%	15%	9%
Vehicle emissions that affect local air quality	5%	6%	15%	32%	43%
Accidents caused by aggressive or absent-minded drivers	1%	4%	12%	29%	55%
Vehicle emissions that contribute to global warming	2%	2%	9%	31%	55%
Unsafe communities because of speeding traffic	3%	6%	19%	32%	41%

Table 2: Manifest Variables

The answers to these questions serve as perceptual indicator variables, which are used for construction of the environmental concern (EC) latent variable. This way, the EC variable measures consumers' concerns and awareness about transportation issues affecting the natural environment (e.g. possibility of reducing car emissions or the introduction of road tolls and gas taxes; problems related to poor local air quality, emissions and global warming) as well as the mobility environment (e.g. traffic congestion, traffic noise, safety concerns). Although we do not present the details here, the structure defining EC as a unidimensional construct – as opposed to a diverse structure differentiating, for instance, the natural and mobility environmental concerns – was tested among alternative relationships according to a MIMIC model and using likelihood ratio tests. We did not use factor analysis (FA) basically because FA does not allow us to distinguish the effects of market segments that are taken into account when estimating the MIMIC models. We checked the reliability of the current structure for the EC variable getting an acceptable level of internal consistency (Cronbach's $\alpha = 0.7018$.)

3 Private vehicle Hybrid Choice Model

3.1 The HCM setting

Econometrically, latent variable models are composed of a set of *structural equations* that describe the latent variables in terms of (latent or observable) exogenous variables, and a group of measurement relationships (*measurement model*) linking latent constructs to manifest variables such as perceptual-attitudinal or behavioral *indicator* variables (Jöreskog and Sörbom, 2008; Bollen, 1989). Since latent variables are unobserved, for identification they need to be linked to measurable responses or indicators. Note that under the RUM framework, the standard choice model is a latent variable model itself. The utility function is a latent construct that measures the individual level of satisfaction conditional on each alternative (*choice model structural equation*). Although the utility function is unobservable, revealed or stated choices serve as indicator variables of the underlying choice process. Thus, a general HCM setting involves working with a simultaneous system defined by both the structural-measurement discrete choice model and the structural-measurement latent variable model. The standard discrete choice model inside an HCM can be viewed as the kernel of a more general model where attitudes and perceptions are incorporated.

In this particular choice context, we aim to explain the process of individual choice among the mutually exclusive, exhaustive and finite group of the personal vehicle alternatives: *standard gasoline vehicle* (SGV), *alternative fuel vehicle* (AFV), *hybrid electric vehicle* (HEV), and *hydrogen fuel cell vehicle* (HFC). At the same time, we postulate that the latent *environmental concern* (EC) variable, which reflects pro-environmental preferences, has a significant impact on the vehicle purchase decision. The whole behavioral process is represented by the following HCM group of structural and measurement equations (cf. Bolduc et al., 2008):

Structural equations

$$\mathrm{EC}_n = w_n b + \zeta_n, \quad \zeta_n \sim N(0,1) \tag{1}$$

$$U_n = X_n\beta + \Gamma \cdot \mathrm{EC}_n + \upsilon_n \tag{2}$$

Measurement equations

$$I_n = \Lambda \cdot \mathrm{EC}_n + \varepsilon_n, \quad \varepsilon_n \sim MVN(0, \mathrm{I}_{14}) \tag{3}$$

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} \geq U_{jn}, \forall j \in C_n, j \neq i \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where EC is the latent environmental concern variable; w_n is a (1×10) vector of explanatory variables affecting the latent variable; b is a (10×1) vector of unknown parameters used to describe the effect of w_n on the latent variable. The choice model in equation (2) is written in vector form where we include the 4 private vehicle alternatives. Therefore,

U_n is a (4×1) vector of utilities; υ_n is a (4×1) vector of error terms associated with the utility terms. X_n is a (4×8) attribute matrix – including 5 experimental attributes and 3 alternative specific constants (ASC) – with X_{in} designating the ith row of X_n. β is a (8×1) vector of unknown parameters. Γ is a (4×4) diagonal matrix of unknown parameters associated with the latent variable EC, with Γ_i designating the ith diagonal element of matrix Γ.

In the set of measurement equations (3), I_n corresponds to a (14×1) vector of the 14 indicators of latent variable EC associated with individual n; and Λ is a (14×1) vector of unknown parameters that relate the latent variable EC to the indicators. Even though the indicator variables are ratings (1-5), we treat them as being continuous according to standard practice in latent variable models. The term ε_n is a (14×1) vector of independent error terms with unitary variance – I_{14} being the identity matrix of size 14. Regarding independence of the measurement equations, we do recognize in our model that indicators are highly correlated variables, but we assume that the correlation structure is due to commonality of each indicator with the latent construct EC. Once we account for this commonality by modeling each indicator as a function of EC, then the residual of each indicator can reasonably be assumed to be uncorrelated with the other residuals. Additionally, a diagonal matrix is required for identification of the model.

Finally, we stack each individual choice indicator variable y_{in} into a (4×1) vector called y_n. For a full description of the equations and variables, see Appendix A.

The hybrid model setting that we consider is represented in Figure 2, where the complete set of structural and measurement equations is sketched, depicting the relationships between explanatory variables and each partial model. Specifically, we can distinguish the choice model, which is centered on the utility function (equation 2) and on the stated choice (equation 4), the latent variables structural model (equation 1), which links the latent variable EC with the characteristics of the traveler, and the latent variable measurement model (equation 3), which links EC with the indicators.

Figure 2: Private vehicle purchase HCM

If the latent variable EC were not present, the personal vehicle choice probability would correspond exactly to the standard choice probability $P(y_{in} = 1\,|X_n, \beta\,) \equiv P_n(i\,|X_n, \beta\,)$. In a setting with given values for the EC variable, the choice probability would be represented by $P_n(i\,|\mathrm{EC}, X_n, \theta\,)$ where θ contains all the unknown parameters in the choice model of equation (2). Since EC is not actually observed, the (expected) choice probability is obtained by integrating the latter expression over the whole space defined by the density function of EC:

$$P_n(i|X_n, w_n, \theta, b) = \int\limits_{\mathrm{EC}} P_n(i\,|\mathrm{EC}, X_n, \theta\,) g(\mathrm{EC}|w_n, b) d\mathrm{EC}, \tag{5}$$

where $g(\mathrm{EC}_n|w_n, b)$ is the density of $N(w_n b, 1)$.

The indicators are manifest variables that permit identification of the parameters present in the distribution of the latent variable EC. Given our assumptions, the joint probability $P(y_{in}=1, I_n) \equiv P_n(i, I)$ of observing jointly the choice y_n and the indicators I_n may be written as:

$$P_n(i, I|X_n, w_n, \delta) = \int_{\text{EC}} P_n(i\,|\text{EC}, X_n, \theta) f(I_n|\text{EC}, \Lambda) g(\text{EC}\,|w_n, b) d\text{EC}, \tag{6}$$

where $f(I_n|\text{EC}, \Lambda)$ is the density of I_n implied by equation (3). The term δ designates the full set of parameters to estimate (i.e. $\delta = \{\theta, b, \Lambda\}$).

Although not the case of the application analyzed in this paper, including numerous attitudes in HCMs with large sets of potentially interrelated choices directly entails the simulation of high dimensional integrals. We can address this problem using classical methods, which use a valid simulator for the choice probability through maximum simulated likelihood (MSL) estimation (Bolduc and Alvarez-Daziano, 2010). HCM classical full information estimation requires maximizing the log likelihood function: $\sum_{n=1}^{N} \sum_{i \in C_n} y_{in} \ln P_n(i, I\,|X_n, w_n, \delta)$. In practice, with a large number of latent variables we need to replace the multidimensional integral with a smooth simulator with good statistical properties, leading to a maximum simulated likelihood (MSL) solution (Walker, 2002; Bolduc and Alvarez-Daziano, 2010). Although feasible, the MSL approach necessary for classical HCM estimation is very demanding in situations with a huge choice set of interdependent alternatives with a large number of latent variables. Even though classical estimation of HCMs is possible using a sequential approach (Ashok et al., 2002; Johansson et al., 2006; Tam et al., 2010), the results of this method are not efficient (Ben-Akiva et al., 2002a).

For these reasons, we propose to go beyond classical methods by introducing Bayesian techniques. Building on the rapid development of Markov Chain Monte Carlo (MCMC) techniques, and on the idea that Bayesian tools (with appropriate priors) can be used to produce estimators that are asymptotically equivalent to those obtained using classical methods, we define the goal of both theoretically and empirically implementing a Bayesian approach to hybrid choice modeling. This paper represents the first step in developing a Bayesian estimator for HCMs, specifically for the vehicle purchase context we have introduced.

