

**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 such advanced vehicular technologies. The deployment and penetration of advanced vehicular technologies in the marketplace, and planning for possible market adoption scenarios, calls for the collection and analysis of consumer preference data related to these emerging technologies. This study aims to address this need, offering a detailed analysis of consumer preference for alternative fuel types and technology options using data collected in stated choice experiments conducted on a sample of consumers from six metropolitan cities 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 less 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; 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 enhance the driving experience and 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 an 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 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 the market depends substantially 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 in-vehicle travel time more productive and enjoyable as vehicle occupants will be able to multitask during the trip. Alternative fuel types offer energy and environmental benefits in terms of a reduced 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 the difficult task of understanding 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, a greater understanding of consumer preferences and willingness to pay for these technology options is needed. This paper aims to address this need by modeling consumer preferences and willingness to pay for smart vehicular options and applications using a stated preference data set collected from a sample of individuals in South Korea. As these options have not yet made their way into the marketplace in a 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) and hence appropriate for a study of this nature.

The analysis presented in this paper consists of two parts. First, this study presents an analysis of 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 multiple choice 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 multinomial probit model (MNP). 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 on emerging vehicular technologies, fuels, and options and recent work on modeling consumer preferences for 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 the array of technology and fuel options that constitute the heart of the emerging automotive revolution. To provide some clarity on the options considered in this paper, this section offers a definition of various terms in light of the emerging convergence of automotive and information technologies, and provides a description of the label “smart vehicle” as used in this study.

As noted by Kirk (2011), emerging automotive technology increasingly 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 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 technologies such as global positioning systems (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 functions of an autonomous car in terms of safety and convenience, as well as the provision of infotainment systems that offer a variety of accessible content.

The emergence of advance vehicular technologies has led to increased consumer interest in smart vehicles. As the adoption of new products and technologies is affected by consumer beliefs about and attitudes towards new technologies, theories of consumer adoption behavior have been developed. Examples of such theories include the theory of reasoned action (Fishbein and Ajzen, 1975), the theory of planned behavior (Ajzen and Madden, 1986), and random utility theory (McFadden, 1974). The adoption of new technologies has also been described by product diffusion theories (Bass, 1969; Rogers, 1962), which are normally utilized when dealing with aggregate market-level data. When individual-level consumer choice data is available, theories of behavior offer frameworks for the development and specification of econometric choice models that shed considerable light on the influence of various factors on choice of various options.

The research in this study builds on the existing literature on consumer choices for new and emerging vehicular options. There has been considerable research in modeling consumer preference 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 reflect key behavioral phenomena at play (as identified in the discrete choice modeling literature) as the structure of the logit model does not allow for the simultaneous choice of multiple technology options, and does not account for correlation of unobserved factors that affect multiple choice alternatives as well as heterogeneity in consumer preferences. To our knowledge, despite the rapid evolution of technology and potential consumer interest in smart vehicle options, there is limited research on consumer preferences for emerging vehicular technologies. In an effort to fill this gap, this study employs 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 multinomial probit (MNP) model, which explicitly considers heterogeneity in consumer preferences while relaxing the IIA assumption, this study presents an analysis of consumer willingness to pay (WTP) for 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 of Vehicle Type Choice

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 and different utility variances 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 and different utility variances. 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  $i^{\text{th}}$  consumer choose from among  $K$  alternatives and consume  $m_k$  units of each of the  $K$  alternatives. The utility for the  $i^{\text{th}}$  consumer is represented as follows (suppressing the index  $i$  for the consumer):

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

In Equation (1),  $K$  represents the number of alternatives that exist in the choice set.  $\Psi(\mathbf{x}_k)$  represents the baseline utility for the  $k^{\text{th}}$  alternative,  $\mathbf{x}_k$  represents the attributes that affect the utility of the  $k^{\text{th}}$  alternative, and  $m_k$  is the amount of usage (consumption) of the  $k^{\text{th}}$  alternative (which is equal to zero for non-consumed (non-chosen) alternatives).  $\gamma_k$  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  $k^{\text{th}}$  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).  $\alpha_k$  is a satiation parameter that implies the degree of diminishing marginal utility. To satisfy the law of diminishing marginal utility,  $\alpha_k$  has a value below unity. For this reason,  $\alpha_k$  is reparameterized as  $\alpha_k = [1 - \exp(-\delta_k)]$  (Bhat, 2008).

