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Analysis of New Product Adoption Behavior Based on Consumers' Heterogeneity in Status Quo

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이 논문을 공학박사학위 논문으로 제출함

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Abstract

Analysis of New Product Adoption Behavior Based on Consumers' Heterogeneity in Status Quo

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The purpose of this study is to analyze consumer preference for semi-durable products that are purchased regularly, in consideration of the effect of the consumers' currently owned products on the selection of new products. When consumers purchase new products, they are likely to be affected greatly by the condition of their currently owned products and their experiences with those products; therefore, it is difficult to forecast accurately the preference of consumers merely from a comparison of new products. In particular, this study analyzes factors involving the level of obsolescence of consumer-owned products and any similarities they share with the products to be purchased. Such a choice model that considers the condition of currently owned products can be used to select products in the same category; it can also be extended to products in other categories that may be mutually influential.

Empirical analysis is conducted with three smart devices: smart phones, smart pads, and smart TVs. By using a hierarchical Bayesian multinomial logit, the status-quo effect on new choices is analyzed. It is found that the relative importance of the status-quo effect is considerable, and that choice probabilities that consider status-quo alternatives are significantly different from those that do not. The change in choice probabilities over time can be simulated if the magnitude of the obsolescence effect can be estimated. Analyzing the change in choice probabilities over time, even in the absence of time-series data, is one of the remarkable advantages of this study's methodology.

From the perspective of interaction between multi-product categories, the choice model that incorporates the status quo can be extended by using a bivariate multinomial probit model. Through the use of this model, the current study analyzes how consumer preference for a smart pad or TV differs from each other, as a function of having selected a smart phone. Kernel-density plots highlight this difference, and the variance–covariance matrix shows the correlation among alternatives. Obviously, the status-quo effect of a smart phone on choosing a new smart pad or TV can be analyzed.

In summary, this study explains why a choice model should consider the status-quo effect, and it offers an empirical analysis method that incorporates this effect.

Keywords: consumer preference, hierarchical Bayesian multinomial logit, bivariate multinomial probit, status quo, obsolescence, similarity

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Chapter 1. Introduction

1.1 Research Background

How do consumers decide which particular product to purchase, and when? These are key research questions asked by practitioners of marketing and demand forecasting alike. Under a situation in which a variety of competition goods exist, information about when a consumer decides to purchase what kinds of products is useful for companies in determining their R&D direction, product design, production, and inventory management (Luo, 2011; Cachon and Swinney, 2011; Lee et al., 2009; Ahn et al., 2006); it is also useful for a government as it makes policy decisions (Hong et al., 2012; Cho et al., 2011; Alvarez–Farizo and Hanley, 2002). Especially in cases involving high-tech products—which are innovated rapidly and have short product lifecycles—analyzing consumer demand for unreleased products is very important, because companies really cannot wait until sufficient sales data have been accumulated.

A variety of methodologies have been proposed from this viewpoint, vis-à-vis the forecast of consumer demand for products. A qualitative demand forecasting model like Delphi, or brainstorming or expert forecasting, is used when no past market data exist or when it is difficult to create a theoretical model supported by mathematics or statistics. However, such models are likely to be influenced considerably by researcher subjectivity, compared to quantitative analysis; it is also difficult to verify forecasting results.

Further to quantitative demand forecasting models, there is the diffusion model, choice-based conjoint analysis, the contingent valuation method (CVM), and multi-attribute utility theory (MAUT), among many others.

Diffusion models are growth models that include logistic or Gompertz growth models or the diffusion of innovation models which stem originally from Bass (1969). Such models are mainly used to estimate sales within a specific product category, based on time-series analysis. On the other hand, choice-based conjoint analysis estimates consumer preference and the choice probabilities for new products based on individual stated preferences, through the use of discrete choice models—that is, diffusion models have mainly focused on "when" to purchase product, while conjoint analysis focuses on "which" product is to be purchased. Recently, in order to analyze both adoption time and behavior, some models have been proposed that simultaneously analyze both the "when" and "which" of the product purchase by combining a diffusion model with individual level choice behavior, or by using a discrete choice model with panel data.

The current study proposes a new framework by which to analyze consumer preference and forecast a dynamically changing market; this framework is based on choice-based conjoint analysis that uses an advanced discrete choice model to incorporate a missing, albeit important, factor: the status-quo effect with regard to the adoption of new-product alternatives.