3.2 HCM Gibbs sampler implementation

The parameters to estimate in the private vehicle choice case we are analyzing are $\theta' = [ASC_{AFV}\ ASC_{HEV}\ ASC_{HFC}\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \Gamma_{\text{EC},AFV}\ \Gamma_{\text{EC},HEV}\ \Gamma_{\text{EC},HFC}]$, b and Λ. Bayes estimation implementation for these parameters requires making draws from the joint posterior distribution:

$$P(\theta, b, \Lambda|y, I), \tag{7}$$

or, using data augmentation from:

$$P(\mathrm{EC}, \theta, b, \Lambda | y, I), \tag{8}$$

where $\mathrm{EC} = (\mathrm{EC}_1, \ldots, \mathrm{EC}_N)'$, $y = (y_1, \ldots, y_N)'$ and $I = (I_1, \ldots, I_N)'$ capture the information for the full group of individuals.

Using Gibbs sampling, the estimators are obtained from draws inside an iterative process involving the set of *full conditional distributions*. Namely, at the g-*th* iteration:

$$\begin{aligned}
\mathrm{EC}_n^{(g)} &\sim \pi(\mathrm{EC}_n | \theta^{(g-1)}, b^{(g-1)}, \Lambda^{(g-1)}, y_n, I_n), \forall n && (9)\\
b^{(g)} &\sim \pi(b | \mathrm{EC}^{(g)}, \theta^{(g-1)}, b^{(g-1)}, y, I) && (10)\\
\Lambda^{(g)} &\sim \pi(\Lambda | \mathrm{EC}^{(g)}, \theta^{(g-1)}, b^{(g)}, y, I) && (11)\\
\theta^{(g)} &\sim \pi(\theta | \mathrm{EC}^{(g)}, b^{(g)}, \Lambda^{(g)}, y, I). && (12)
\end{aligned}$$

Since the latent variable EC is not observable, we need to incorporate the information provided by the indicator I_n on EC. This information is explicitly given by the conditional probability $\pi(\mathrm{EC}|I_n)$ whose expression depends on the assumptions we make. We assume then a multivariate normal distribution:

$$\begin{bmatrix} \mathrm{EC}_n \\ I_n \end{bmatrix} \sim N\left(\begin{bmatrix} w_n b \\ \Lambda w_n b \end{bmatrix}, \begin{bmatrix} 1 & \Lambda' \\ \Lambda & \Lambda\Lambda' + \mathrm{I}_{14} \end{bmatrix} \right), \forall n, \tag{13}$$

where I_{14} represents the identity matrix of size 14. Equation 13 implies

$$\pi(\mathrm{EC}|\theta, b, \Lambda, y_n, I_n) \sim N(\mu_{\mathrm{EC}_n|I_n}, \sigma^2_{\mathrm{EC}_n|I_n}), \forall n, \tag{14}$$

where

$$\begin{aligned}
\mu_{\mathrm{EC}_n|I_n} &= w_n b + \Lambda' \left[\Lambda\Lambda' + \mathrm{I}_{14}\right]^{-1} \left[I_n - \Lambda w_n b\right] && (15)\\
\sigma^2_{\mathrm{EC}_n|I_n} &= 1 - \Lambda' \left[\Lambda\Lambda' + \mathrm{I}_{14}\right]^{-1} \Lambda. && (16)
\end{aligned}$$

Note that the latter expression is independent of individual n, so we can write $\sigma^2_{\mathrm{EC}|I}$.

When using data augmentation, the latent variable EC becomes observable through $\pi(\mathrm{EC}|\theta, b, \Lambda, y_n, I_n)$. This fact implies that the conditional distributions for b and Λ simply correspond to ordinary Bayesian regressions (b and Λ are assumed independent):

$$\begin{aligned}
\pi(b|\mathrm{EC}, \theta, b, \Lambda, y, I) &\sim N(\bar{b}, \bar{V}_b) && (17)\\
\pi(\Lambda|\mathrm{EC}, \theta, b, y, I) &\sim N(\bar{\Lambda}, \bar{V}_\Lambda). && (18)
\end{aligned}$$

If prior beliefs for b and Λ are described by $p(b) \sim N(\check{b}, \check{V}_b)$ and $p(\Lambda) \sim N(\check{\Lambda}, \check{V}_\Lambda)$ respectively, then we can show that

$$\begin{aligned}
\bar{V}_b &= (\check{V}_b^{-1} + w'w)^{-1}, \;\; \bar{b} = \bar{V}_b(\check{V}_b^{-1} + w'\mathrm{EC}) && (19)\\
\bar{V}_\Lambda &= (\check{V}_\Lambda^{-1} + \mathrm{EC}'\mathrm{EC})^{-1}, \;\; \bar{\Lambda} = \bar{V}_\Lambda(\check{V}_\Lambda^{-1} + \mathrm{EC}'I). && (20)
\end{aligned}$$

3.3 The discrete choice kernel

The analytical form of the conditional distribution $\pi(\theta|\mathrm{EC}, b, \Lambda, y_n, I_n)$ for the discrete choice kernel depends on the assumptions regarding the distribution of the random term υ_n defined in equation (2).

We can derive a probit kernel if we make the assumption that the error terms υ_n are multivariate normal distributed. When using classical techniques, the burdensome classical multinomial probit estimation process reduces the practicability of the standard probit model. In fact, simulated maximum likelihood estimation (SML) of mixed logit models outperforms the SML estimation of probit because of the good statistical properties that can be derived for the former estimator (Munizaga and Alvarez-Daziano, 2005). However, Bayesian methods breaks down the complexity of classical estimation of the probit model (Bolduc, Fortin, and Gordon, 1997). HCM Bayesian estimation with a probit kernel is straightforward because the properties of the normal distribution allow us to exploit data augmentation techniques, basically because the utility function follows a normal distribution (Albert and Chib, 1993; McCulloch et al., 2000).

In discrete choice models, decisions are based on utility differences, so we can consider a utility difference model with respect to the base alternative SGV that, in our particular case, leads us to write the structural equation in a system of three equations:

$$\widetilde{U}_n = \widetilde{V}_n + \widetilde{\upsilon}_n, \quad \widetilde{\upsilon} \sim MVN(0, \mathrm{I}_3), \tag{21}$$

where I_3 is the identity matrix of size 3 – which is the number of alternatives for the utility difference model. We can get the vector form of the model by stacking the individual utilities into $\widetilde{U} = \widetilde{V} + \widetilde{\upsilon}$, where $\widetilde{\upsilon} \sim MVN(0, \mathrm{I}_{(N\times 3)})$.

Note that to obtain the utility difference model in its estimable form (equation 21) from equation (2), we use the matrix difference operator $\Delta_{SGV}(\cdot)_{jn} = (\cdot)_{jn} - (\cdot)_{SGVn}, j = \{AFV, HEV, HFC\}$:

$$\Delta_{SGV} U_n = \Delta_{SGV} V_n + \Delta_{SGV} \upsilon_n, \tag{22}$$

where $\Delta_{SGV} V_n$ denotes the (3×1) extended deterministic part of the utility difference expression for individual n, composed by $\Delta_{SGV} V_{jn} = ASC_j + \beta_1 \Delta_{SGV} X_{1jn} + \cdots + \beta_5 \Delta_{SGV} X_{5jn} + \Gamma_{\mathrm{EC},j}\mathrm{EC}_n \equiv \widetilde{\mathrm{X}}_{jn}\theta, j = \{AFV, HEV, HFC\}$, where $\widetilde{\mathrm{X}}_{jn}$ is a row vector that contains the incremental specification of the attributes of alternative j (attribute changes with respect to the base alternative's values) and the latent variable EC, and where θ is a column vector of unknown parameters. The matrix $\widetilde{\mathrm{X}}$ is built by stacking the vectors $\widetilde{\mathrm{X}}_{jn}$ for each alternative j and each individual n. The assumption for a probit model is that $\upsilon_n \sim MVN(0_{4\times 4}, \Sigma_{4\times 4})$, and so we have $\Delta_{SGV}\upsilon_n \sim MVN(0_{3\times 3}, \Omega_{3\times 3} = [\Delta_{SGV}\Sigma\Delta'_{SGV}])$. Let L be the Cholesky root of Ω^{-1}. Then, the model can be reexpressed as:

$$L'\Delta_{SGV} U_n = L'\Delta_{SGV} V_n + L'\Delta_{SGV}\upsilon_n, \tag{23}$$

leading to equation (21) above.