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

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

where,  $\boldsymbol{\beta}$  is vector of coefficients to be estimated, and  $\varepsilon_k$  represents unobserved characteristics that affect the baseline utility. The vector  $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_K)'$  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, the alternatives refer to vehicles of different fuel/body types and smart car options that are presented to respondents in a stated preference survey setting. The reported total annual vehicle mileage is presented to the respondent as a budget constraint, and the respondent has the option of choosing multiple vehicles and using the chosen vehicles to different extents (i.e., allocating differential mileage amounts among the chosen vehicles). Thus, 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  $k^{\text{th}}$  alternative.

The constrained utility maximization problem represented by Equations (2) and (3) can 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  $\alpha$ -profile of the maximum approximate composite marginal likelihood (MACML) approach (Bhat et al, 2013).

### 3.2 Multinomial Probit (MNP) Model of Smart Vehicle Options

The multinomial probit (MNP) 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 formulations, the multinomial probit (MNP) model considers a utility function that may be divided into observed (deterministic) and unobserved (stochastic) parts. The utility function of alternative  $j$  for the  $i^{\text{th}}$  consumer is:

$$U_{ij} = \kappa_i' \mathbf{Z}_{ij} + \tilde{\eta}_{ij} \quad (4)$$

where  $U_{ij}$  is a latent utility that the  $i^{\text{th}}$  consumer derives from choosing alternative  $j$ .  $\kappa_i$  is an individual-specific coefficient vector on the explanatory variable vector  $\mathbf{Z}_{ij}$ . To accommodate heterogeneity in consumer preferences,  $\kappa_i$  is set to be a vector following a multivariate normal density function with a mean of  $\mathbf{b}$  and a covariance matrix of  $\mathbf{\Sigma}$ . In addition, this study assumes that the off-diagonal matrix of  $\mathbf{\Sigma}$  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  $\kappa_i = \mathbf{b} + \tilde{\kappa}_i$ , with  $\kappa_i = \mathbf{b} + \tilde{\kappa}_i \sim MVN(\mathbf{0}, \mathbf{\Sigma})$ . Let  $\mathbf{U}_i = [U_{i1}, U_{i2}, \dots, U_{iJ}]'$ ,  $\mathbf{Z}_i = (\mathbf{Z}_{i1}, \mathbf{Z}_{i2}, \dots, \mathbf{Z}_{iJ})'$ , and  $\tilde{\boldsymbol{\eta}}_i = [\tilde{\eta}_{i1}, \tilde{\eta}_{i2}, \dots, \tilde{\eta}_{iJ}]'$ , then Equation (4) may be rewritten as:

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

The likelihood function corresponding to the random coefficients model above requires the evaluation of multi-dimensional integrals. Although the Maximum Simulated Likelihood (MSL) estimation method could be applied to estimate parameters, multi-dimensional integrals need to be evaluated due to the general error covariance structure embedded in the probit-based model. As mentioned in Bhat and Sidharthan (2011) and Bhat (2011), the evaluation of multidimensional integrals of the multivariate normal distribution can be cumbersome in the MSL estimation method. Therefore, this study utilizes the MACML estimation method proposed by Bhat (2011), which is computationally more efficient and recovers actual parameters more accurately than the MSL estimation method (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, Incheon, Gwangju, and Daejeon. The interviewers underwent extensive training so that they could present choice scenarios to respondents in an effective and informative way. Upon completion of the training, interviewers conducted face-to-face interviews with survey respondents. They presented detailed information about emerging vehicular technologies, smart vehicle features and options, and characteristics of alternative fuel vehicles. They first presented a few illustrative sample choice scenarios to the respondents so that the respondents would become familiar with the survey protocols and expectations. Interviewers were instructed to limit all explanations to facts on various emerging technologies, thus minimizing the introduction of any interviewer bias. In addition, to further enhance the validity of responses obtained in the stated preference survey, the response time was controlled so that respondents had adequate time to understand and answer each question. Respondents were not allowed to rush through the survey and exercise choices in a hasty manner. 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. A sample choice scenario presented to the respondents is shown in Figure 1. Through the exercise of a rigorous and careful survey protocol, the study aimed to minimize measurement error that is inevitably associated with surveys of human subjects.

