CONSUMER PREFERENCES AND WILLINGNESS TO PAY FOR ADVANCED VEHICLE TECHNOLOGY OPTIONS AND FUEL TYPES

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ABSTRACT
The automotive industry is witnessing a revolution with the advent of advanced vehicular technologies, smart vehicle options, and fuel alternatives. However, there is very limited research on consumer preferences for these types of vehicles. But the deployment and penetration of advanced vehicular technologies in the marketplace, and planning for possible market adoption scenarios, calls for collection and analysis of consumer preference data related to these emerging technologies. This study aims to address this gap, offering a detailed analysis of consumer preference for alternative fuel types and technology options using data collected in choice experiments conducted on a sample of consumers in South Korea. The results indicate that there is considerable heterogeneity in consumer preferences for various smart technology options such as wireless internet, vehicle connectivity, and voice command features, but relatively little heterogeneity in the preference for smart vehicle applications such as real-time traveler information on parking and traffic conditions.

Keywords: smart vehicle; advanced vehicular technology; consumer preference; willingness to pay; multiple discrete-continuous probit; mixed multinomial probit.

1. INTRODUCTION

The automotive industry is going through a period of rapid change (CAR, 2010). In the past few years, automobile manufacturers and technology developers have been moving rapidly to develop advanced vehicular technologies, smart vehicle options, and alternative fuel types that are cleaner and greener in terms of their carbon footprint. In addition to moving forward with the deployment of alternative fuel vehicles (such as hybrid, electric, natural gas, and hydrogen vehicles), many auto manufacturers are teaming up with technology providers to enhance the driving experience, both from a safety and a convenience perspective (Kirk, 2011; NIPA, 2013). Toyota is teaming up with Microsoft for the development of cloud telematics, and with RIM to offer a multimedia platform in vehicles that is compatible with both Android and Apple phones. Ford has teamed up with Microsoft to provide consumers the "SYNC" telematics platforms in select Ford vehicles and developed the "Hohm" application that provides information about electric power usage in Ford electric cars. General Motors has teamed up with Google to install the Android operating system in electric vehicles, and with Verizon to provide internet-based multimedia service in the GM OnStar platform. Likewise, Hyundai is collaborating with Samsung and Korea Telecom, and BMW is working in tandem with Vodafone, to develop communication modules and multimedia platforms in their respective vehicles (BusinessKorea, 2013). In the meantime, Google and a number of other auto manufacturers are moving forward with the development of self-driving or autonomous driving systems using a number of sensor-based systems (USA Today, 2012).

Technology development, obviously, is occurring at a rapid pace, but there remains considerable debate about consumer preferences and willingness to pay for these emerging vehicular technologies and smart vehicle options. The rate at which these technologies, features, and fuel types penetrate into the market depends on whether consumers are interested in and willing to pay for these technologies and options. There are many potential benefits that advanced vehicular features and fuel types can offer. Sensor-based intelligent/autonomous driving systems can virtually eliminate human error, the primary contributing factor for highway crashes (Nelson, 2014). Multimedia platforms, when combined with intelligent and autonomous driving systems, could make the time in the vehicle more productive and enjoyable as vehicle occupants are able to multitask during the trip. Alternative fuel types offer energy and environmental benefits in terms of a smaller carbon footprint. Advanced communication systems embedded in automobiles could lead to more efficient vehicular navigation and traffic flow, resulting in decreased congestion and elimination of critical bottlenecks (Kraan et al, 2000).

The planning community is grappling with trying to understand the implications of the advent of these technologies, smart vehicle options, and alternative fuel types in the marketplace. To effectively forecast and plan for the adoption of these technologies and options by consumers, there needs to be a greater understanding of consumer preferences and willingness to pay for these technology options. This paper aims to address this gap in the literature by modeling consumer preferences and willingness to pay for smart vehicular options and applications using a stated choice data set collected from a sample of individuals in South Korea. As these options have not yet made their way into the marketplace in any significant way, typical revealed preference travel survey data will not include information on consumer preferences and willingness to pay for these emerging technologies and options. The use of stated choice experiments for understanding consumer preferences, adoption, and willingness to pay is well established in the field of transportation and choice modeling (Rose et al, 2009).

The analysis presented in this paper consists of two parts. First, this study analyzes consumer preferences for smart technology options and alternative fuel types using the multiple discrete-continuous probit (MDCP) model. The MDCP model is ideally suited for this modeling effort due to its ability to (1) accommodate consumer choices of multiple smart technology options simultaneously (multiple discreteness), (2) capture both the discrete choice and continuous usage dimensions embedded in consumer preferences, and (3) account for correlated unobserved factors that may affect these dimensions. Within this paper, differences in preferences across socio-economic groups defined by age, income, and driving status are explored. Second, the study analyzes consumer willingness to pay (WTP) for smart options and technologies through the use of the mixed multinomial probit model (MMNP). This model offers the ability to account for heterogeneity in consumer preferences while relaxing the assumption of independence from irrelevant alternatives (IIA) that characterizes the logit-based discrete choice model formulations.

The remainder of this paper is organized as follows. The next section offers a brief discussion about emerging vehicular technologies, fuels, and options and recent work on modeling consumer adoption of these entities. The third section presents the modeling methods used in this paper while the fourth section offers a description of the survey data set. Results of model estimation are provided in the fifth section, and conclusions and directions for future research are presented in the sixth and final section.

2. EMERGING VEHICULAR TECHNOLOGIES

The phrase "emerging vehicular technologies" refers to an array of intelligent navigation and safety systems, fuel options, communications devices, and multimedia platforms that are under development or finding their way into the marketplace. All of these options are intended to make the vehicle "smarter" and the term "smart vehicle" is used in this paper to reflect this array of technology and fuel options that are the focus of the emerging automotive revolution. To provide some clarity on the options considered in this paper, this section offers a definition of these terms in light of the emerging convergence of automotive technology and information technology, and defines the label "smart vehicle" as used in this study.

As noted by Kirk (2011), emerging automotive technology features mobile device connectivity and enables vehicle-to-vehicle communication and vehicle-to-infrastructure communication, resulting in the notion of *connected vehicles*. The connected vehicle offers the ability to perform various tasks and provides services on-the-go via mobile Wi-Fi. The *infotainment systems* that have recently appeared in some vehicle models combine information and entertainment, allowing users to connect to in-vehicle entertainment and multimedia systems. The infotainment systems may be included in vehicles regardless of whether they are connected vehicles. The recently launched in-car application suites Ford SYNC, MyFord Touch, Toyota Entune, and Kia Motors UVO include these infotainment features (although the vehicles themselves are not "connected"). The *autonomous vehicle*, currently being developed by Google and several automobile manufacturers, relies more heavily on advanced control and sensor systems, as the vehicle drives itself to the user-specified destination. Unlike connected vehicles which utilize an array of communications systems (such as cellular communication) to facilitate transmission and exchange of information across vehicles and between vehicles and infrastructure, autonomous vehicles focus on the use of sensor-based systems so that the vehicle can independently and safely navigate through the network using such technology as GPS, radar, laser, and computer vision.