Assuming that $\widetilde{U}$ is observable, that Ω is known, and that prior beliefs for θ are described by $p(\theta) \sim N(\check{\theta}, \check{V}_\theta)$, then the model becomes a simple Bayesian regression with known variance (Albert and Chib, 1993; Bolduc et al., 1997):

$$\pi(\theta|\widetilde{U}, \Omega, \mathrm{EC}, b, \Lambda, y, I) \sim N(\bar{\theta}, \bar{V}_\theta), \tag{24}$$

$$\bar{V}_\theta = (\check{V}_\theta^{-1} + \widetilde{\mathrm{X}}'\widetilde{\mathrm{X}})^{-1}, \ \ \bar{\theta} = \bar{V}_\theta(\check{V}_\theta^{-1} + \widetilde{\mathrm{X}}'\widetilde{U}). \tag{25}$$

In the conditional distribution of θ, $\pi(\theta|\widetilde{U}, \Omega)$ indicates the use of data augmentation techniques. This is possible if and only if the conditional distributions of $\widetilde{U}$ and Ω are easy to describe. Note that $\widetilde{U}_{AFVn} \sim N(\widetilde{V}_{AFVn}, 1)$, $\widetilde{U}_{HEVn} \sim N(\widetilde{V}_{HEVn}, 1)$, and $\widetilde{U}_{HFCn} \sim N(\widetilde{V}_{HFCn}, 1)$. However, since $y_n = i \Longleftrightarrow U_{in} = max(U_{SGVn}, U_{AFVn}, U_{HEVn}, U_{HFCn})$ then conditional on y_n, $\widetilde{U}_n$ follows a truncated multivariate normal (TMVN) distribution:

$$\pi(\widetilde{U}_n|\mathrm{EC}, \Omega, \theta, b, \Lambda, y_n, I_n) \sim \mathrm{TMVN}_{\Re|y_n}\left(\widetilde{V}_n, \mathrm{I}_3\right), \forall n, \tag{26}$$

where the truncation region $\Re$ is defined by the measurement equation of y_n:

$$y_n = \begin{cases} SGV & \text{if } (\widetilde{U}_{AFVn} < 0) \wedge (\widetilde{U}_{HEVn} < 0) \wedge (\widetilde{U}_{HFCn} < 0) \\ AFV & \text{if } (\widetilde{U}_{AFVn} \geq 0) \wedge (\widetilde{U}_{AFVn} > \widetilde{U}_{HEVn}) \wedge (\widetilde{U}_{AFVn} > \widetilde{U}_{HFCn}) \\ HEV & \text{if } (\widetilde{U}_{HEVn} \geq 0) \wedge (\widetilde{U}_{HEVn} > \widetilde{U}_{AFVn}) \wedge (\widetilde{U}_{HEVn} > \widetilde{U}_{HFCn}) \\ HFC & \text{if } (\widetilde{U}_{HFCn} \geq 0) \wedge (\widetilde{U}_{HFCn} > \widetilde{U}_{AFVn}) \wedge (\widetilde{U}_{HFCn} > \widetilde{U}_{HEVn}) \end{cases}. \tag{27}$$

Finally, if prior beliefs for Ω are described by an inverted-Wishart $IW(\check{\nu}, \check{V})$ distribution, then it can be shown that

$$\pi(\Omega|\mathrm{EC}, \widetilde{U}_n, \theta, b, \Lambda, y_n, I_n) \sim IW(\bar{\nu}, \bar{V}), \tag{28}$$

where $\bar{\nu} = \check{\nu} + N$ and $\bar{V} = \check{V} + \sum_{n=1}^{N}(\Delta_{SGV}\upsilon_n)(\Delta_{SGV}\upsilon_n)'$. This conditional distribution completes the set of distributions needed for Gibbs sampling with a probit kernel.

Note that it is possible to make an extension of the probit-kernel Gibbs sampler we developed to a normal error component model – such as randomly normal distributed taste variations with a probit kernel.

On the other hand, when modeling a normal error component model with a multinomial logit kernel – which results in a mixed logit or MMNL model – we no longer have the advantageous properties that make implementing the probit-kernel Gibbs sampler straightforward. Since the MMNL distribution of $\widetilde{U}$ is hard to describe, i.e. there is no closed form full conditional distribution for $\widetilde{U}$, data augmentation implementation for the utility function is no longer as simple. Thus, MMNL Bayesian estimation does not allow us to use a simple regression for θ and, as we will show, the use of Metropolis-Hastings (MH) methods is needed. The Bayesian procedure for a standard MMNL – without an associated structure of latent variables – described by Train (2009) can be simply plugged into the HCM Gibbs sampler. If we focus on the normal random taste parameters case, then

$$U_n = X_n\beta_n + \Gamma_n \cdot \mathrm{EC}_n + \upsilon_n \equiv \widetilde{X}_n\theta_n + \upsilon_n, \tag{29}$$

where $\widetilde{X}$ is the extended matrix of the alternative attributes, including the latent variable EC; $\theta_n \sim MVN(\theta, \Sigma_\theta)$ is the unknown vector of randomly distributed taste parameters, with θ representing the population mean; and υ_n is a vector of independent and identically distributed extreme value type 1 error terms.

Following Train (2009), if prior beliefs for θ and Σ_θ are described by $p(\theta, \Sigma_\theta) = p(\theta)p(\Sigma_\theta)$, where $p(\theta) \sim N(\check{\theta}, \check{\Sigma})$ with extremely large variance, and $p(\Sigma_\theta)$ is inverted-Wishart $IW(\check{\nu_\Sigma}, \check{V_\Sigma})$, then the mixed logit kernel HCM Gibbs sampler is completed considering the following conditional posteriors:

$$\pi(\theta|\mathrm{EC}, \theta_n, \Sigma_\theta, b, \Lambda, y_n, I_n) \sim MVN(\bar{\theta}, \Sigma_\theta/N) \tag{30}$$

$$\pi(\Sigma_\theta|\mathrm{EC}, \theta, \theta_n, b, \Lambda, y_n, I_n) \sim IW\left(\check{\nu_\Sigma} + N, \frac{\check{\nu_\Sigma}\check{V_\Sigma} + N\bar{\Sigma}}{\check{\nu_\Sigma} + N}\right), \tag{31}$$

where $\bar{\theta} = \sum \theta_n/N$, $\bar{\Sigma} = \sum(\theta_n - \theta)(\theta_n - \theta)'/N$; and

$$\pi(\theta_n|\mathrm{EC}, \theta, \Sigma_\theta, b, \Lambda, y_n, I_n) \propto \frac{e^{\widetilde{X}_{y_n n}\theta_n}}{e^{\widetilde{X}_{SGVn}\theta_n} + e^{\widetilde{X}_{AFVn}\theta_n} + e^{\widetilde{X}_{HEVn}\theta_n} + e^{\widetilde{X}_{HFCn}\theta_n}}\varphi(\theta_n|\theta, \Sigma_n), \forall n \tag{32}$$

where $\varphi(\theta_n|\theta, \Sigma_n)$ is the normal density function. Note that the Metropolis-Hastings algorithm is needed to draw θ_n from the distribution in equation 32. We will describe the MH algorithm for the multinomial logit (MNL) model. The MNL model is a particular case of the mixed logit model, where the taste parameters are fixed to the population means. In the MNL case, we fail to find a closed form full conditional distribution for θ. However, we can use an asymptotic approximation to the posterior (Scott, 2003):

$$\pi(\theta|\mathrm{EC}, b, \Lambda, y_n, I_n) \propto |H|^{\frac{1}{2}} \exp\left(\frac{1}{2}(\theta - \hat{\theta_{ML}})'H(\theta - \hat{\theta_{ML}})\right), \tag{33}$$

with $\hat{\theta_{ML}}$ being the maximum likelihood solution for θ, and with H being the asymptotic variance obtained from the expected sample information matrix ($\otimes$ denotes the Kronecker product):

$$H = -E\left[\frac{\partial^2 \ln l}{\partial\theta\partial\theta'}\right] = -\sum_{n=1}^{N}(\mathrm{diag}(P_n) - P_nP_n') \otimes \widetilde{X}_n\widetilde{X}_n', \tag{34}$$

which is the Hessian matrix of the observed MNL log-likelihood $\ln l = \sum_{n=1}^{N} \ln P_{y_n}$, where $P_n = (P_{SGVn}, P_{AFVn}, P_{HEVn}, P_{HFCn})$, and with P_{in} below being the standard MNL form of the choice probability of alternative i for individual n:

$$P_{in} = \frac{e^{\widetilde{X}_{in}\theta_n}}{e^{\widetilde{X}_{SGVn}\theta_n} + e^{\widetilde{X}_{AFVn}\theta_n} + e^{\widetilde{X}_{HEVn}\theta_n} + e^{\widetilde{X}_{HFCn}\theta_n}}. \tag{35}$$

For Metropolis-Hastings implementation, a candidate θ^{cand} is drawn from a given distribution depending on whether we are using a random walk chain or an independence chain (Rossi et al., 2006). The candidate realization θ^{cand} is then compared to the current θ^{curr} through:

$$\alpha = \min\left\{1, \frac{l(\theta^{cand}|y,\tilde{X})\pi(\theta^{cand})}{l(\theta^{curr}|y,\tilde{X})\pi(\theta^{curr})} \times \frac{q(\theta^{cand},\theta^{curr})}{q(\theta^{curr},\theta^{cand})}\right\}, \tag{36}$$

where $q(i,j)$ is the probability of generating candidate j given i. The candidate is accepted as the new $\theta^{curr} = \theta^{cand}$ with probability α, while the old one is preserved $\theta^{curr} = \theta^{curr}$ with probability $1-\alpha$. By plugging this MH procedure into the Gibbs sampler developed in the previous section for b and Λ, we obtain a Bayesian MNL solution for the full set of parameters to estimate.