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 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. The survey had an almost equal split of male and female respondents, with a slightly higher percentage of females than males. The average age of respondents of the survey is 38 years, indicating that younger individuals are more interested in and responsive to surveys covering new technologies. This finding is consistent with results reported by Dubin (2011), who found that early adopters of electric vehicles will be younger individuals. A majority of respondents in the survey come from 4-person households. This characteristic may explain, at least in part, the preference for larger sport utility vehicles (which are more spacious and comfortable) over standard sedans by a majority of the respondents. The average household monthly income of respondents is about 4.1 million KRW (~\$4,000 in 2014). For purposes of analysis, respondents



making less than 4 million KRW (i.e., less than average) were treated as being in lower-income households, while those in households with incomes greater than this average value were considered as being in higher-income households. Respondents were also asked to report their average annual usage of vehicles; these values were used to derive budget constraints (total kilometers) for modeling purposes. The survey results show that 46.9% of the one-car households in the sample accrue over 20,000 km per year on average. In two-car households, only 19.3% of the second cars are driven an average of more than 20,000 km per year. This result suggests that, in most instances, the first car is driven more than the second car in two-car households. The average annual mileage reported by the respondents in the survey sample is 19,261.9 km.

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 were 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  $4 \times 2 \times 3 \times 4 \times 3 \times 2 = 576$  for vehicle choice and  $3 \times 2 \times 2 \times 2 \times 2 = 96$  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 multinomial probit (MNP) 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 vehicles, 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 were allowed to choose multiple options (in other words, they did 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. Results in Table 3 suggest 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, and recognize the lower fuel (operating) costs associated with driving these vehicles in comparison to more traditional gasoline and diesel vehicles. All other things being equal, they are more prone to utilize electric and hybrid vehicles to a greater degree when faced with a choice.<sup>1</sup>

Table 4 presents estimation results considering several demographic attributes present in the data set. In this table, estimation results are provided for the entire survey sample taken 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 comfortable with emerging vehicular options and prefer to stick with the trusted and ubiquitous gasoline and diesel vehicular types that have a long and proven track

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<sup>1</sup> The covariance matrix  $\Lambda$  is not estimable, only the covariance matrix of utility differences taken with respect to one base alternative. The reader is referred to Bhat et al. (2013) for a detailed methodological discussion of the required identification considerations. At the same time, the use of a general differenced covariance matrix as used here (subject to identification) renders the estimated differenced covariance matrix uninterpretable (see Bhat et al., 2013; Train, 2009, page 113 also discusses a similar issue for the case of a traditional multinomial probit model). So, we do not present the elements of the general differenced covariance matrix.

record. Respondents who consider smart vehicle applications to be useful (these include real-time traveler information applications) have a higher proclivity to choose alternative fuel vehicle types over the gasoline vehicle type, as indicated by the positive coefficients on the “application usefulness” variable for all non-gasoline vehicle types in Table 4. The usefulness variables<sup>2</sup> in Table 4 are based on questions where respondents rated the usefulness of each smart vehicle option – “connectivity including infotainment”, “voice command”, “autonomous driving”, “wireless internet”, and “smart vehicle applications”. Thus, the usefulness variables indicate respondents’ perceptions of the value of advanced vehicular technologies. Based on the model estimation results, it appears 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. It is possible that individuals who value vehicle connectivity are those who drive longer distances and accrue more vehicle kilometers of travel; as a result they are likely to have a lower preference for electric vehicles owing to their limited range. Nevertheless, this is a finding that merits further investigation.

As expected, the fuel cost and purchase price of the vehicle (towards 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 and newer vehicles with lower operating costs than older fossil-fuel burning vehicles.

Among the sample of 633 respondents, 322 were drivers and 311 were non-drivers. The second broad column titled “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 also 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. The 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

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<sup>2</sup> The usefulness variables measured the level of intention to use each smart option based on a five-point scale. For instance, if respondents answered that “connectivity including infotainment” is very useful, the usefulness value for this smart option was set to 5. In contrast, if respondents answered that “connectivity including infotainment” is not useful, the usefulness value for this smart option was set to 0.

of the alternative specific constants show that the higher 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 lower income respondents are inclined to choose vehicle types with a proven track record (and also less expensive in terms of purchase price) over emerging vehicles. In the lower income group, individuals in larger families have a particularly greater 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. As mentioned earlier, diesel vehicles are more likely to be associated with the larger SUVs, and lower income respondents may view the diesel SUV as providing the best overall value. In terms of satiation parameters, differences are significant between these market segments. While lower income respondents generally follow the pattern of all respondents (taken together), the higher income group respondents show a greater inclination to use diesel vehicles and electric vehicles (alternative fuel vehicle types) and lower levels of consumption for hybrid and gasoline vehicles. As income is usually strongly correlated with education, it is possible that this finding is a result of higher income respondents being more knowledgeable of the advantages offered by alternative fuel vehicles.