This study defines a *smart vehicle* as an extension of the concept of a connected vehicle – a human-friendly, internet-connected car that can transport passengers safely and conveniently in real-time, real-world conditions. Therefore, this definition is all-encompassing, including the function of an autonomous car in terms of safety and convenience, as well as the provision of an infotainment system that offers a variety of accessible content.

There has been considerable research into modeling consumer choice of vehicle types, particularly in the context of the emergence of hybrid and electric vehicles in the marketplace (e.g., Bhat and Sen, 2006; Bunch et al, 1993; Ewing and Sarigollu, 2000; Shin et al., 2012; van Rijnsoever et al, 2013). Ewing and Sarigollu (2000) used a multinomial logit model to analyze consumer preferences for clean-fuel vehicles, such as electric cars, and used the estimation results to analyze changes in consumer demand in response to changes in purchase price, vehicle attributes, and government policies. van Rijnsoever et al (2013) used an ordinal logit model to analyze consumer preference for alternative fuel vehicles (AFVs), such as those relying on electricity, fuel cells, and biogas. However, these studies do not fully reflect behavioral choice processes at play because the structure of the logit model does not allow for the choice of multiple technology options simultaneously, and does not account for correlation in unobserved factors that affect multiple choice alternatives as well as heterogeneity in consumer preferences. More generally, despite the rapid evolution of technology and potential consumer interest in smart vehicle options, there is very limited research on consumer preferences for emerging vehicular technologies. In an effort to fill this gap, this study uses the multiple discrete continuous probit (MDCP) modeling methodology to analyze consumer behavior in terms of both the choice (discrete component) and usage (continuous component) of vehicles equipped with smart options and fueled by alternative sources. In addition, using the mixed multinomial probit (MMNP) model, which explicitly considers consumer heterogeneity while relaxing the IIA assumption, this study presents an analysis of consumer willingness to pay (WTP) and the relative importance of various smart vehicle technology options. Through the analysis of consumer preferences for vehicle technology and fuel options, the study aims to offer insights into how these technologies may find their way into the marketplace and the resulting planning implications.

3. MODEL STRUCTURE AND METHODOLOGY

This section provides an overview of the modeling methodology employed in this paper.

3.1 The Multiple Discrete-Continuous Probit (MDCP) Model

The multivariate logit model and multivariate probit model (Baltas, 2004; Edwards and Allenby, 2003) are approaches that may be considered for modeling multiple discrete choice situations (i.e., where individuals are exercising multiple choices as opposed to a single discrete choice). However, these models are not able to capture the additional utility derived from usage of the chosen alternatives. In contrast, the multiple discrete continuous extreme value (MDCEV) model proposed by Bhat (2005; 2008) is able to consider multiple discrete choice behavior and continuous product usage simultaneously. However, the MDCEV model does not accommodate for correlated unobserved factors that may affect the choice of multiple alternatives. To overcome this limitation of the MDCEV model, the MDCP model is used in this study.

The MDCP model can be used to both consider multiple discrete choice behavior and analyze additional utility derived from usage of the chosen alternatives, while accounting for correlation in unobserved factors. Additional utility derived from the continuous usage dimension follows the law of diminishing marginal utility of consumption, which implies that marginal utility gradually decreases as usage increases. In the MDCP model, let the i^{th} consumer choose from among K alternatives and consume m_k units of each of the K alternatives. The utility for the i^{th} consumer is represented as follows:

$$U(m_1, m_2, ...m_K) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \Psi(\boldsymbol{x}_k) \left(\left(\frac{m_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right) \quad (1)$$

In Equation (1), K represents the number of alternatives that exist in the choice set. $\Psi(\boldsymbol{x}_k)$ represents the baseline utility for the k^{th} alternative, $\boldsymbol{x}_k$ represents the attributes that affect the utility of the k^{th} alternative, and m_k is the amount of usage (consumption) of the k^{th} alternative (which is equal to zero for non-consumed (non-chosen) alternatives). γ_k is a parameter to determine whether an interior or corner solution will be found. If $\gamma_k \neq 0$, a corner solution can exist because the k^{th} alternative may not be chosen. However, if $\gamma_k = 0$ for all k, an interior solution always exists because usage of all alternatives is greater than zero (Bhat, 2005). α_k is a satiation parameter that implies the degree of diminishing marginal utility. To satisfy the law of diminishing marginal utility, α_k has a value below unity. For this reason, α_k is reparameterized as $\alpha_k = [1 - \exp(-\delta_k)]$ (Bhat, 2008).

The baseline utility, $\Psi(\boldsymbol{x}_k)$, is defined as an exponential function to ensure non-negativity, resulting in the following formulation for the overall random utility:

$$U(m_1, m_2, ...m_K) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \exp(\boldsymbol{\beta}'\boldsymbol{x}_k + \varepsilon_k) \left(\left(\frac{m_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right) \quad (2)$$

where, $\boldsymbol{\beta}$ is vector of coefficients to be estimated, and ε_k represents unobserved characteristics that affect the baseline utility. The vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ...\varepsilon_K)'$ is assumed to be multivariate normally distributed with a mean vector of zero and a covariance matrix $\boldsymbol{\Lambda}$.

Consumers choose a set of alternatives to maximize their utility subject to budget constraints. In this study, as we will discuss more later, the alternatives refer to vehicles of different fuel/body types and smart car options (available or not) that are presented to respondents in a stated preference setting. The total annual vehicle mileage is pre-specified and presented to the respondent as a budget constraint, and the respondent has the option of choosing multiple vehicles and using each chosen vehicle to different extents. That is, the total annual mileage M is defined as the budget constraint, yielding,

$$\sum_{k=1}^{K} m_k = M \quad (3)$$

where, m_k represents the mileage for the k^{th} alternative.

The constrained utility maximization problem represented by Equations (2) and (3) may be solved using the Lagrangian method and the resulting Karush-Kuhn-Tucker (KKT) conditions. Parameter estimation to satisfy the KKT conditions is accomplished in this study using the α-

profile of the maximum approximate composite marginal likelihood (MACML) approach (Bhat et al, 2013).