1.2 Research Objectives

Humans generally rely upon their past experiences and personal histories when making decisions. Each person can make a different decision, because each person has different experiences. Such decision-making parameters come into play with the purchase of products. Each consumer purchases a different product at a different time, although the same kinds of products are offered within the market at the same time. The different decisions that occur, even given identical choice sets, can be explained in two ways: consumers have different, unobserved tastes that cannot be captured in terms of observable characteristics, and consumers have heterogeneous past experiences that affect their present and future choices (Smith, 2005). With respect to the latter explanation—which is a focus of this research—Heckman (1981) states that "past experience has a genuine behavioral effect in the sense that an otherwise identical individual who did not experience the event would behave differently in the future than individuals who experienced the event" (p. 91). There is an abundance of literature that emphasizes the importance of considering the previous state of respondents. The following are representative excerpts:

> In conventional consumer theory each individual's choices are determined by a preference ordering over consumption bundles; this

> ordering is independent of the individual’s endowment. However, a number of recent papers have suggested that preferences may be conditioned on current endowments.… (Bateman et al., 1997; p. 479)

> In frequently-purchased-consumer-goods markets, consumer brand choices exhibit substantial persistence across purchase occasions…. A basic fact about panel data on consumer-goods purchases is that brand choices of individual consumers exhibit persistence over time…. (Keane, 1997; p. 310)

> A household’s prior purchase experiences with specific brands typically influence the households purchase propensities for the same brands in the future…. (Seetharaman, 2004; p. 263)

Such a phenomenon—wherein past choices affect future behavior—is often referred to as “state dependence” (Heckman, 1981) or “status quo bias” (Samuelson and Zeckhauser, 1988).

From the perspective of state dependence, researchers consider the effect of past choices on the purchase of new products. In particular, the literature related to state dependence focuses on the fact that the brand choices of individual consumers exhibit persistence over time (Keane, 1997). Several studies have found that purchase histories have a significant effect on behavior vis-à-vis new purchases (Smith, 2005; Seetharaman, 2004; Moeltner and Englin, 2004; Keane, 1997; Jones and Landwehr, 1988). To analyze the effect of state dependence, typically, long and wide panel datasets containing individual level purchase histories have been required; for example, Keane uses 60 weeks of scanner panel data on ketchup. However, it is difficult to obtain such well-constructed panel data for the various kinds of products we want to know about, as Smith (2005) points out:

> To model state dependence, one needs many repeated choices of the same agents. … Such long and wide panels are rarely available. … As a result of computational and data limitations, most researchers ignore either state dependence or heterogeneity. (p. 320)

Similarly, Horsky et al. (2011) state that

> By observing the same consumers over repeated purchase occasions researchers assess whether consumers become loyal to brands they purchased in the past, controlling for marketing mix variables. Although individual consumer panel data are much preferred in this type of analysis, they are often available only for a small number of product categories, stores, and regions. (p. 2)

Although Horsky et al. propose a method that uses aggregate level data—in order to overcome problems that stem from a lack of individual level data—it does require time-series data. Consequently, while the motivation to incorporate past purchasing history is reasonable, given the lack of data, it is difficult to adopt the model when repurchases do not occur frequently enough.

In the other literature, with respect to the status-quo bias, Samuelson and Zeckhauser (1988) initiate a rigorous study of it in the decision-making process. They design questionnaires for decision-making experiments in order to test status-quo bias, and find that decision-makers clearly show a bias whereby they adhere to the status quo. They explain the status-quo bias in terms of the following three categories: rational decision-making, cognitive misperception, and psychological commitment.[1]

Kahneman et al. (1991) introduce a similar concept: the endowment effect. With this effect, it is assumed that consumers obtain more product value after possessing it; this effect therefore resembles the status-quo bias. They discuss that both the endowment effect and status-quo bias can be explained as consequences of loss aversion. Rabin (1998) summarizes cases in terms of the reference-level effect—which includes the endowment effect and the status-quo bias—and argues that "people are often more

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[1] With rational decision-making, an individual compares costs—including those related to transition and uncertainty—incurred by changing one's status quo, to the benefits of adopting a new product. The idea of cognitive misperception is based on the concept of loss aversion (Kahneman and Tversky, 1979), wherein losses are weighted more heavily than gains in the decision-making process. Finally, psychological commitment refers to justifications of previous commitments, regret-avoidance, and efforts to feel in control of oneself.

sensitive to changes than to absolute levels” (p. 13).