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 (for both age groups). Although younger individuals are less likely to choose diesel vehicles, they do show a greater preference for the larger SUV body type (they appear to 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 group indicating a high level of intended use defined as consumers who scored a four or higher (on a five point scale) for level of intended use of a smart vehicle (n=169). The group indicating a low level of intended use included consumers who scored 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 diesel vehicles to a lesser degree, over gasoline vehicles. This result signifies that individuals with a higher level of intention to use a smart vehicle have a greater probability of choosing hybrid or electric vehicles over conventionally fueled vehicles as their next vehicle. Presumably these individuals are more interested in and willing to explore the use of emerging vehicular technologies and fuel types. On the other hand, the group expressing a low level of intended use prefers traditional gasoline vehicles due to their limited interest in using emerging vehicular technology and fuel options. Other explanatory 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, consistent with the notion that these vehicles have the lowest operating cost. Ranked second for the high level of use group is the diesel vehicle, while the hybrid vehicle type 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 Multinomial Probit (MNP) Model of Smart Vehicle Options

This section presents results of the multinomial probit (MNP) model estimation effort with a view to understand consumer heterogeneity and willingness to pay for various smart vehicle options. The model includes several 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 and traffic conditions)

In the choice experiments considering smart vehicle options, respondents were asked to choose the most preferred hypothetical alternative depending on the options present and the 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. Parasuraman and Moulona (1996) found significant errors in human performance related to the use of advanced driver assistance systems, which included lane keeping technology. In a study on lane keeping in automated truck platoons, Aoki (2013) indicated that the lateral deviation is about 2 m even in the presence of lane keeping technology. These studies suggest that lane keeping technology is still a work in progress. The negative preference for the lane keeping option could suggest 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 (real-time information) where the respondents appear to exhibit considerable homogeneity in their preference for such applications. With real-time traffic information becoming increasingly available on smart phones and other portable and mobile navigation devices, the presence of significant consumer heterogeneity in the preference for smart applications is not unexpected. Many consumers may be accessing real-time traffic information through other mobile devices, thus rendering a lower level of interest in such applications being embedded in the vehicle.

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. Under the assumption that the deterministic portion of the utility ( $V_j$ ) may be divided

into that dependent on the price attribute ( $Z_{j,price}$ ) and that dependent on other attributes ( $Z_{j,l}$ ),  $MWTP$  may be calculated as follows:

$$MWTP_{Z_{j,l}} = -\frac{\partial U_j / \partial Z_{j,l}}{\partial U_j / \partial Z_{j,price}} = -\frac{\kappa_l}{\kappa_{price}} \quad (6)$$

The estimation results show that consumers have the largest willingness-to-pay 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. In the context of 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). 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, diesel, 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 obtained through the collection and analysis of data on consumer preferences for the various technology options and fuel types being introduced into the market.

Currently, there is very limited (if any), data on how consumers may value and adopt emerging vehicular technologies and fuel alternatives. In an effort to fill this gap, this research study 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 evaluates the marginal willingness-to-pay for various smart vehicle features. 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 was 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. For example, it was found that 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. Model estimation results showed that consumers are generally inclined to purchase vehicles (any fuel type) with smart applications that offer an array of real-time traveler information on parking and traffic conditions. This finding is somewhat different from that reported by Desomer (2013) - who presents the results of the 2013–2014 Global Automotive Survey that collected 20,000 responses from 20 countries. In that survey,

respondents expressed conflicting opinions about the usefulness of such applications owing to the potential for distracted driving.