3.2 Mixed Multinomial Probit (MMNP) Model

The mixed multinomial probit (MMNP) model offers two key advantages over the traditional multinomial logit model. First, it relaxes the restrictive IIA assumption associated with the logit formulation and second, it accounts for heterogeneity in consumer preferences and willingness to pay. As with many discrete choice model formulation, the mixed multinomial probit (MMNP) model considers a utility function that may be divided into deterministic and unobserved stochastic parts. The utility function of the i^{th} consumer for alternative j is:

$$U_{ij} = \kappa_i' \boldsymbol{Z}_{ij} + \tilde{\eta}_{ij} \tag{4}$$

where U_{ij} is a latent utility that the i^{th} consumer derives from choosing alternative j. κ_i is an individual-specific coefficient vector on the explanatory variable vector $\boldsymbol{Z}_{ij}$. To accommodate heterogeneity in consumer preferences, κ_i is set to be a vector following a multivariate normal density function with a mean of $\boldsymbol{b}$ and a covariance matrix of $\boldsymbol{\Sigma}$. In addition, this study assumes that the off-diagonal matrix of $\boldsymbol{\Sigma}$ is zero, implying that the random coefficients are independent of one another. As the attributes in the choice experiments that yielded the data for this study were designed to be orthogonal to one another, this assumption is consistent with the nature of the data set and does not constitute a limitation in the context of this study. Similar to the formulation in Bhat and Sidharthan (2011), $\tilde{\eta}_{ij}$ represents an unobserved disturbance term with the assumption that $\tilde{\eta}_{ij}$ is independently and identically normal distributed (across alternatives and individuals) with a mean zero and a variance of one-half.

From the definitions, it is possible to express $\kappa_i = \boldsymbol{b} + \breve{\kappa}_i$, with $\breve{\kappa}_i \sim MVN(\mathbf{0}, \boldsymbol{\Sigma})$. Let $\mathbf{U}_i = [U_{i1}, U_{i2}, \cdots, U_{iJ}]'$, $\boldsymbol{Z}_i = (\boldsymbol{Z}_{i1}, \boldsymbol{Z}_{i2}, \ldots \boldsymbol{Z}_{iJ})'$ and $\tilde{\boldsymbol{\eta}}_i = [\tilde{\eta}_{i1}, \tilde{\eta}_{i2}, \cdots, \tilde{\eta}_{iJ}]'$, then Equation (4) may be rewritten as:

$$\boldsymbol{U}_i = \boldsymbol{b}'\boldsymbol{Z}_i + [\breve{\kappa}_i' \boldsymbol{Z}_i + \tilde{\boldsymbol{\eta}}_i] = \mathbf{V}_i + \boldsymbol{\eta}_i, \tag{5}$$

The likelihood function corresponding to the random coefficients model above requires the evaluation of multi-dimensional integrals. As mentioned in Bhat and Sidharthan (2011) and Bhat (2011), the multidimensional integrals can be cumbersome to evaluate in the classical Maximum Simulated Likelihood (MSL) estimation method. Therefore, this study utilizes the MACML estimation method proposed by Bhat (2011). As the MACML estimation method approximates the multidimensional integration as a series of univariate and bivariate cumulative normal distribution evaluations, it is computationally efficient. Moreover, the MACML method yields a consistent parameter estimator (Bhat and Sidharthan, 2012).

4. CHOICE EXPERIMENTS

This study uses stated preference survey data collected from a sample of 675 respondents between March and May 2012 in six metropolitan cities of South Korea: Seoul, Busan, Daegu, Inchon, Gwangju, and Daejeon. The use of stated preference data is appropriate in the context of assessing consumer preference for emerging vehicular technologies and fuel types because these options are not yet widely available in the marketplace. Revealed preference data sets do not offer insights into how individuals would choose and value emerging vehicular technology and fuel options.

Due to the targeted nature of the study, the sample for the study was chosen using a quota sampling method (considering age and gender) to reflect the characteristics of the actual population. After extensive cleaning and filtering, the final data set comprised of 633 respondents who offered complete information. The demographic characteristics of the sample are shown in Table 1. Among the 633 respondents, about 77 percent (485) have only one vehicle in their household, nine percent (57) possess two vehicles, and 14 percent (91) do not own any vehicles.

Two choice experiments were conducted to analyze consumer preferences for vehicle attributes and smart vehicle options. The first set of choice experiments focused on vehicle choice considering the attributes of fuel type, vehicle body type, fuel operating cost (won/km), purchase price of vehicle, accessibility of fueling stations, and provision of smart vehicle options. The second set of choice experiments focused more in-depth on consumer preferences for various smart options including option price, connectivity, voice command, autonomous driving features, wireless internet, and real-time information applications. Table 2 provides a description of the attributes, the attribute levels, and attribute descriptions used in the design of each set of choice experiments.

It should be noted that certain attributes are considered invariant across the alternatives presented to respondents in the choice experiments. Attributes such as engine displacement, engine size, and maintenance cost, for example, are measurable and influence consumers when it comes to vehicle choice. However, the inclusion of all attributes that affect vehicle choice would make the choice experiments complex and require respondents to consider (and trade-off) many different attributes, potentially compromising the quality and reliability of the responses. Therefore, this study uses only six attributes for each choice experiment, with the assumption that all non-considered attributes are invariant across alternatives. This assumption was explained in detail to all respondents.

Even with the limited set of attributes considered, the number of possible combinations is quite large at 4 x 2 x 3 x 4 x 3 x 2 = 576 for vehicle choice and 3 x 2 x 2 x 2 x 2 x 2 = 96 for smart option choice. As respondents cannot be expected to consider all possible combinations, this study employed a fractional factorial design maintaining orthogonality among attributes to reduce the number of scenarios. Under this design, respondents were asked to consider 24 and 16 alternatives respectively in the two sets of choice experiments (one set for vehicle type choice and one set for smart vehicle option choice). In each choice scenario, respondents were presented with four vehicle alternatives defined by six attributes set at levels according to the fractional factorial design. Six sets (choice scenarios) of four alternatives were developed for the vehicle choice experiment (and presented to each respondent, who could choose multiple alternatives in each choice scenario), and four sets (choice scenarios) of four alternatives were developed for the smart vehicle option experiment (and presented to each respondent, who could choose only one alternative in each choice scenario).