Several derivative studies analyze status-quo bias on the marketing side. For example, Kleiser and Wagner (1999) provide a theoretical two-stage framework to examine pioneering advantages in different product categories, by integrating the ideas of product involvement and status-quo bias. They propose that pioneers are likely to be chosen on account of status-quo bias, although followers are highly relevant to pioneers. Masatlioglu and Ok (2005) propose the modified rational choice theory, which incorporates status-quo bias or endowment effect; they show how results differ when current choices are considered. Based on the revealed preference approach, they introduce a set of axioms and characterize choice correspondences wherever status-quo bias or the endowment effect is assumed to exist. Modified choice theory can explain the discrepancy between buying and selling prices. Kim and Kankanhalli (2009) demonstrate how status-quo bias makes consumers resist the adoption of a new information system; they consider the switching cost associated with moving from the status quo to a new system, and how it is a key determinant of user resistance. Similarly, Claudy et al. (2010) apply Kim and Kankanhalli’s approach to research antecedents of consumer resistance to green innovation, in the broader framework of status-quo bias theory.

Given that every consumer has different status-quo alternatives, status-quo bias seems to explain why consumers make different choices, even in the presence of the same choice set. Studies that initially test a hypothesis relating to the existence of the status-quo bias tend to examine how it affects the outcomes of choice models. Haaijer et al. (2001), Scarpa et al. (2005), Vermeulen et al. (2008), Meyerhoff (2009), and others incorporate status-quo bias into their choice models by adding a constant for the status-quo option. However, the models proposed so far have a limitation in their ability to explain how status-quo alternatives affect new-product adoption behavior; this is because they simply try to reduce the bias that derives from choosing the status-quo or no-choice option, when not all proposed choice alternatives are sufficient choices. In addition, other studies that estimate status-quo bias show there is also *negative* status-quo bias, i.e., a utility premium for moving away from the status quo (Kim and Kankanhalli, 2009; Mogas et al., 2006; Scarpa et al., 2005; Haaijer et al., 2001). The tendency to purchase a new product can prevail in the high-tech product market, which rapidly changes. Thus, discussions of status-quo bias need to be extended to the overall effect of the status quo on new-product adoption, as has been seen in the state-dependence literature.

As mentioned, despite the importance of state dependence, this phenomenon is usually considered only with respect to non-durable (consumable) products, due to a lack of data. However, high-tech products, which periodically evolve from older-generation products and usually require pre-launch forecasting, do not have sufficiently large purchase histories to facilitate analysis. These kinds of products are called “semi-durable products,” which are “those goods whose quality deteriorates over time, so that used units of output have a lower quality than new units” (Schiraldi, 2006); examples include LCD TVs (Cho and Koo, 2012) and automobiles (Schiraldi, 2006; Stolyarov, 2002), which are often investigated from the perspective of the secondary market effect on account of their obsolescence over time.

The purpose of the current study is to incorporate the status-quo effect[2] on purchase decisions vis-à-vis semi-durable products, in order also to analyze consumer preference for high-tech products. To achieve this purpose, this new framework will be used only with cross-sectional stated-preference data. The different effects stemming from status-quo alternatives—such as the types of products purchased and the timing of purchases—are to be considered with a status-quo option.

[2] In this study "status quo" refers to the *currently owned product of consumers*; the status-quo effect, which differs somewhat from status-quo bias, refers here to the *effect of a status quo alternative on new product adoption*.

1.3 Research Framework

Figure 1 provides a general schematic detailing how the status quo affects the choice of a new alternative. The main point here is to consider a status-quo alternative that is the most competitive alternative versus other new alternatives. Suppose there are n consumers who have a currently owned product and three kinds of new alternatives, *A*, *B*, and *C*. U_{SQ_i} represents consumer i's utility of a currently owned product and U_{A_i}, U_{B_i}, and U_{C_i} represent consumer i's utilities in choosing new alternatives *A*, *B*, and *C*. $SQ_{i,Int}$ and $SQ_{i,Ext}$ represent consumer i's status-quo effect on the utility of currently owned product and new products, respectively.

First, the time at which a consumer purchases a product can be an element of $SQ_{i,Int}$. The purchase time may indicate how much the currently owned products have been obsolesced. A consideration of the degree of obsolescence is important, because this study focuses on semi-durable products whose quality deteriorates over time. Concerned with the status-quo effect, the first hypothesis is as follows:

H1: The older a currently owned product becomes, the less utility a consumer derives from it.