The modeling effort in this paper involved an examination of consumer preferences for various technologies and fuel types by socio-economic market segment. The preferences expressed by different segments may be used to develop marketing strategies and provide customized information to different travelers. For instance, younger individuals appear to value the autonomous driving feature in hybrid and electric vehicles more than older individuals, and are also more likely to select electric and hybrid vehicles in the portfolio of their vehicles. These findings suggest that this segment is particularly conducive to receiving information about emerging autonomous driving non-conventional fuel vehicles. This finding is consistent with the results reported by Dubin (2011), who found that early adopters of electric vehicles tend to be younger than the rest of population. On the other hand, low income individuals appear to be rather resistant to purchasing alternative fuel vehicles, although they seem to embrace smart car applications (such as real-time traffic information) more so than high income individuals. Because high income individuals are likely to be accessing such real-time traffic information applications through their mobile devices already, it is possible that this group does not value the inclusion of such applications within the vehicle as much as lower income individuals. The higher prices of alternative fuel vehicles are likely contributing to the lower interest in the purchase of such vehicles among low-income individuals. Desomer (2013), on the other hand, reports that a majority of respondents (across all socio-economic groups) are interested in purchasing alternative fuel vehicles. Thus, there is a need to better understand the reluctance of the low-income segment to embrace non-conventional fuel vehicles. The findings in this paper suggest that special incentives, rebates, and information about operating and lifecycle costs of different vehicle types may be needed to entice lower income groups to purchase alternative fuel vehicles. In addition, this segment may be targeted for purchases of vehicles equipped with smart applications offering real-time traffic and parking information.

The model system presented in this paper may also be used to assess consumer vehicle choices under alternative demographic and vehicular characteristic 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 a region's vehicle fleet would greatly aid in more accurately depicting traffic patterns that may emerge under alternative scenarios of technology and fuel type deployment.

Second, the paper employs a multinomial probit (MNP) model to evaluate consumer's willingness to pay (*WTP*) for various smart vehicle options. The MNP model accommodates the presence of consumer heterogeneity in willingness to pay and preferences in a straightforward manner. The model results show that individuals are rather homogeneously sensitive to price, but exhibit considerable heterogeneity in their preferences towards various smart vehicle options such as vehicle connectivity, voice command, autonomous driving, and wireless internet/communications. Computations of *WTP* show that price is the most important aspect driving vehicle option choice (purchase). Vehicle connectivity and wireless internet/communications are next in importance, suggesting that consumers are more interested in features that leverage the connectivity capabilities of their mobile devices. Travelers are not interested in lane-keeping technology, a finding consistent with that reported in the literature. 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 for 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 can be used to simulate traffic flow patterns that emerge as a result of these vehicles being present in the traffic stream to different extents. A critical consideration in this context is the need to recognize that emerging vehicular technologies will be adopted by travelers at varying rates depending on socio-economic attributes, affordability, and contextual variables. The market penetration of advanced vehicular options and features will occur over an extended period of time as individuals learn about, adapt to, and adopt various emerging technological advances. In the behavioral modeling domain, operational models of human learning and technology diffusion are lacking and theories of behavioral adaptation and technology adoption that recognize the time-sensitive nature of market penetration phenomena should be developed so that planning models are better able to capture such behavioral processes. The models developed in this paper are not intended to capture the behavioral learning mechanisms and time to adoption for various technologies, but rather intended to shed light on, the degree to which various factors contribute to the choice of emerging vehicular technologies, consumer preferences for different advanced vehicular options, the heterogeneity associated with consumer preferences, and the marginal willingness-to-pay of alternative vehicular features. The development of operational modeling frameworks that capture learning processes, experimentation and adaptation, and time to adoption remains a promising future research direction. Future research efforts in this domain should also focus on analysis of data that includes a richer set of attributes (e.g., vehicle range). In addition, 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).