4 Application to vehicle choice data

In the previous section we discussed how to methodologically implement Bayesian estimation using different models for the discrete choice kernel. Although the probit kernel formulation is analytically straightforward, taking draws from a truncated multivariate normal distribution is necessary. For our empirical application we implemented an MNL kernel to avoid convergence problems due to truncation. HCM estimation with an MNL kernel requires an MH-within-Gibbs algorithm that does not make use of draws from a multivariate normal distribution. Thus, we do not expect a slowed-down estimation process because of rejection methods for truncation. Additionally, implementation of an MNL kernel also facilitates the comparison of our results with models estimated previously using the same data, namely classical estimation of an HCM with an MNL kernel to incorporate environmental preferences (Bolduc et al., 2008), as well as the standard discrete choice model originally calibrated after the survey (Horne, 2003).

We will now present the results of the HCM Bayesian estimation process for the vehicle choice data. Using the R language, we implemented the MNL Kernel Gibbs sampling routine presented earlier:

$$\begin{aligned}
\pi(\theta|\mathrm{EC},b,\Lambda,y,I) &\propto |H|^{\frac{1}{2}}\exp\left(\frac{1}{2}(\theta-\hat{\theta_{ML}})'H(\theta-\hat{\theta_{ML}})\right) && (37)\\
\pi(\mathrm{EC}_n|\theta,b,\Lambda,y_n,I_n) &\sim N(\mu_{\mathrm{EC}_n|I_n},\sigma^2_{\mathrm{EC}|I}), \forall n && (38)\\
\pi(b|\mathrm{EC},\theta,b,\Lambda,y,I) &\sim N(\bar{b},\bar{V}_b) && (39)\\
\pi(\Lambda|\mathrm{EC},\theta,b,y,I) &\sim N(\bar{\Lambda},\bar{V}_\Lambda). && (40)
\end{aligned}$$

To construct the reported results we considered 5,000 draws – or iterations of the Gibbs sampler sequence – with a burn-in period of the first 500 draws. The mean of the Gibbs sampler draws is a consistent estimator for the posterior mean of the parameters of interest. Recall that under fairly weak conditions (Gelfand and Smith, 1990), the Gibbs sampler sequence of random draws forms an irreducible and ergodic Markov chain representing the joint posterior distribution. For this application, we adopt diffuse priors. In addition, the standard deviations used for the calculation of t-statistics are simply the standard deviations of the artificial samples generated by the Gibbs sampler. 5,000 draws (4,500 without the burn-in period) appear to be enough to reproduce the maximum likelihood results with a fair degree of accuracy. In fact, to test whether we achieved convergence we made several trials, including broken MCMC chains (for instance we tried 25,000 draws with thinning parameter k=5); using more draws or breaking the MCMC chain we recovered the same results. To give an idea from a similar context, note that in the case of mixed logit, Godoy and Ortúzar (2009) find that 5,000 draws appear as a good number to assure convergence even in the presence of serial correlation. The total time taken for parameter estimation was 120 minutes in an ordinary PC (cf. 90 minutes for classical estimation; note however that the processing time for the Bayesian approach is for the whole distribution of the parameters and not for just the point estimates, as is the case of the classical approach. Also, the processing time for the Bayesian approach includes the calculations needed for prediction).

Although the estimation process implies that all the equations are calibrated simultaneously, we will present the results separately for each HCM sub-model, i.e. the car choice model, the latent variable structural model and the latent variable measurement model. Since this is the first application of MCMC methods to a hybrid choice model, we first focus on the results of the estimated parameters using diffuse priors. We also present the results of a classical HCM with an MNL kernel (Bolduc and Alvarez-Daziano, 2010).

4.1 Car Choice Model

First, we present the results of the car choice model (Table 3.) As explained before, the car choice corresponds to the (MNL) discrete choice kernel, where the parameters to estimate are described by the taste parameter vector θ of the utility function. The deterministic utility contains the experimental attributes purchase price, fuel cost, fuel availability, express lane access, and power, as well as alternative specific constants for the alternative fuel vehicle AFV, the hybrid vehicle HEV, and the hydrogen fuel cell vehicle HFC. The utility specification also contains the effect of the latent variable EC. The latent variable related to environmental concern (EC) was not considered for the standard gasoline vehicle SGV.

Unsurprisingly – and yet, reassuringly – Gibbs sampling and classical maximum likelihood parameters have the same sign and magnitude. The environmental concern latent variable enters very significantly and positively into the choice model specification. Thus, environmental concern (EC) encourages the choice of green automobile technologies through a positive impact in the choice probability of those alternatives. In fact,

Car Choice Model	Bayesian Estimates estimates	t-stat	Classical Estimates estimates	t-stat
ASC_{AFV}	-6.185	-7.52	-6.189	-9.73
ASC_{HEV}	-2.530	-3.67	-2.541	-4.43
ASC_{HFC}	-4.049	-5.66	-4.093	-7.82
Purchase Price (β_1)	-0.895	-4.21	-0.894	-4.22
Fuel Cost (β_2)	-0.852	-4.27	-0.854	-4.18
Fuel Availability (β_3)	1.388	7.42	1.398	7.31
Express Lane Access (β_4)	0.158	2.26	0.160	2.26
Power (β_5)	2.729	4.01	2.752	4.13
Latent Variables				
EC on AFV ($\Gamma_{AFV,EC}$)	0.585	3.68	0.592	4.09
EC on HEV ($\Gamma_{HEV,EC}$)	0.411	4.88	0.420	4.45
EC on HFC ($\Gamma_{HFC,EC}$)	0.674	7.37	0.692	6.95
Number of pseudo-individuals	1877		1877	
Number of draws (Burn-in)	5000 (500)		-	
Number of Halton draws	-		500	
Number of iterations	-		326	
Loglikelihood	-1955.34		-1987.52	
Adjusted ρ^2	0.249		0.236	

Table 3: Car Choice Model Results

EC has the highest effect on the hydrogen fuel cell vehicle HFC, followed by the alternative fuel vehicle AFV, and then the hybrid vehicle HEV. Note that HFC represents the cleanest engine technology of the experimental alternatives. The fact that HEV still makes use of standard fuel could explain the lower EC impact.

It is important to mention that our results for both the Bayesian and classical HCM to some extent reproduce the results of an MNL (without latent variables Horne, 2003; Bolduc and Alvarez-Daziano, 2010): common parameters with the standard multinomial logit model have the same sign and magnitude, except for alternative specific constants (which now are affected by the inclusion of the latent variable). It is especially interesting to note that convergence is assured for the maximum likelihood estimation of the standard MNL. Thus, because of the MNL kernel assumption we can take the MNL estimates as 'reference values' for an informal test not only for assuring that the global maximum is achieved (classical estimation), but also for convergence of the Gibbs sampler we have implemented. In fact, since we used diffuse priors, the informal test of convergence – set as reproducing the classical estimates with a certain degree of accuracy – seems appropriate. Also note that the starting values were not data-based. The results presented were calculated using starting values set to zero, and we checked independence of the results and the starting values used for both Bayesian and classical estimation (for the latter, in order to check that a global maximum was attained).

4.2 Structural Model

The structural equation links consumer characteristics with the latent variables through a linear regression equation based on the usual mode of transportation (driving, carpooling or public transportation) either to commute (in the case of workers) or for other main purposes for the rest of the sample, the individual's gender, age, education level, and household income. The estimation results are shown in Table 4:

Structural Model	Bayesian Estimates		Classical Estimates	
	est	t-stat	est	t-stat
Intercept (b_1)	1.840	4.63	2.067	7.08
Driving Alone User (b_2)	-0.157	-2.23	-0.143	-1.86
Carpool User (b_3)	0.236	2.15	0.241	1.72
Transit User (b_4)	0.482	4.76	0.468	3.92
Female Indicator (b_5)	0.344	6.06	0.342	5.52
High Income Indicator >80K$ (b_6)	0.046	0.77	0.050	0.75
University Indicator (b_7)	0.274	4.62	0.285	4.41
Age level: 26-40 years (b_8)	0.447	3.96	0.439	3.35
Age level: 41-55 years (b_9)	0.544	4.81	0.538	4.07
Age level: 56 years & more (b_{10})	0.839	6.70	0.829	5.79
$\bar{R}^2$	0.735		-	

Table 4: Structural Model Results

From this model, we can conclude that environmental concern (EC) is more important for public transportation users than for carpool users. We in fact observe a negative parameter for those who mostly drive alone. The results are in line with the idea that regular drivers may be indifferent to the environmentally adverse effects of private car use (air pollution and congestion). Good public transportation service has been proposed as an alternative for car use reduction; our results show that transit users are more green with regard to the adoption of new transportation technologies.

We also find that concern about environmental issues in the car purchase choice context is more developed in women, older people and more educated people (cf. Johansson et al., 2006). The effect of the high income variable is positive but not significant.

Since each respondent offers up to four SP vehicle-choices, we have repeated individuals in the sample. The structural equation implies that the problem of correlation between observations is addressed indirectly by the individual-specific latent variable via the socio-demographic variables. In effect there is no variation in these socio-demographic variables for a single individual's choice exercise, but there is variation among different groups of individuals. Only people who belong to the same cluster (defined by equal socio-demographic characteristics) will have a common variable (the deterministic part of the latent variable) that does not vary across choice situations. However we do recognize that in this application the structural model for the latent variable assumes independent error terms, even for different responses of the same individual. To address this issue it is possible to assume a common latent variable parameter that varies across individuals. This approach translates into incorporating exactly the same random draw of the latent variable for each choice exercise of a same individual. We tested this specification and the results were not significantly different from zero (implying that the underlying cluster classification was enough to address the problem of repeated choices).