5. MODEL ESTIMATION RESULTS

This section presents model estimation results. Results are presented first for the multiple discrete-continuous probit (MDCP) model of vehicle choice, followed by results for the mixed multinomial probit (MMNP) model of smart vehicle choice and option valuation.

5.1 Multiple Discrete-Continuous Probit (MDCP) Model of Vehicle Choice

Estimation results for this model are presented in Tables 3 and 4. The results in Table 3 provide insights on overall baseline preferences without consideration of demographic attributes; in other words, the parameters in this table represent the overall preference for vehicle types all other things (such as demographics) considered equal. The gasoline vehicle is treated as the base alternative. It is found that, relative to gasoline, respondents have a significantly lower baseline preference for diesel vehicles (which may be viewed as polluting) and electric vehicles (which may be viewed as limited in range and having longer times to refuel/recharge). The baseline parameter for hybrid vehicles is positive, but statistically insignificant, suggesting that consumers have a preference for hybrid vehicles that is similar to that for gasoline vehicles. Fuel cost and purchase price are deterrents to vehicle choice. Vehicles with high accessibility of fueling stations and smart vehicle options are preferred over vehicles that do not have the same attributes.

In the choice experiment, respondents are allowed to choose multiple options (in other words, they do not have to choose a single discrete alternative from the among the four vehicle choices) and allocate the pre-specified total mileage (indicating degree of utilization) to each of the chosen vehicle alternatives. The satiation parameters shown in Table 3 provide an indication of the overall extent to which respondents would use the different vehicle types. A high parameter value indicates a low rate of satiation and hence a larger degree of utilization or consumption. In Table 3, it is found that respondents are likely to drive the electric vehicle the most, followed by the hybrid vehicle. Diesel and gasoline vehicles show a higher rate of satiation and hence a lower level of utilization. It is likely that individuals consider the electric and hybrid vehicles cleaner for the environment and more novel or fun to drive; all other things being equal, they are more prone to utilize these vehicles if chosen.

Table 4 presents estimation results considering several demographic attributes present in the data set. In this table, estimation results are provided considering all respondents together, as well as for various socio-economic groups to understand differences in consumer preferences across demographic segments. The gasoline vehicle alternative is considered the base, and the utility of other vehicle types is calculated relative to the gasoline vehicle. Considering the sample of all respondents, it is found that the hybrid vehicle type is preferred to a similar degree as the gasoline vehicle, while diesel and electric vehicles are less preferred alternatives, as signified by the significant and negative alternative specific constants on these two choice options (see the row labeled “constant” for each vehicle type in Table 4). Older individuals are less likely to prefer hybrid and electric vehicles (see the negative coefficients on the age variable for these two vehicle types in the first column of Table 4); it is likely that older individuals are less confident about these emerging vehicular options and prefer to stick with the trusted and ubiquitous gasoline and diesel vehicular types that have a long and proven track record. Respondents who consider smart vehicle applications to be useful (these include real-time traveler information applications) have a higher predisposition to choose alternative fuel vehicle types as opposed to the gasoline vehicle type (see the positive coefficients on the “application usefulness” variable for all the non-gasoline vehicle types in Table 4; the usefulness variables in Table 4 are based on questions that asked respondents to rate how useful each of “connectivity including infotainment”, “voice command”, “autonomous driving”, “wireless internet”, and “smart vehicle applications” were to them in their vehicles). It is likely that individuals who value smart vehicle applications also value adopting alternative fuel vehicle types. It is somewhat surprising to note that individuals who consider vehicle connectivity useful are less likely to adopt electric vehicles.

As expected, the fuel cost and purchase price of the vehicle (toward the bottom of Table 4 just above the satiation parameters) negatively impact vehicle type choice. The larger sport utility vehicle (SUV) is preferred over the standard sedan, presumably because the larger capacity and flexibility offered by the SUV presents benefits to the consumer. Also consistent with expectations, accessibility of fueling stations and the presence of smart vehicle options are positively associated with vehicle choice. Overall, it is found that the electric and hybrid vehicles would be used the most (if chosen), while gasoline vehicles would be utilized the least. This is indicative of the overall proclivity of individuals to drive and utilize cleaner vehicles more so than the fossil-fuel burning vehicles.

Among the sample of 633 respondents, 322 were drivers and 311 were non-drivers. The second broad column entitled "Driver/Non-Driver" in Table 4 shows that drivers generally show similar preferences across the vehicle types (gasoline, diesel, hybrid, and electric). On the other hand, non-drivers show a preference towards gasoline vehicles with significant negative alternative specific constants for all other vehicle types, presumably because non-drivers (who do not have as much experience and exposure to vehicle usage) are less familiar with alternative fuel vehicle types and would prefer to use gasoline vehicles that have a proven track record. In terms of satiation patterns (bottom of Table 4), non-drivers appear more inclined to use electric vehicles if chosen; relative to drivers, non-drivers are more inclined to consume or utilize diesel vehicles as opposed to hybrid vehicles presumably because non-drivers value the larger diesel vehicles in South Korea. In South Korea, diesel engines are primarily used in the larger vehicle categories (such as SUV and truck), and it is likely that non-drivers prefer diesel vehicles because they associate that fuel type category with the larger SUV body type which affords greater capacity and flexibility (Economic Review, 2014).

Differences in preferences were examined between high and low income groups. High income group includes 259 individuals earning 4 million or more Korean won (KRW) per month, while the low income group includes 374 individuals in households earning less than 4 million KRW per month (4 million KRW is approximately US $3890 in 2014). An examination of the alternative specific constants show that the high income group shows no systematic preferences across the vehicle fuel types; on the other hand, the low income group shows a pattern of preference that follows the sequence of gasoline, diesel, hybrid, and electric. It appears that low income respondents are inclined to choose vehicle types with a proven track record over emerging vehicles. In the low income group, individuals in larger families have a particularly higher preference for diesel vehicles over other non-gasoline vehicle types, and the higher preference for gasoline vehicles over diesel vehicles is also tempered for this group, presumably due to the low maintenance cost and higher fuel efficiency of diesel vehicles. This is further reinforced by the positive significant coefficient on the SUV variable for the low income group. In terms of satiation parameters, differences are significant between these market segments. While low income respondents generally follow the pattern of all respondents, the high income group respondents show a greater inclination to use diesel vehicles and electric vehicles and lower levels of consumption for hybrid and gasoline vehicles. The reasons for these satiation patterns are not immediately clear and warrant further investigation.