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## REFERENCES

- Ajzen, I., Madden, T.J., 1986. Prediction of goal-directed behavior; Attitude, intentions and perceived behavioral control. *Journal of Experimental Social Psychology*, 22(5), 453-474.
- Aoki, K., 2013. Research and development of fully automated vehicles. International Conference on Fluid Dynamics (ICFD), Sendai, Japan, November 25, 2013.
- Bass, F., 1969. A new product growth for model consumer durables. *Management Science*, 15(5), 215-227.
- Baltas, G., 2004. A model for multiple brand choice. *European Journal of Operational Research*, 154(1), 144-149.
- Bhat, C.R., 2005. A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions. *Transportation Research Part B*, 39(8), 679-707.
- Bhat, C.R., 2008. The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B*, 42(3), 274-303.
- Bhat, C.R., 2011. The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models. *Transportation Research Part B*, 45(7), 923-939.
- Bhat, C.R., Sen, S., 2006. Household vehicle type holdings and usage: An application of the multiple discrete-continuous extreme value (MDCEV) model. *Transportation Research Part B*, 40(1), 35-53.
- Bhat, C.R., Sidharthan, R., 2011. A simulation evaluation of the maximum approximate composite marginal likelihood (MACML) estimator for mixed multinomial probit models. *Transportation Research Part B*, 45(7), 940-953.
- Bhat, C.R., Sidharthan, R., 2012. A new approach to specify and estimate non-normally mixed multinomial probit models. *Transportation Research Part B*, 46(7), 817-833.
- Bhat, C.R., Castro, M., Khan, M., 2013. A new estimation approach for the multiple discrete-continuous probit (MDCP) choice model. *Transportation Research Part B*, 55, 1-22.
- Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R., Occhiuzzo, G.P., 1993. Demand for clean-fuel vehicles in California: A discrete-choice state preference pilot study. *Transportation Research Part A*, 27(3), 237-253.
- BusinessKorea, 2013. *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), 2010. *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.
- Desomer, E., 2013. The changing nature of mobility: Exploring consumers' mobility preferences. Deloitte, November 14, 2013.
- Dubin, J., Barenly, R., Csontos, A., Um, J., Wu, N., 2011. Realizing the potential of the Los Angeles electric vehicle market. Luskin Center Electric Vehicle Research Program. UCLA Anderson, Los Angeles, CA, May.
- Economic Review, 2014. *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., Allenby, G.M., 2003. Multivariate analysis of multiple response data. *Journal of Marketing Research*, 40(3), 321-334.
- Ewing, G., Sarigollu, E., 2000. Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment. *Journal of Public Policy and Marketing*, 19, 106-118.
- Fishbein, M., Ajzen, I., 1975. *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*. Addition-Wesley, Reading, MA.
- Kirk, B., 2011. Connected Vehicles: An Executive Overview of the Status and Trends. Globis Consulting Inc., November 2011, [http://www.globisconsulting.ca/Connected\\_Vehicles\\_Globis\\_rpt.pdf](http://www.globisconsulting.ca/Connected_Vehicles_Globis_rpt.pdf). Accessed July 30, 2014.
- Kraan, M., Mahmassani, H.S., Huynh, N., 2000. Traveler responses to advanced traveler information systems for shopping trips: Interactive survey approach. *Transportation Research Record: Journal of the Transportation Research Board*, 1725, 116-123.
- McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In Zarembka, P. (Ed.), *Frontiers of Econometrics*. Academic Press, New York, pp. 105-142.
- National IT Industry Promotion Agency (NIPA), 2013. *The Birth of 'Smart Car' after Combining Vehicles with IT*. Korea, June 24, 2013.
- Nelson, S.P., 2014. *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](http://www.freescale.com/files/training_pdf/VFTF09_AA106.pdf). Accessed July 30, 2014.
- Parasuraman, R., Mouloua, M., 1996. *Automation and human performance: Theory and applications*. Lawrence Erlbaum Associates.
- Rogers, E.M., 1962. *Diffusion of Innovation*. The Free Press, New York.
- Rose, J.M., Hensher, D.A., Caussade, S., Ortúzar, J.D., Jou, R.C., 2009. Identifying differences in willingness to pay due to dimensionality in stated choice experiments: a cross country analysis. *Journal of Transport Geography*, 17(1), 21-29.
- Shin, J., Hong, J., Jeong, G., Lee, J., 2012. Impact of electric vehicles on existing car usage: A mixed multiple discrete-continuous extreme value model approach. *Transportation Research Part D*, 17(2), 2012, 138-144.
- Train, K.E., 2009. *Discrete Choice Methods with Simulation*, 2<sup>nd</sup> ed., Cambridge University Press, Cambridge, U.K.
- USA Today, 2012. Google Discloses Costs of Its Driverless Car Tests. June 14, 2012.
- van Rijnsoever, F.J., Hagen, P., Willems, M., 2013. Preferences for alternative fuel vehicles by Dutch local governments. *Transportation Research Part D*, 20, 15-20.