4.3 Measurement Model

Lastly, several indicators were considered in the latent variable measurement model, which links the latent psychometric environmental concern variable to answers to attitudinal/perceptual qualitative survey questions. The questions selected to define the indicator variables concern the respondent's level of support for or opposition to various transport policies (*Transport Policies Support*), and their opinions on various transport-related issues (*Transport Problems Evaluation*). The results are shown in Table 5.

Measurement Model	Bayesian Estimates		Classical Estimates	
	estimates	t-stat	estimates	t-stat
Transport Policies Support				
Expanding & Upgrading Roads (λ_1)	-0.358	-12.56	-0.375	-13.77
Road Tolls & Gas Taxes (λ_2)	0.541	17.40	0.547	20.05
Bike Lanes & Speed Controls (λ_3)	0.339	13.29	0.344	8.85
Regular Testing for Reducing Car Emissions (λ_4)	0.277	10.86	0.283	8.01
High Occupancy Vehicles & Transit Priorities (λ_5)	0.426	16.08	0.426	11.63
Improving Transit Service (λ_6)	0.278	11.49	0.278	7.08
Promoting Compact Communities (λ_7)	0.257	8.77	0.250	10.77
Encouraging Short Work Weeks (λ_8)	0.234	9.14	0.230	7.67
Transport Problems Evaluation				
Traffic Congestion (λ_9)	0.365	12.01	0.355	13.20
Traffic Noise (λ_{10})	0.575	19.17	0.569	18.28
Poor Local Air Quality (λ_{11})	0.649	23.26	0.655	15.04
Accidents Caused by Bad Drivers (λ_{12})	0.313	11.99	0.305	8.71
Emissions & Global Warming (λ_{13})	0.445	17.32	0.446	9.32
Speeding Drivers in Neighborhoods (λ_{14})	0.472	18.02	0.466	13.57

Table 5: Measurement Model

As explained previously, this model measures the effect of the latent variable on each indicator. While indicator variables permit identification of the latent variables and provide efficiency in estimating the choice model with latent variables (indicators add information content), at the same time some interesting conclusions can be drawn from the estimations. For instance, the effect of environmental concern EC on the indicator related to the support of *expanding and upgrading roads* is negative. This sign reflects the idea that environmentally-conscious consumers negatively perceived the priority given to cars by policies aimed at raising road capacity because of the negative impact on the environment. Expansion of the road network is not environmentally sustainable for city development, and our results show that green consumers are aware of this problem.

In addition, we see that the effect of environmental concern EC on the indicator related to support for applying road tolls and gas taxes is positive, indicating a perceived positive environmental impact of measures allowing for a presumably more rational use of private vehicles. A similar analysis can be done for the remaining indicator variables – all of them with a significant positive impact – with the corresponding effect of encouraging sustainable transport. For example, the positive sign of the effect of EC on support for reducing vehicle emissions with regular testing and manufacturer emission standards; the perception of poor local air quality motivating the adoption of green vehicles; and the encouragement of the expansion of the bicycle path network.

Note that according to the results *poor local air quality* is a major problem (respondents' opinions about this issue in our model weigh higher than other transport problems). At the same time, the variable *road tolls and gas taxes* has the highest weight among transport policies. Considering both results we can identify carbon pricing as an efficient instrument to encourage the adoption of low-emission vehicles.

We can also see that the effect of other indicators that may seem conceptually unrelated to environmental preferences do not have lower coefficients when compared to more traditional indicators. For instance, the correlation between EC and *speeding drivers in neighborhoods*, clearly a concept related to safety, is almost the same as the correlation between EC and concerns about *emissions and global warming*. Even though the alternatives in our model are differentiated by their impacts on the natural environment, as we mentioned earlier, the EC latent variable reflects concerns about the adverse effects of personal transportation on both the natural (e.g. *emissions and global warming*) and the mobility (e.g. *speeding drivers in neighborhoods*) environments. Other concepts affect both, such as *traffic congestion* (reflecting indiscriminate car use with corresponding externalities such as higher emission levels produced at low speeds), *noise* (that can be viewed as an externality of traffic congestion), *promoting compact communities* (implying reduced distances and therefore less emissions) and *encouraging short work weeks* (through a reduction of transportation needs). The derived correlation structure is a posterior justification of the unidimensionality of the EC variable.

In sum, using real data about virtual personal vehicle choices we have shown that HCM is genuinely capable of adapting to practical situations. HCM combines the direct effect of environment-related underlying latent variables on the private vehicle choice probabilities with the socio-demographic characteristics of the consumers that enter the choice probabilities through the environmental concern latent variable. HCM also takes into account opinions and attitudes through the consumer's response to attitudinal environment-related rating exercises. Finally, these responses are taken as indicators of the environmental concern latent variable.

4.4 Forecasting

For forecasting, we have to consider the results of both the discrete choice kernel and the structural model. The choice model explains behavior and the structural model not only serves to build clusters of consumers, but also to predict values of the unobserved EC variable necessary for the choice model. This prediction can be done through the measurement model, which provides the necessary indicators for identification of the latent variable. Once the structural model is estimated, for forecasting there is no need for the latent variable measurement model.

Forecasting with discrete choice models is a question of consumers' trade-offs produced by changes in the values of the attributes. The first step in understanding these trade-offs is to derive willingness to pay (WTP) values from the estimates of the discrete choice kernel. Although the parameters associated with each attribute in the discrete choice kernel represent marginal utilities, since the utility function is only ordinal (i.e. not ratio-scaled) it is hard to interpret the estimates of the model. However, the ratios of the parameters represent marginal rates of substitution that provide information about the trade-offs being made. For instance, WTPs correspond to marginal rates of substitution of some characteristics and price, in this case how much additional money the consumer is willing to pay to purchase a particular car given the increase (decrease) of an attribute that provides a higher (dis-)utility level while keeping the same level of satisfaction. In Table 6 we report the WTPs obtained from the model. A negative sign represents the amount of money [CAD/10000] that the consumer is willing to pay for the increase of one unit of an attribute that raises the general utility level, while a positive sign indicates the expected reduction in price for the increase of an attribute that decreases the utility level (or the willingness to pay for a reduction in one unit of that particular attribute).

WTP [CAD/10000-unit]	mean	s.e.	**Quantiles** 2.5%	5%	50%	95%	97.5%
Fuel Cost	1.018	0.42	0.45	0.53	0.96	1.72	2.00
Fuel Availability	-1.660	0.59	-3.01	-2.63	-1.56	-1.02	-0.92
Express lane access	-0.189	0.11	-0.44	-0.37	-0.18	-0.05	-0.02
Power	-3.258	1.35	-6.39	-5.43	-3.08	-1.63	-1.35
Latent Variables							
EC on AFV	-0.701	0.32	-1.42	-1.21	-0.66	-0.33	-0.27
EC on HEV	-0.492	0.19	-0.97	-0.82	-0.46	-0.27	-0.23
EC on HFC	-0.807	0.29	-1.49	-1.29	-0.76	-0.50	-0.45

Table 6: Willingness to pay - Bayesian Quantiles

For instance, on average a consumer is willing to pay \$166 for an increase of 1% of the service network density (cf. Achtnicht et al., 2008). Note that we are presenting not only the mean WTPs but also the WTPs' standard deviations and quantile estimates. The distribution of the WTPs is a direct result of Bayesian estimation, whereas the estimation of confidence intervals for WTP is particularly tricky when using classical techniques (Armstrong et al., 2001).

An interesting exercise is to derive the capital-cost equivalency from the results of the WTPs, i.e. how much (or less) of each attribute would be equal to an increase of $1000 in purchase price (see Table 7, where we also present the original equivalencies based on the MNL results by Horne, 2003). According to our results, if the cost of fuel is reduced in $9.82 per month, the consumer is willing to buy a new vehicle costing $1000 more. This measures a trade-off that is important for policy making: a reduction in taxes on alternative fuels (or an increase in taxes on fossil fuels) can compensate for higher prices of green technologies.

WTP [CAD/10000-unit]	Change equal to 1000 CAD increase in capital cost	
	HCM	Horne et al. (2005)
Fuel Cost	-9.82 [CAD/month]	-19.59 [CAD/month]
Fuel Availability	6.02%	8.00%
Express lane access	53.00%	56.00%
Power	3.07%	4.00%

Table 7: Capital-cost equivalency for vehicle attributes

Since the measurement scale for the EC latent variable is unknown, it is hard to interpret the values obtained for WTPs related to environmental preferences. However, from the Bayesian estimates we can describe the density function for EC. For instance, EC has a mean of 2.687 [units], a standard deviation equal to 0.908, and maximum and minimum values equal to 4.891 and -0.017, respectively. In addition, we can compare the different degrees of EC given by the different clusters obtained in the structural model. Women are more environmentally concerned than men; the mean value of EC for women is 2.816, while it is equal to 2.513 for men. Using the WTPs obtained from the model, this difference implies that on average women are willing to pay more for green technologies than men are. In Table 8 we show the derived average marginal WTPs for women and drive-alone commuters (the latter showing a environmentally indifference tendency according to our model). For example, women are willing to pay $2440 more than men for an HFC vehicle. Drive-alone commuters are willing to pay $2486 less for an AFV than commuters who carpool or do not use private vehicles.