An examination of differences by age group was facilitated through the division of the sample into 294 individuals 40 years of age or older and 339 individuals younger than 40 years of age. The younger age group exhibits a negative propensity to purchase electric vehicles, possibly due to concerns about cost and range. As expected, fuel cost and purchase price negatively impact consumer preference for a vehicle while accessibility of fueling stations and availability of smart vehicle options positively impact consumer vehicle choice. Although young individuals are less likely to prefer diesel vehicles, they do show a significant preference for larger SUV body type (perhaps they prefer the gasoline or hybrid SUV as opposed to the diesel SUV) when compared with the older individuals.

Finally, the analysis included an examination of preferences by level of intended use of a smart vehicle. The sample was divided into two groups, with the high level of intended use group defined as consumers who indicated a four or higher (on a five point scale) for level of intended use of a smart vehicle (n=169). The low level of intended use group included consumers who indicated a rating of three or lower for level of intended use of a smart vehicle (n=464). An examination of the baseline constants shows that individuals in the high use group prefer hybrid vehicles and electric vehicles, and to a lesser degree diesel vehicles, over gasoline vehicles. This is presumably because they are individuals who are more willing and interested in emerging vehicular technologies and fuel types. On the other hand, the low level of intended use group prefers traditional gasoline vehicles due to their limited interest in using emerging vehicular technology and fuel options. Other variables provide indications rather similar to those seen for other demographic segments. A review of the satiation parameters shows that individuals in both groups are likely to utilize electric vehicles the most. Ranked second for the high level of use group is the diesel vehicle, while hybrid vehicle is ranked third. For the low level of smart vehicle use group, the ranking is reversed suggesting the presence of significant differences between consumers depending on their intended level of use of smart vehicles.

5.2 Mixed Multinomial Probit (MMNP) Model of Smart Vehicle Options

This section presents results of the mixed multinomial probit (MMNP) model estimation effort with a view to understanding consumer heterogeneity and willingness to pay for various smart vehicle options. The model includes various options as follows (with the variable taking a value of one if the feature is present and zero otherwise):

- Vehicle connectivity with smart devices
- Voice command capability
- Autonomous driving capability (=1 if both automotive speed control and lane keeping are possible; =0 if only automotive speed control is possible)
- Wireless internet (3G or 4G service in vehicle)
- Smart applications (e.g., real-time traveler information on parking, traffic conditions)

In the choice experiments considering smart vehicle options, respondents were asked to choose the most preferred hypothetical alternative depending on the options and their pricing of the package of options included. The model is estimated using the MACML method and results are presented in Table 5.

As expected, the parameter corresponding to the option package price has a significant negative mean value, with an insignificant standard deviation suggesting that there is virtually no consumer heterogeneity in terms of sensitivity to option package pricing. The parameters associated with various options are all positive except for the parameter associated with lane-keeping capability. It appears that individuals are positively inclined towards choosing vehicles equipped with smart options, except for the lane keeping option suggesting that consumers are reluctant to adopt lane keeping technology due to lingering safety concerns or because they do not consider such capabilities useful or valuable at this time. An examination of the standard deviations on the parameters shows that there is considerable consumer heterogeneity in terms of preferences for these options (as signified by the statistically significant standard deviations), with the exception of smart applications where the respondents appear to exhibit considerable homogeneity in their preference for such applications.

To gain further insights into consumer preferences for these options, the marginal willingness-to-pay (MWTP) is computed for each attribute. MWTP represents the amount of money required to maintain a consumer's current level of utility when one unit of an attribute is changed. In addition, based on the worth of each attribute, the relative importance (RI) of the options is computed. Under the assumption that the determinate portion of the utility (V_{nj}) may be divided into that dependent on the price attribute ($x_{j,price}$) and that dependent on other attributes (x_{jk}), MWTP and RI may be calculated as follows:

$$MWTP_{x_{jk}} = -\frac{\partial U_{nj} / \partial x_{jk}}{\partial U_{nj} / \partial x_{j,price}} = -\frac{\beta_k}{\beta_{price}} \tag{6}$$

$$RI_K = \frac{part-worth_K}{\sum_k part-worth_k} \times 100 \tag{7}$$

The estimation results show that consumers have the largest WTP for wireless internet in a smart car (KRW 1.7 million; ~USD 1,508.43). The second largest WTP (KRW 1.6 million; ~USD 1,419.70) is for connectivity in a smart vehicle. According to these results, consumers have a relatively large WTP for smart options that could leverage the capabilities of their smart devices such as smartphones and tablets. For autonomous driving, if speed control is included in a smart car without the function of lane keeping, consumers are willing to pay 0.9 million KRW (USD 798.58). The RI (relative importance) computations show that consumers are most sensitive to option package price. After the price attribute, the RI results for the remaining options are similar to the MWTP results. In other words, the functions of wireless internet and connectivity are relatively more important than autonomous driving, voice command, and smart applications.

6. CONCLUSIONS

The technology and automotive industries are increasingly seeking to enhance the capabilities and functionality of vehicles while simultaneously reducing the carbon footprint associated with their use. Advances include the use of alternative fuel sources (such as electric, hybrid, compressed natural gas, and hydrogen) and the introduction of smart features such as autonomous driving, connected systems, wireless internet and communication, and real-time traveler information. An understanding of the potential scenarios that may play out in the context of the introduction of these technologies and fuel types may be developed through the collection and analysis of data on consumer preferences for the various technology options and fuel types being introduced into the market.

At this time, there is very limited, if any, data on how consumers may value and adopt these technologies and fuel alternatives. In order to fill this gap, this paper uses stated preference data collected from a sample of individuals in South Korea to assess consumer preferences for various technology options and vehicle fuel types and evaluate the marginal willingness-to-pay for various smart vehicle features. In this paper, five different smart vehicle features are considered – vehicle connectivity, voice command, autonomous driving, wireless internet and communications, and smart vehicle applications (such as real-time traveler information on parking and traffic conditions).