**TABLE 1. Data Description of the Survey Sample**

<b>Demographic Properties of Respondents</b>					
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		
<b>Annual Vehicle Mileage</b>					
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**

<b>Vehicles (Used in the First Set of Choice Experiments)</b>		
<b>Attributes</b>	<b>Levels</b>	<b>Details</b>
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.
<b>Smart Options (Used in the Second Set of Choice Experiments)</b>		
<b>Attributes</b>	<b>Levels</b>	<b>Details</b>
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**

<b>Baseline Preferences</b>		
<b>Variable</b>	<b><math>\beta</math></b>	<b>t-value</b>
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
<b>Satiation</b>		
<b>Vehicle Type</b>	<b><math>\alpha</math></b>	<b>t-value</b>
Gasoline	0.71	35.91
Diesel	0.86	44.21
Hybrid	0.88	26.88
Electric	0.95	60.48

Mean log-likelihood value at convergence = -4.92

**TABLE 4. MDCP Model of Vehicle Choice by Demographic Segment**

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

Note: 1. <sup>a</sup> 1% significance level, <sup>b</sup> 5% significance level, <sup>c</sup> 10% significance level

2. To identify the preference differences among demographic segments, this study considers several demographic variables and the level of intention to use smart options as the basis for segmentation. Model parameters are derived from model estimations performed separately for each demographic segment.

**TABLE 4. MDCP Model of Vehicle Choice by Demographic Segment (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
<b>Baseline (<math>\beta</math>)</b>									
Electric									
Constant	-0.2404	-0.1895	-0.5380 <sup>b</sup>	-0.1657	-0.9948 <sup>a</sup>	-0.8765 <sup>b</sup>	-0.3117 <sup>c</sup>	0.6245 <sup>a</sup>	-0.3875 <sup>b</sup>
Male	0.1543 <sup>a</sup>	-	-	0.0210	0.2169 <sup>a</sup>	-0.0464	0.0784 <sup>c</sup>	-	0.0001
Age	-0.0580 <sup>a</sup>	-0.0128	0.0373 <sup>b</sup>	-0.0387	0.0126	0.1523 <sup>b</sup>	-0.0051	-0.0244	0.0143
Income	-	-0.0042	0.0210	-	-	-	-	0.0040	-0.0096
Family Size	-	-	-	-	-	-	-	-	-
Dwelling Size	-	-	-	-0.0543	0.0687 <sup>b</sup>	-	-	-0.1346 <sup>a</sup>	0.0723 <sup>c</sup>
Connectivity Usefulness	-0.0922 <sup>a</sup>	-	-	-	-	-	-	-	-
Voice Command Usefulness	-	-0.0161	0.1070 <sup>b</sup>	-	-	-	-	-0.0706 <sup>b</sup>	-0.0192
Autonomous Driving Usefulness	-	0.0453	-0.0904 <sup>b</sup>	-0.0515	-0.0039	-0.0569	0.0423	-	-
Wireless Internet Usefulness	-	-0.0400 <sup>c</sup>	0.0245	0.0044	-0.0256	-	-	-	-
Smart Application Usefulness	0.1423 <sup>a</sup>	-	-	0.0980	0.1677 <sup>b</sup>	-	-	-	-
SUV	0.0550 <sup>a</sup>	0.0428 <sup>c</sup>	0.0579 <sup>b</sup>	0.0321	0.0565 <sup>b</sup>	0.0098	0.0758 <sup>a</sup>	0.0929 <sup>b</sup>	0.0249
Fuel Cost	-0.3133 <sup>a</sup>	-0.2802 <sup>a</sup>	-0.3172 <sup>a</sup>	-0.4235 <sup>a</sup>	-0.2646 <sup>a</sup>	-0.4048 <sup>a</sup>	-0.2852 <sup>a</sup>	-0.1531 <sup>a</sup>	-0.3727 <sup>a</sup>
Purchase Price	-0.1940 <sup>a</sup>	-0.1723 <sup>a</sup>	-0.1937 <sup>a</sup>	-0.1898 <sup>a</sup>	-0.1848 <sup>a</sup>	-0.1817 <sup>a</sup>	-0.2209 <sup>a</sup>	-0.1145 <sup>a</sup>	-0.2240 <sup>a</sup>
Accessibility of Fueling Station	0.4503 <sup>a</sup>	0.3451 <sup>a</sup>	0.5077 <sup>a</sup>	0.7886 <sup>a</sup>	0.3608 <sup>a</sup>	0.3888 <sup>a</sup>	0.5763 <sup>a</sup>	0.4410 <sup>a</sup>	0.4489 <sup>a</sup>
Smart Car Options	0.0996 <sup>a</sup>	0.0937 <sup>a</sup>	0.0858 <sup>a</sup>	0.0477	0.0834 <sup>a</sup>	0.1136 <sup>a</sup>	0.1034 <sup>a</sup>	0.0968 <sup>a</sup>	0.0978 <sup>a</sup>
<b>Satiation (<math>\alpha</math>)</b>									
Gasoline	0.7113 <sup>a</sup>	0.7400 <sup>a</sup>	0.6720 <sup>a</sup>	0.6989 <sup>a</sup>	0.7169 <sup>a</sup>	0.6916 <sup>a</sup>	0.7461 <sup>a</sup>	0.6502 <sup>a</sup>	0.7330 <sup>a</sup>
Diesel	0.8508 <sup>a</sup>	0.8421 <sup>a</sup>	0.8705 <sup>a</sup>	0.9388 <sup>a</sup>	0.8012 <sup>a</sup>	0.8687 <sup>a</sup>	0.8329 <sup>a</sup>	0.9372 <sup>a</sup>	0.8248 <sup>a</sup>
Hybrid	0.8737 <sup>a</sup>	0.9189 <sup>a</sup>	0.8472 <sup>a</sup>	0.6850 <sup>a</sup>	0.9227 <sup>a</sup>	0.8418 <sup>a</sup>	0.8422 <sup>a</sup>	0.8631 <sup>a</sup>	0.8726 <sup>a</sup>
Electric	0.9454 <sup>a</sup>	0.9571 <sup>a</sup>	0.9468 <sup>a</sup>	0.9152 <sup>a</sup>	0.9555 <sup>a</sup>	0.9166 <sup>a</sup>	0.9519 <sup>a</sup>	0.9564 <sup>a</sup>	0.9390 <sup>a</sup>
Mean Log-Likelihood Value at Convergence	-4.8981	-4.8321	-4.9688	-4.8169	-4.9350	-4.7234	-5.0427	-5.1077	-4.8132