Green Vehicles	Average marginal **WTP**	
	Women (vs men)	Drive-alone travelers (vs non-drive-alone users)
AFV	2119 [CAD]	-2486 [CAD]
HEV	1487 [CAD]	-1745 [CAD]
HFC	2440 [CAD]	-2862 [CAD]

Table 8: Average marginal willingness to pay for low-emission vehicles

Finally, we simulate the impact of different policies. It is important to mention first that the experimental market shares obtained from the survey differ from current conditions in the automotive market (see Horne et al., 2005). In fact, actual market shares show that green vehicles still have a small penetration. HFC technologies have not even been introduced into the market yet. Thus, the hypothetical market conditions for the baseline scenario can be interpreted as a future market where green technologies have been introduced and where the attributes for the different alternatives have reached levels comparable to those considered in the experimental design. We consider the following scenarios:

- *Baseline scenario*: experimental situation presented in the survey.
- *Scenario 1*: 100% fueling network density for every alternative.
- *Scenario 2*: 25% increase in fueling network density for green vehicles.
- *Scenario 3*: 25% tax on fossil fuel costs.
- *Scenario 4*: 10% reduction in purchase price for green vehicles.
- *Scenario 5*: 50% increase in purchase price for new technologies (HEV and HFC).
- *Scenario 6*: Augmentation in EC equal to its mean value.
- *Scenario 7*: Baseline considering only women.

Whereas in the case of classical estimation extra simulation of the choice probabilities is required in forecasting, when using Bayesian techniques we make use of the sample of draws generated by the Gibbs sampler for estimating the model. (The Gibbs sampler generates simulations from the unconditional posterior distribution for the parameters.) For each draw a predicted policy outcome is calculated; what we obtain is a sample of simulations for the predictive distribution of the effects of each scenario (Bolduc et al., 1997). From the sample of draws for each policy simulation we obtain the point estimates – the predicted average market share for each scenario – with standard deviations provided in Table 9.

First, the baseline scenario (simulated market shares) replicates the known market shares of the SP experiment: this can be statistically assessed through the Chi-squared index $\chi^2 = 4.63 < \chi^2_{c,(95\%,3)} = 7.815$ (Gunn and Bates, 1982).

Limited fuel availability for green vehicles is an important concern for consumers (Brownstone et al., 1996; Potoglou and Kanaroglou, 2007). Scenario 1 represents an ideal situation where the fueling station network is expanded to its maximum (set by the SGV fueling network). In this context, important differences in the market shares are obtained. AFVs and HFCs are the alternatives that benefit from the increase in fuel availability (the increase being in the range of 25%-75%) and the model predicts that the market shares of both alternatives would increase significantly to the extent that the market shares of both SGVs and HEVs decline (hybrid vehicles share the same network as SGVs). Because Scenario 1 represents an extreme situation, we simulate scenario 2 where the fueling network for alternative fuels is expanded by 25%. Both scenarios show that green

	Market Shares			
	SGV	AFV	HEV	HFC
Observed	11.35%	3.73%	48.85%	36.07%
Baseline	12.88%	3.75%	48.45%	34.92%
s.d.	0.73%	0.44%	1.13%	1.07%
Scenario 1: 100% fuel net	9.53%	5.16%	35.32%	49.99%
s.d.	0.69%	0.62%	1.98%	2.25%
Percent Change	-25.95%	37.41%	-27.10%	43.14%
Scenario 2: ↑ 25% fuel net for AFV & HFC	10.62%	4.30%	45.31%	39.80%
s.d.	0.74%	0.52%	1.23%	1.33%
Percent Change	-17.55%	14.67%	-6.48%	13.97%
Scenario 3: 25% tax on fossil fuel	11.80%	4.10%	46.13%	37.97%
s.d.	0.72%	0.52%	1.48%	1.59%
Percent Change	-8.32%	9.17%	-4.78%	8.72%
Scenario 4: ↓ 10% price of green vehicles	11.41%	3.79%	49.26%	35.55%
s.d.	0.75%	0.45%	1.15%	1.09%
Percent Change	-11.42%	0.92%	1.67%	1.79%
Scenario 5: ↑ 50% price of HEV & HFC	20.67%	6.20%	41.73%	31.41%
s.d.	3.33%	1.48%	2.88%	1.93%
Percent Change	60.53%	65.14%	-13.88%	-10.07%
Scenario 6: Social marketing campaign	3.87%	6.01%	41.65%	48.46%
s.d.	0.77%	1.47%	3.01%	3.19%
Percent Change	-69.97%	60.29%	-14.03%	38.78%
Base (women)	12.08%	3.90%	48.55%	35.47%
s.d.	0.71%	0.46%	1.15%	1.09%
Percent Change	-6.16%	3.98%	0.20%	1.57%

Table 9: Policy Scenarios - Predicted Market Shares

alternatives become more attractive to consumers when the fueling infrastructure is competitive (Achtnicht et al., 2008).

Because of the environmental externalities caused by gasoline consumption, carbon pricing is increasingly considered by policy makers as a valid instrument to reduce oil dependency and as an appropriate response to deal with the problems causing global warming (Bento et al., 2009). Scenario 3 considers an augmentation in fossil fuel costs by 25%, simulating the impact of a gas tax policy – which is equivalent to a carbon emission tax. As expected, both SGVs and HEVs reduce their market shares. The impact of the fuel tax is higher for SGVs (a reduction equivalent to 8.32% compared to 4.78% for HEVs), simply because hybrid vehicles require less fuel than standard vehicles do.

To encourage the adoption of new automobile technologies, certain Canadian provinces are considering providing tax incentives for buyers of low-emission vehicles. The impact of such a policy can be measured by reducing the purchase price of the green alternatives (scenario 4). A reduction by 10% of the capital cost of clean vehicles implies a reduction by 11.42% in the market share of SGVs. The resulting market share gains are bigger for HEVs, but small overall. According to Horne (2003), the attribute levels for the low-emission vehicles were set in the survey to values that seem particularly attractive, especially when compared with the actual market conditions. Thus we construct scenario 5, where we consider less attractive purchase prices for the most expensive technologies, namely HEVs and HFCs. The market shares of SGVs and AFVs rise dramatically; the overall penetration of green vehicles is however still high.

The previous scenarios can all be studied using standard discrete choice models (although the results will vary because of different ASCs and potentially different parameters). The innovation of our model results from incorporating environmental concerns through the latent construct EC. As discussed above, even though we do not know the measurement scale of the EC variable, once the model is estimated we can describe its distribution. EC reflects environmental preferences, and the higher its level the more likely consumers are to choose a low-emission vehicle. Scenario 6 seeks to represent a situation where through a social marketing campaign, environmentally unaware consumers are exposed to information on the benefits of reducing carbon emissions and the problems associated with the indiscriminate use of private cars (especially when using fossil fuels). Technically, this scenario is constructed by censoring the density function of the EC variable: all consumers are constrained to have an EC level at least equal to the mean of the EC variable. In practical terms, the information campaign has successfully changed the concerns of the formerly environmentally unaware consumers. The impact of this simulated campaign is huge, reducing by 69.97% the number of consumers who decide to buy an SGV. In line with the magnitude of the estimated parameters for EC, the augmentation of the market shares is bigger for AFVs and HEVs.

The last scenario is built by considering the baseline but for female consumers only, making it easier to interpret the effect of the EC variable. (Note however that this is not a ceteris paribus analysis.) Our results show that women are more environmentally aware (they constitute a cluster of consumers with a higher level of EC), and so the expected result will be that women favor more low-emission vehicles. Even though the results here are not striking, the predicted market shares do show an increase in favor of green technologies.