The analysis was conducted in two parts. First, the paper employed the multiple discrete-continuous probit (MDCP) model to shed light on consumer preferences for various vehicle (fuel) types including gasoline, diesel, hybrid, and electric vehicles. It is found that the choice of vehicle type is not only influenced by socio-economic and demographic variables, but also by the types of smart vehicle options included in the vehicle choice. Consumers who value the presence of a voice command option in the vehicle are less inclined to purchase a diesel vehicle, possibly because the noise of the diesel engine would interfere with the operation of the voice command feature. In general, consumers are inclined to purchase vehicles (any fuel type) with smart applications that offer an array of real-time traveler information on parking and traffic conditions. The preferences expressed by demographic segment may be used to develop marketing strategies, providing customized information to different travelers based on their preferences. For instance, younger individuals appear to value the autonomous driving feature in hybrid and electric vehicles more than older individuals, and also are more likely to select electric and hybrid vehicles in the portfolio of their vehicles, suggesting that this segment is particularly "ripe" for "selling" autonomous driving non-conventional fuel vehicles. On the other hand, low income individuals appear to be rather resistant to non-conventional fuel vehicles, though they seem to embrace smart car applications (such as real-time traffic information) more so than high income individuals. This suggests that there is a need to better understand the reluctance of this segment to embrace non-conventional fuel vehicles, and perhaps target this segment for purchases of conventional, but smart applications-laden, vehicles. The model system also may be used to assess consumer vehicle choice under alternative demographic and vehicle characteristics scenarios, thus offering the ability to inform traffic models that utilize vehicle ownership and operation (smart vehicle options such as vehicle connectivity and real-time traveler information availability) information to simulate traffic patterns. Knowledge of the level of penetration of different vehicle types in the vehicle population would greatly aid in more accurately depicting traffic patterns that may emerge under alternative scenarios of technology and fuel type deployment.

Second, the paper employed the mixed multinomial probit (MMNP) model to evaluate the consumer willingness to pay (WTP) and relative importance (RI) for various smart vehicle options. The MMNP model accommodates the presence of consumer heterogeneity in willingness to pay and preferences, while relaxing the restrictive IIA (independence from irrelevant alternatives) assumption associated with logit-based models. The model results show that individuals are rather homogeneously sensitive to price, but show considerable heterogeneity in their preferences towards various smart vehicle options such as vehicle connectivity, voice command, autonomous driving, and wireless internet and communications. Computations of WTP and RI show that price is the most important aspect driving vehicle option choice (purchase). Vehicle connectivity, and wireless internet and communications, are next in importance, suggesting that consumers are more interested in features that leverage the capabilities of their mobile devices. Travelers are not interested in lane-keeping technology. On average, the study shows that individuals in South Korea are willing to pay the equivalent of US $1500 for wireless connectivity and internet/communications, and about US $500 for voice command and smart real-time applications features.

From a travel behavior and planning standpoint, knowledge of the sensitivity and willingness to pay to various smart vehicle options and fuel types provides the ability to construct scenarios of vehicle penetration/adoption as a function of the price and availability of various technology and fuel options. Planning models, such as activity-based travel models, can be applied to these scenarios to assess changes in travel demand that may result from the introduction of these technologies, and traffic microsimulation models would be capable of simulating traffic flow patterns that emerge as a result of these vehicles being present in the traffic stream to different extents. Future research in this domain should focus on analysis of data that includes a richer set of attributes (e.g., vehicle range). Also, collection and analysis of data from different geographic contexts would aid in assessing differences in consumer preferences and willingness to pay (and therefore market penetration rates).

REFERENCES

Baltas, G. A Model for Multiple Brand Choice. *European Journal of Operational Research*, Vol. 154, No. 1, 2004, pp. 144–149.

Bhat, C. R. A Multiple Discrete-continuous Extreme Value Model: Formulation and Application to Discretionary Time-use Decisions. *Transportation Research Part B*, Vol. 39, No. 8, 2005, pp. 679-707.

Bhat, C. R. The Multiple Discrete-continuous Extreme Value (MDCEV) Model: Role of Utility Function Parameters, Identification Considerations, and Model Extensions. *Transportation Research Part B*, Vol. 42, No. 3, 2008, pp. 274-303.

Bhat, C. R. The Maximum Approximate Composite Marginal Likelihood (MACML) Estimation of Multinomial Probit-Based Unordered Response Choice Models. *Transportation Research Part B*, Vol. 45, No. 7, 2011, pp. 923-939.

Bhat, C. R., and S. Sen. Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model. *Transportation Research Part B*, Vol. 40, No. 1, 2006, pp. 35-53.

Bhat, C. R., and R. Sidharthan. A Simulation Evaluation of the Maximum Approximate Composite Marginal Likelihood (MACML) Estimator for Mixed Multinomial Probit Models. *Transportation Research Part B*, Vol. 45, No. 7, 2011, pp. 940-953.

Bhat, C. R., and R. Sidharthan. A New Approach to Specify and Estimate Non-normally Mixed Multinomial Probit Models. *Transportation Research Part B*, Vol. 46, No. 7, 2012, pp. 817-833.

Bhat, C. R., M. Castro, and M. Khan. A New Estimation Approach for the Multiple Discrete-continuous Probit (MDCP) Choice Model. *Transportation Research Part B*, Vol. 55, 2013, pp. 1-22.

Bunch, D. S., M. Bradley, T. F. Golob, R. Kitamura, and G. P. Occhiuzzo. Demand for Clean-fuel Vehicles in California: a Discrete-choice State Preference Pilot Study. *Transportation Research Part A*, Vol. 27, No. 3, 1993, pp. 237–253.

BusinessKorea. *Hyundai and Kia Group Set New Market Share Record Last Year*. Seoul, Korea. Feb. 2013, http://www.businesskorea.co.kr/article/1142/news-hyundai-and-kia-group-set-new-market-share-record-last-year. Accessed July 30, 2014.

Center for Automotive Research (CAR). *Contribution of the Automotive Industry to the Economies of All Fifty States and the United States*. Ann Arbor, Michigan. April 2010, http://www.cargroup.org/?module=Publications&event=View&pubID=16. Accessed July 30, 2014.

Economic Review. *Increase Diesel Usage per Person by 4.5% Due to Popularity of Diesel Car*. Seoul, Korea. Feb. 2014, http://www.econovill.com/archives/155334. Accessed July 30, 2014.

Edwards, Y. D., and G. M. Allenby. Multivariate Analysis of Multiple Response Data. *Journal of Marketing Research*, Vol. 40, No. 3, 2003, pp. 321–334.

Ewing, G., and E. Sarigollu. Assessing Consumer Preferences for Clean-fuel Vehicles: A Discrete Choice Experiment. *Journal of Public Policy and Marketing*, Vol. 19, 2000, pp. 106-118.

Kirk B. Connected Vehicles: An Executive Overview of the Status and Trends. *Globis Consulting Inc*., November 2011, http://www.globisconsulting.ca/Connected_Vehicles_Globis_rpt.pdf. Accessed July 30, 2014.

Kraan, M., H. S. Mahmassani, and N. Huynh. Traveler Responses to Advanced Traveler Information Systems for Shopping Trips: Interactive Survey Approach. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1725*, Transportation Research Board of the National Academies, Washington, D.C., 2000, pp. 116-123.