By analyzing the obsolescence effect, the timing of a consumer's adoption of a new product can be calculated; this adoption-time information will be valuable for companies as they decide upon the timing of a new-product launch. This is the important contribution of the model proposed in the current study: through its use, researchers can analyze the adoption pattern of new products over time, even in the absence of time-series data.

Second, the similarity between currently owned and new products can be an element of $SQ_{i,Ext}$. One should be mindful of the fact that the literature that analyzes state dependence focuses on whether or not consumers persistently choose the same brand. In the current study, state dependence can be extended to other physical similarities, as well as brand similarity. However, consumers may have a higher or lower utility when a new alternative is similar to currently owned products. Concerning the status-quo effect, the second hypothesis, in two parts, is as follows:

H2a: Compared to currently owned products, consumers derive higher utility from more similar products

H2b: Compared to currently owned products, consumers derive lower utility from the more similar products

In addition to the obsolescence and similarity effects, these other kinds of effect may differ as a function of consumer use pattern or satisfaction with currently owned products.

Simply, I consider use and satisfaction level, which influence the obsolescence and similarity effects, respectively. The third hypothesis, in two parts, is as follows:

> *H3a: The more a consumer uses a currently owned product, the more quickly that product obsolesces.*
>
> *H3b: A consumer who is satisfied more with his or her status quo prefers more similar products.*

Other main effects besides obsolescence or similarity effects, or sub-effects besides use or satisfaction level, can be flexibly considered within the same framework proposed here.

By comparing the utility of a currently owned product to those of new products, a consumer will choose a new product, when the highest utility of the new product exceeds the utility of a currently owned product.

This study will analyze how individual differences with respect to currently owned products affect new-product adoption, based on the discrete choice model; this model is able to analyze the part-worth of attributes of unreleased products and forecast their market share at the brand level. Choice probability as a function of a type of currently owned product for each consumer can be represented as a logit choice form, and it can be extended to an hierarchical Bayesian (HB) multinomial logit model to incorporate consumer heterogeneity. A more specific description of discrete choice models is offered in Chapters 2 and 3.