5 Conclusions

Our paper has two main contributions. The first is the Bayesian simultaneous estimation approach to Hybrid Choice models. The second is the empirical application that not only proves that our method works in practice but also provides an interesting analysis of pro-environmental preferences toward low-emission vehicles. Our specification is consistent with the reemerged trend in discrete choice modeling toward incorporating perceptual/attitudinal factors into the behavioral representation of the decision process, specifically using simultaneous estimation techniques. Our paper demonstrates the practical feasibility of the Gibbs sampler we developed for HCM estimation, exploiting data augmentation techniques for the latent variables. To our knowledge, this is the first empirical application of the HCM Gibbs sampler. Whereas Gibbs sampling for a probit kernel is analytically straightforward because it also admits the use of data augmentation, in the case of both a multinomial logit (MNL) kernel and a mixed logit (MMNL) kernel one fails to find a closed form full conditional distribution for the taste parameters of the utility function. However, we explain that it is possible to exploit Metropolis-Hastings (MH) methods for both the MNL and MMNL cases. In fact, our numerical application involves an MNL kernel. Even though the probit kernel formulation breaks down the methodological complexity of the model, the data augmentation step for the utility function is very demanding in computational terms, and eventually could be outperformed by a logit-based kernel – even with the additional MH step required by logit models. In general, classical estimation of HCMs is very demanding in situations with a large number of latent variables – each additional latent variable sums another dimension in the joint choice probability. Thus, Bayesian HCM estimation has the potential to outperform simulated maximum likelihood in the sense that the inclusion of additional latent variables under the Bayesian approach implies simply working with ordinary regressions (i.e. sampling additional draws from a normal distribution). Another advantage of the Bayesian approach is that it allows us to forecast using the same sample generated for estimation. In fact, the Bayesian estimates describe the posterior distribution, permitting a direct calculation of standard deviations for both the choice probabilities and market shares as well as Bayes confidence intervals for WTPs. Bayes confidence intervals work for small samples because the intervals are not based on asymptotic theory.

The HCM formulation offers an attractive improvement in modeling private vehicle choice behavior. In HCMs the choice model is only a part of the whole behavioral process in which we now incorporate individual attitudes, opinions and perceptions, thus yielding a more realistic econometric model. This improved representation outperforms standard discrete choice models because now we can simultaneously build a profile of Canadian consumers and their ability to adapt to technological innovation with regard to sustainable private vehicle alternatives. Indeed, a latent environmental concern EC – related to the perceived adverse effects of personal transportation on both the natural and mobility environments – enters very significantly and positively in the discrete choice kernel of our model, thus favoring the adoption of green automobile technologies through a positive impact in the choice probabilities.

After estimating the model using the Gibbs sampler we developed, we can summarize some of our practical results: ECs are more important for public transportation users than for car pool users; car drivers may be indifferent to the environmentally adverse effects of private car use; concern about environmental issues are more developed in women, older people and more educated people; environmentally-conscious consumers negatively perceive car priority resulting from policies of raising road capacity, and hence there is a perceived positive environmental impact of measures allowing a rational use of private vehicles as well as a measurable positive effect of encouraging sustainable transport. Whereas the discrete choice kernel and the structural model can be used for policy simulations, as we have shown, the measurement model helps us infer which policies can be more effective in encouraging the adoption of green technologies. For instance, our results support fossil fuel taxation: the composite *road tolls and a tax on vehicle carbon emissions* is the transport policy that shows the highest correlation level with the EC variable. If fuel taxes are applied, our policy simulation consistently predicts deeper market penetration for low-emission vehicles.

Further research is needed to generalize the HCM Gibbs sampler we developed in this paper. By testing the general HCM Gibbs sampler, we expect to analyze the impact of different discrete choice kernel formulations and to determine when Bayesian MCMC outperforms classical simulated maximum likelihood according to empirical results based on correct identification restrictions and accurate predictions.

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Appendix A: Variable description

In the following tables we give the details of the different components of the vectors of equations 1, 2, 3 and 4.

Variable	Description
U_{SGV}	Utility associated with a Standard Gas Vehicle (SGV)
U_{AFV}	Utility associated with an Alternative Fuel Vehicle (AFV)
U_{HEV}	Utility associated with a Hybrid Electric Vehicle (HEV)
U_{HFC}	Utility associated with a Hydrogen Fuel Cell vehicle (HFC)
EC	Environmental Concern latent variable
I_1	Expanding & Upgrading Roads - Support Indicator
I_2	Road Tolls & Gas Taxes - Support Indicator
I_3	Bike Lanes & Speed Controls - Support Indicator
I_4	Reducing Car Emissions - Support Indicator
I_5	High Occupancy Vehicles & Transit Priorities - Support Indicator
I_6	Improving Transit Service - Support Indicator
I_7	Promoting Compact Communities - Support Indicator
I_8	Encouraging Short Work Weeks - Support Indicator
I_9	Traffic Congestion - Evaluation Indicator
I_{10}	Traffic Noise - Evaluation Indicator
I_{11}	Poor Local Air Quality - Evaluation Indicator
I_{12}	Accidents Caused by Bad Drivers - Evaluation Indicator
I_{13}	Emissions & Global Warming - Evaluation Indicator
I_{14}	Speeding Drivers in Neighborhoods - Evaluation Indicator

Table 10: Dependent Variables

Parameter	Variable	Description
b_1	w_1	Intercept
b_2	w_2	Driving Alone User
b_3	w_3	Car Pool User
b_4	w_4	Transit User
b_5	w_5	Female Indicator
b_6	w_6	High Income Indicator (>80K$)
b_7	w_7	Education: University
b_8	w_8	Age level: 26-40 years
b_9	w_9	Age level: 41-55 years
b_{10}	w_{10}	Age level: 56 years & more
ASC_{AFV}	$X_{AFV,1}$	Alternative Fuel Vehicle (AFV) constant
ASC_{HEV}	$X_{SGV,2}$	Hybrid Electric Vehicle (HEV) constant
ASC_{HFC}	$X_{SGV,3}$	Hydrogen Fuel Cell Vehicle (HFC) constant
β_1	$X_{\cdot,4}$	Purchase Price
β_2	$X_{\cdot,5}$	Fuel Cost
β_3	$X_{\cdot,6}$	Fuel Availability
β_4	$X_{\cdot,7}$	Express lane access
β_5	$X_{\cdot,8}$	Power
$\Gamma_{AFV,\mathrm{EC}}$	EC	EC effect on AFV
$\Gamma_{HEV,\mathrm{EC}}$	EC	EC effect on HEV
$\Gamma_{HFC,\mathrm{EC}}$	EC	EC effect on HFC
λ_1	EC	EC effect on Expanding & Upgrading Roads
λ_2	EC	EC effect on Road Tolls & Gas Taxes
λ_3	EC	EC effect on Bike Lanes & Speed Controls
λ_4	EC	EC effect on Reducing Car Emissions
λ_5	EC	EC effect on High Occupancy Vehicles & Transit Priorities
λ_6	EC	EC effect on Improving Transit Service
λ_7	EC	EC effect on Promoting Compact Communities
λ_8	EC	EC effect on Encouraging Short Work Weeks
λ_9	EC	EC effect on Traffic Congestion
λ_{10}	EC	EC effect on Traffic Noise
λ_{11}	EC	EC effect on Poor Local Air Quality
λ_{12}	EC	EC effect on Accidents Caused by Bad Drivers
λ_{13}	EC	EC effect on Emissions & Global Warming
λ_{14}	EC	EC effect on Speeding Drivers in Neighborhoods

Table 11: Independent Variables and Parameters

Appendix B: Posterior distributions and MCMC sequences

Figure 3: Posterior distribution of selected parameters

Figure 4: MCMC sequence of selected parameters

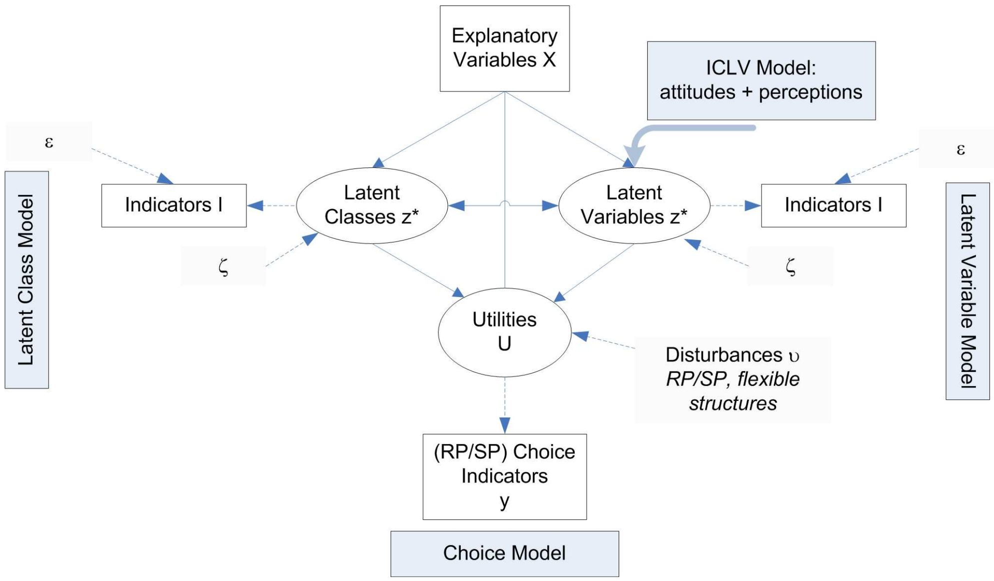

Figure 1: Hybrid Choice Model
175x100mm (300 x 300 DPI)