National IT Industry Promotion Agency (NIPA). The Birth of ‘Smart Car’ after Combining Vehicles with IT. Korea, June 24, 2013.

Nelson, S. P. *Challenges and Technologies: The Human Friendly Vehicle in 2030 and Beyond*. Freescale Semiconductor Inc., July 2014, http://www.freescale.com/files/training_pdf/VFTF09_AA106.pdf. Accessed July 30, 2014.

Rose, J. M., D. A. Hensher, S. Caussade, J. D. Ortúzar, and R. C. Jou, R. C. Identifying differences in willingness to pay due to dimensionality in stated choice experiments: a cross country analysis. *Journal of Transport Geography*, Vol. 17, No. 1, 2009, pp. 21-29.

Shin, J., J. Hong, G. Jeong, and J. Lee. Impact of Electric Vehicles on Existing Car Usage: a Mixed Multiple Discrete-continuous Extreme Value Model Approach. *Transportation Research Part D*, Vol. 17, No. 2, 2012, pp. 138-144.

USA TODAY. Google Discloses Costs of Its Driverless Car Tests Valley?. June 14, 2012.

van Rijnsoever, F. J., P. Hagen, and M. Willems. Preferences for Alternative Fuel Vehicles by Dutch Local Governments. *Transportation Research Part D*, Vol. 20, 2013, pp. 15–20.

TABLE 1. Data Description of the Survey Sample

Demographic Properties of Respondents					
Attribute		Respondents	Percentage (%)	Average	Standard deviation
Sample Size		633	100	-	-
Gender	Male	301	47.6	-	-
	Female	332	52.4		
Age	20-29	169	26.7	38.4	10.88
	30-39	170	26.9		
	40-49	174	27.5		
	50-59	120	19		
Number in family	≤ 2	78	12.3	3.6	0.96
	3	146	23.1		
	4	353	55.8		
	≥ 5	56	8.9		
Household monthly income (10,000 KRW)	Under 199	11	1.7	413.38	149.85
	200–299	80	12.6		
	300–399	213	33.6		
	400–499	142	22.4		
	500–599	119	18.8		
	Over 600	68	10.7		

Annual Vehicle Mileage			
Annual Vehicle Mileage	Percent of Vehicles		
	Vehicle 1 N=542	Vehicle 2 N=57	No vehicle N=91
< 10,000 km	10.50%	43.90%	-
10,000–14,999 km	20.80%	22.80%	-
15,000–19,999 km	21.80%	14.00%	-
20,000–24,999 km	24.00%	8.80%	-
25,000–29,999 km	8.50%	5.30%	-
30,000–39,999 km	11.80%	5.30%	-
≥ 40,000 km	2.60%	-	-

Note: 1 USD is equal to approximately 1,127 KRW in March, 2012. Vehicle 1 is the vehicle that is driven the most (in the case of two-vehicle households).

TABLE 2. Attributes and Attribute Levels for Design of the Choice Experiments

Vehicles (Used in the First Set of Choice Experiments)		
Attributes	Levels	Details
Fuel type	Gasoline, diesel, hybrid (gasoline + battery), electric (battery)	Compared to the existing fossil-fuel cars, electric vehicles need 4 hours for charging or 2 minutes of replacement time for the battery.
Vehicle type	SUV, Sedan	
Fuel cost (won/km)	50, 100, 200	Fuel cost is defined as the cost of 1 km of driving.
Purchase price (10,000 won)	2,500; 3,000; 3,500; 4,000	The cost of buying a car.
Accessibility of fueling station (%)	50, 80, 100	Accessibility of gasoline fueling stations is considered 100. The accessibility of stations for other fuel types is measured relative to this value.
Smart car option	Provided, not provided	Smart options provided including wireless internet, speed control, automated parking, and so on.
Smart Options (Used in the Second Set of Choice Experiments)		
Attributes	Levels	Details
Option price (10,000 won)	100, 300, 500	Price of smart car option
Connectivity	Possible, not possible	If smart devices can be connected to the vehicle, remote control of vehicle is possible via smart devices, and information about vehicle could be checked by smart devices, then connectivity is present.
Voice command	Possible, not possible	Control vehicle by voice command.
Lane keeping	Possible, not possible	Lane keeping would control for lane departure automatically.
Wireless internet	Provided, not provided	3G or 4G internet service provided.
Smart Application	Provided, not provided	Smart car applications are similar to smart phone applications; they provide real-time information about parking, traffic conditions, and incidents.

TABLE 3. MDCP Model of Vehicle Choice – All Respondents

Baseline Preferences		
Variable	β	t-value
Gasoline (Base)	-	-
Diesel	-0.19	-5.27
Hybrid	0.01	0.33
Electric	-0.21	-4.83
SUV	0.05	2.27
Fuel Cost	-0.30	-9.06
Purchase Price	-0.19	-6.61
Accessibility of Fueling Station	0.44	5.67
Smart Car Options	0.10	4.61
Satiation		
Vehicle Type	α	t-value
Gasoline	0.71	35.91
Diesel	0.86	44.21
Hybrid	0.88	26.88
Electric	0.95	60.48
Log-likelihood value at convergence = -4.92		