Note: 1. <sup>a</sup> 1% significance level, <sup>b</sup> 5% significance level, <sup>c</sup> 10% significance level

2. To identify the preference differences among demographic segments, this study considers several demographic variables and the level of intention to use smart options as the basis for segmentation. Model parameters are derived from model estimations performed separately for each demographic segment.

**TABLE 5. Multinomial Probit (MNP) Model Estimation Results**

Attribute	Parameter Mean	Parameter Std Dev	Marginal Willingness to Pay (MWTP)
Option price	-0.4014 <sup>a</sup>	0.0002	-
Connectivity	0.6450 <sup>a</sup>	0.0003 <sup>c</sup>	1.6 million KRW
Voice command	0.2562 <sup>a</sup>	0.4699 <sup>b</sup>	0.6 million KRW
Lane keeping	-0.3559 <sup>a</sup>	0.0004 <sup>b</sup>	-0.9 million KRW
Wireless internet	0.6644 <sup>a</sup>	1.2092 <sup>a</sup>	1.7 million KRW
Smart Applications	0.2536 <sup>a</sup>	0.4181	0.6 million KRW

Log-likelihood value at convergence = -1.1701

Note: <sup>a</sup>1% significance level, <sup>b</sup>5% significance level, <sup>c</sup>10% significance level



Question ① Please choose the alternatives that you would purchase (multiple choices are allowed)  
 ② Based on your annual usage of cars, please allocate the car usage among your selected alternatives

Question 1 for vehicles

Attributes		Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Vehicle Attributes	1. Fuel Type	Electric	Gasoline	Hybrid	Diesel
	2. Fuel Cost (Won/km)	200	100	200	100
	3. Purchase Price (10,000 won)	4000	3000	3500	2500
	4. Maintenance cost (10,000 won/year)	20	50	100	50
	5. Accessibility of Fueling Station (%)	80%	100%	100%	80%
① Willingness to purchase					
② Allocate the car usage per year		km	km	km	km

Note: Assume that the other attributes remain the same.

Question. ① Please choose the most preferred alternative (single choice)

Question 1 for smart option

Attributes		Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Smart Option Attributes	1. Option Price (10,000 won)	500	100	300	100
	2. Connectivity	Possible	Possible	Not Possible	Not Possible
	3. Voice Command	Possible	Not Possible	Not Possible	Not Possible
	4. Autonomous Driving	Control Speed	Control Speed	Control Speed	Control Speed + Lane Keeping
	5. Wireless Internet	Provided	Not Provided	Provided	Not Provided
	6. Application	Not Provided	Provided	Not Provided	Not Provided
① The most preferred alternative					

Note: Assume that the other attributes remain the same.

Figure 1. Sample Choice Experiment in Stated Preference Survey