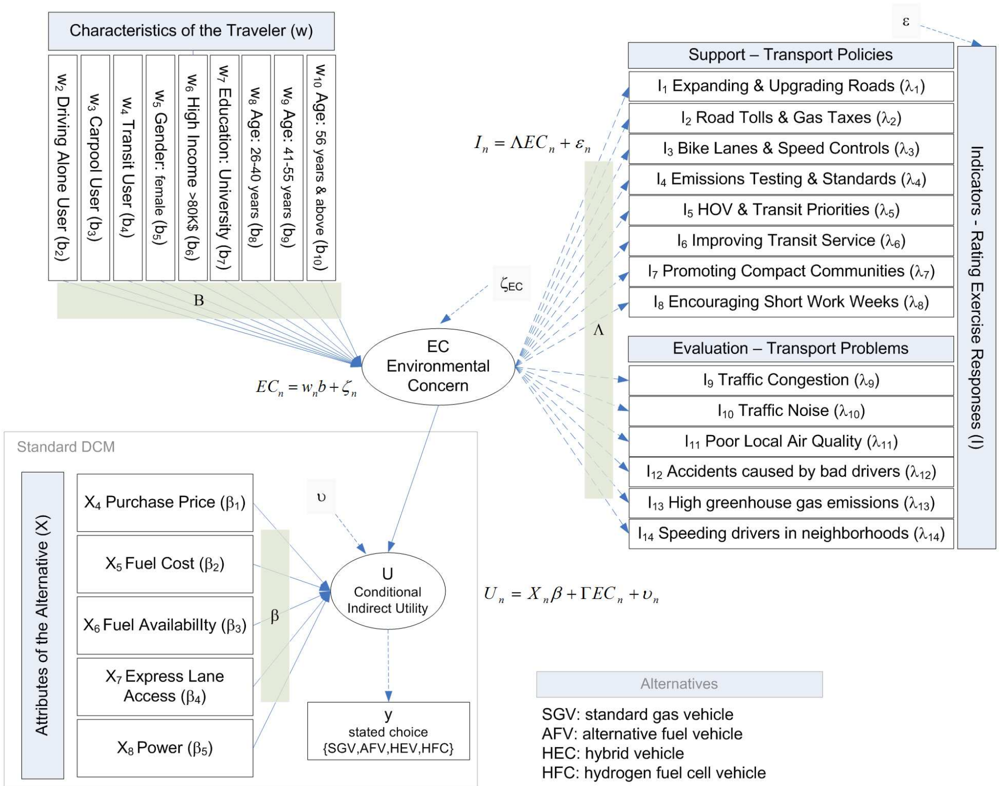

Figure 2: Private vehicle purchase HCM
165x129mm (300 x 300 DPI)

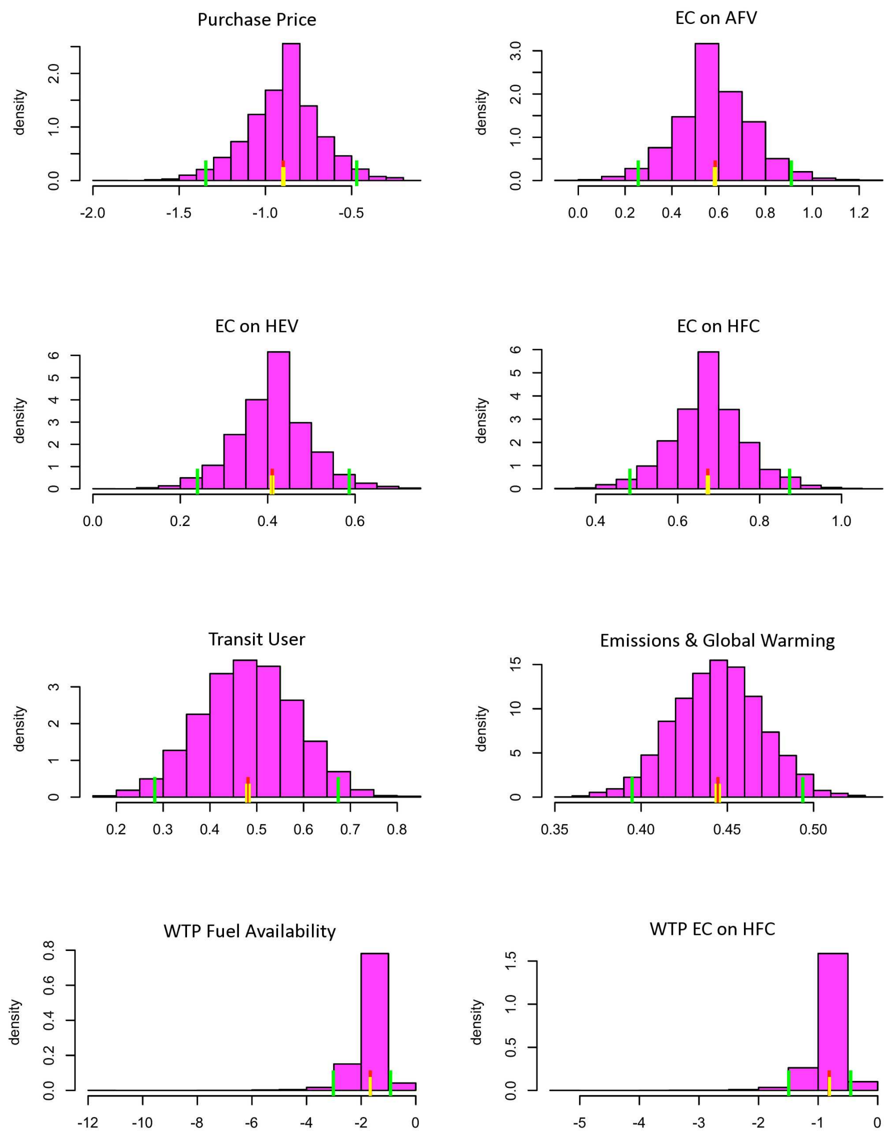

Figure 3: Posterior distribution of selected parameters
174x230mm (300 x 300 DPI)

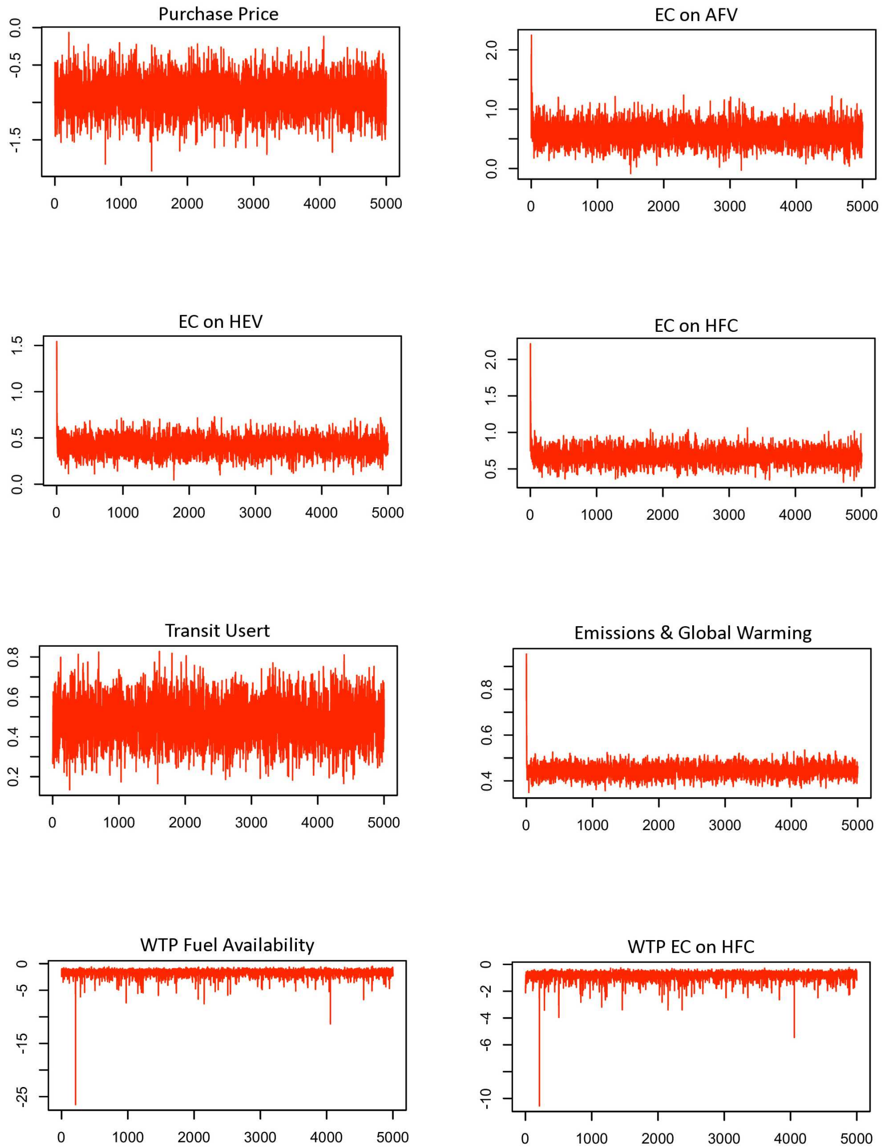

Figure 4: MCMC sequence of selected parameters
173x228mm (300 x 300 DPI)