TABLE 4. MDCP Model of Vehicle Choice Considering Demographic Attributes

	All Respondents	Driver/Non-Driver		Income		Age		Level of Intended Use	
		Driver	Non-Driver	High Income	Low Income	Old	Young	Higher Level	Lower Level
Baseline(β)									
Gasoline (Base)	-	-	-	-	-	-	-	-	-
Diesel									
Constant	-0.6079[a]	-0.1504	-0.3398[b]	-0.3247	-0.4207[b]	-0.2988[c]	-0.1925[c]	0.3987[c]	-0.2724[c]
Male	0.1228[b]	0.0237	0.0217	0.0150	0.1938[a]	-0.0601	0.1676[b]	-	-
Age	-	-0.0355	0.0417[c]	-	-	-	-	-	-
Income	-0.0310[b]	-	-	-0.0337[c]	-0.1893[a]	-	-	-0.0108	-0.034[c]
Family Size	0.0261	0.0484[b]	-0.0315	0.0087	0.0628[b]	0.0363	-0.0135	-	-
Dwelling Size	-0.0226	-	-	-	-	-	-	-0.0826[b]	0.0443
Connectivity Usefulness	-	-	-	-0.0397	0.1085[a]	-0.0212	-	-	-
Voice Command Usefulness	-0.0743[a]	-	-	-0.0017	-0.1298[a]	-	-	-0.1039[b]	-0.0264
Autonomous Driving Usefulness	0.0359	-	-	-	-	-	-	0.0395	0.0466
Wireless Internet Usefulness	-	-	-	-	-	-	-	-	-
Smart Application Usefulness	0.1654[a]	-	-	0.1026[c]	0.1841[a]	-	-	-	-
Hybrid									
Constant	-0.1965	-0.1639	-0.5300[b]	-0.1936	-0.9226[a]	-0.5288[b]	-0.0483	0.7924[a]	-0.2997[b]
Male	0.1493[a]	-0.0200	-0.0075	-0.0076	0.2245[a]	-	-	-	-
Age	-0.072[a]	-	-	-	-	-	-	-	-
Income	-	-	-	-	-	0.0396[b]	-0.0167	-	-
Family Size	-	-	-	-	-	-	-	-	-
Dwelling Size	-	-	-	-0.0156	0.0746[b]	-	-	-0.0614[c]	0.0504
Connectivity Usefulness	-	-	0.0885[b]	-	-	-	-	-	-
Voice Command Usefulness	-	0.0079	0.1457[a]	-	-	0.0950[b]	0.0302	-	-
Autonomous Driving Usefulness	-	0.0476	-0.0955[b]	-	-	-0.0228	0.0330	-	-
Wireless Internet Usefulness	-0.0113	-	-	0.0468	-	-	-	0.0048	0.0117
Smart Application Usefulness	0.1280[a]	0.0344[c]	-0.0159	0.0567	0.1662[a]	-	-	-0.1282[a]	0.0279

Note: [a] 1% significance level, [b] 5% significance level, [c] 10% significance level

TABLE 4. MDCP Model of Vehicle Choice with Demographic Attributes (Continued)

	All respondents	Driver/Non-Driver		Income		Age		Level Of Intended Use	
		Driver	Non-Driver	High Income	Low Income	Old	Young	Higher Level	Lower Level
Baseline(β)									
Electric									
Constant	-0.2404	-0.1895	-0.5380^{b}	-0.1657	-0.9948^{a}	-0.8765^{b}	-0.3117^{c}	0.6245^{a}	-0.3875^{b}
Male	0.1543^{a}	-	-	0.0210	0.2169^{a}	-0.0464	0.0784^{c}	-	0.0001
Age	-0.0580^{a}	-0.0128	0.0373^{b}	-0.0387	0.0126	0.1523^{b}	-0.0051	-0.0244	0.0143
Income	-	-0.0042	0.0210	-	-	-	-	0.0040	-0.0096
Family Size	-	-	-	-	-	-	-	-	-
Dwelling Size	-	-	-	-0.0543	0.0687^{b}	-	-	-0.1346^{a}	0.0723^{c}
Connectivity Usefulness	-0.0922^{a}	-	-	-	-	-	-	-	-
Voice Command Usefulness	-	-0.0161	0.1070^{b}	-	-	-	-	-0.0706^{b}	-0.0192
Autonomous Driving Usefulness	-	0.0453	-0.0904^{b}	-0.0515	-0.0039	-0.0569	0.0423	-	-
Wireless Internet Usefulness	-	-0.0400^{c}	0.0245	0.0044	-0.0256	-	-	-	-
Smart Application Usefulness	0.1423^{a}	-	-	0.0980	0.1677^{b}	-	-	-	-
SUV	0.0550^{a}	0.0428^{c}	0.0579^{b}	0.0321	0.0565^{b}	0.0098	0.0758^{a}	0.0929^{b}	0.0249
Fuel Cost	-0.3133^{a}	-0.2802^{a}	-0.3172^{a}	-0.4235^{a}	-0.2646^{a}	-0.4048^{a}	-0.2852^{a}	-0.1531^{a}	-0.3727^{a}
Purchase Price	-0.1940^{a}	-0.1723^{a}	-0.1937^{a}	-0.1898^{a}	-0.1848^{a}	-0.1817^{a}	-0.2209^{a}	-0.1145^{a}	-0.2240^{a}
Accessibility of Fueling Station	0.4503^{a}	0.3451^{a}	0.5077^{a}	0.7886^{a}	0.3608^{a}	0.3888^{a}	0.5763^{a}	0.4410^{a}	0.4489^{a}
Smart Car Options	0.0996^{a}	0.0937^{a}	0.0858^{a}	0.0477	0.0834^{a}	0.1136^{a}	0.1034^{a}	0.0968^{a}	0.0978^{a}
Satiation(α)									
Gasoline	0.7113^{a}	0.7400^{a}	0.6720^{a}	0.6989^{a}	0.7169^{a}	0.6916^{a}	0.7461^{a}	0.6502^{a}	0.7330^{a}
Diesel	0.8508^{a}	0.8421^{a}	0.8705^{a}	0.9388^{a}	0.8012^{a}	0.8687^{a}	0.8329^{a}	0.9372^{a}	0.8248^{a}
Hybrid	0.8737^{a}	0.9189^{a}	0.8472^{a}	0.6850^{a}	0.9227^{a}	0.8418^{a}	0.8422^{a}	0.8631^{a}	0.8726^{a}
Electric	0.9454^{a}	0.9571^{a}	0.9468^{a}	0.9152^{a}	0.9555^{a}	0.9166^{a}	0.9519^{a}	0.9564^{a}	0.9390^{a}
Log-Likelihood Value at Convergence	-4.8981	-4.8321	-4.9688	-4.8169	-4.9350	-4.7234	-5.0427	-5.1077	-4.8132

Note: ^{a} 1% significance level, ^{b} 5% significance level, ^{c} 10% significance level

TABLE 5. Mixed Multinomial Probit (MMNP) Model Estimation Results

Attribute	Parameter Mean	Parameter Std Dev	Relative Importance (%)	Marginal Willingness to Pay (MWTP)
Option price	-0.4014[a]	0.0002	42.5%	-
Connectivity	0.6450[a]	0.0003[c]	17.1%	1.6 million KRW
Voice command	0.2562[a]	0.4699[b]	6.8%	0.6 million KRW
Lane keeping	-0.3559[a]	0.0004[b]	9.4%	-0.9 million KRW
Wireless internet	0.6644[a]	1.2092[a]	17.6%	1.7 million KRW
Smart Applications	0.2536[a]	0.4181	6.7%	0.6 million KRW

Log-likelihood value at convergence = -1.1701

Note: [a]1% significance level, [b]5% significance level, [c]10% significance level