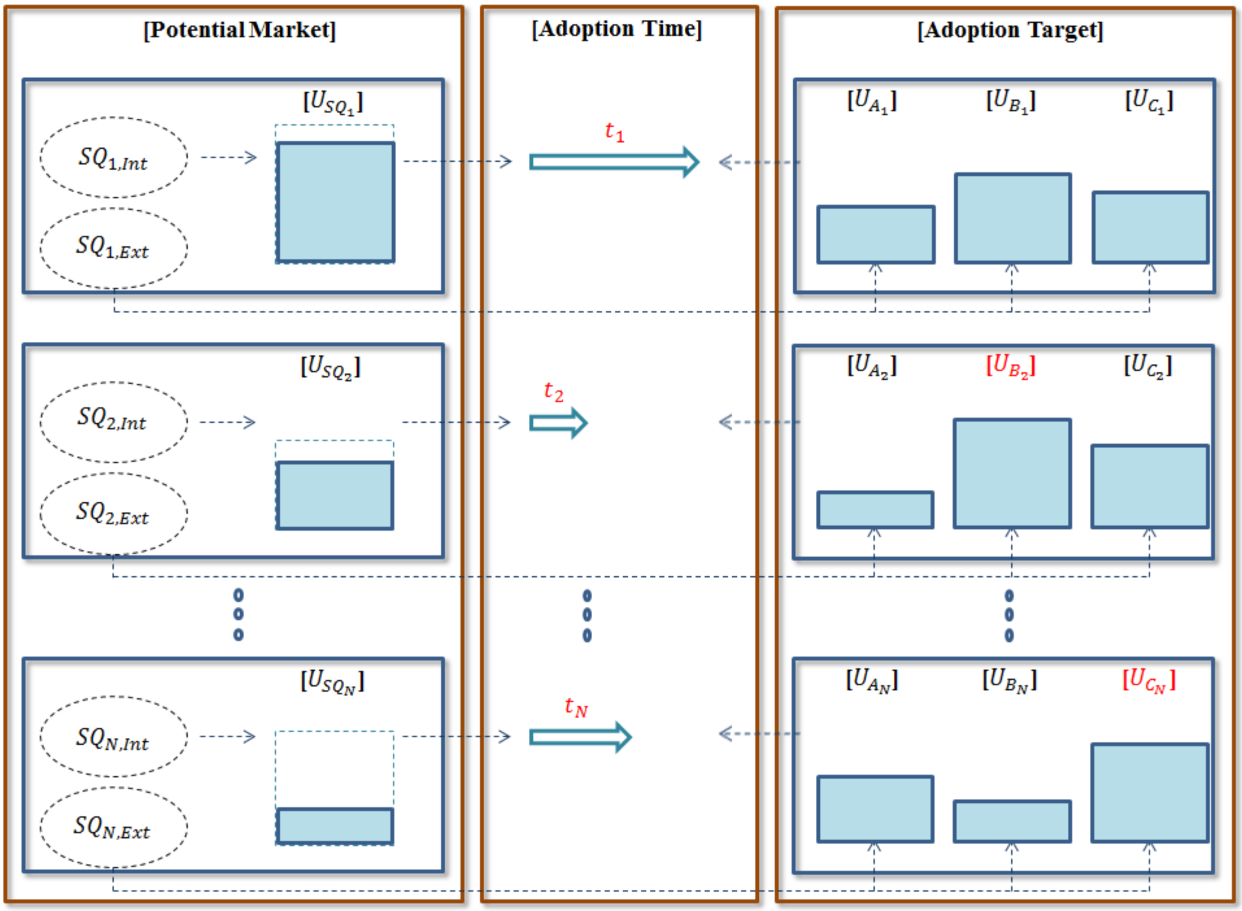


Figure 1. Schematic illustrating how consumer heterogeneity of the status quo affects new-product adoption behavior

Though status-quo effects, as explained thus far, occur within single-product categories, it is possible to expand the concept to multi-product categories—that is, if there is a product category *A* that affects other product categories, then consumers' status-quo alternatives in product category *A* can affect their choice of other products in another category, *B*. For example, with respect to ICT products (smart phones, smart pads, smart

TVs, and the like) that share the same operating system (OS) across categories, considerations of the status-quo effect stemming from other product categories should be analyzed. In other words, if a smart phone and a smart pad use the same OS, they can share purchased applications, documents, and photos easily through a cloud service; a higher learning cost could be incurred when one starts to use a different OS, and so there may be a tendency to continue to use the same OS in both smart phones and smart pads. If there is no mature market yet for smart TVs, it is possible to incorporate the status-quo effects from a smart phone, even though it is difficult to analyze them with the conventional state-dependence framework. To the best of my knowledge, the analysis of status-quo effects across product categories has not been investigated previously. With respect to status-quo effects among multiple categories, the final hypothesis is as follows:

H4: The status quo may influence choice in more than one product category.

To analyze more than one choice, other choice models that analyze multivariate dependent variables are required, rather than an HB multinomial logit model.

In summary, the purpose of this study is to analyze the status-quo effect—such as obsolescence and similarity effects—within a single-product category and across multi-product categories.

1.4 Research Outline

This research consists of five chapters, which are organized as follows. Chapter 2 reviews previous research about standard discrete choice models and their flexible forms, for single-choice and derivative discrete choice models that analyze multiple choices across other categories that may be mutually influential. The purpose of the current study is also more clearly detailed, in reference to the literature. Chapter 3 proposes an advanced choice model that considers the status-quo effect derived from a currently owned product. The proposed model is then extended to multi-product category cases. Chapter 4 provides empirical results for several ICT devices: smart phones, smart pads, and smart TVs. Finally, Chapter 5 summarizes the content of the current study and states the contributions and limitations of this research.

Chapter 2. Literature Review and Research Purpose

This chapter reviews the literature that relates mainly to discrete choice models that incorporate status-quo alternatives, as well as other forms of consumer heterogeneity. Additionally, other new-product adoption models—such as innovation diffusion and technology acceptance models—are reviewed.

2.1 Discrete Choice Models that Consider Consumer Heterogeneity

The discrete choice model is one of the most useful methods for analyzing consumer preference when consumers select an alternative discretely. Because there are several types of advanced discrete choice models, one must be careful to select the most appropriate type to incorporate status-quo effects. In the following section, some discrete choice models—especially those that focus on incorporating consumer heterogeneity—are described in mathematical terms. Also, I investigate the literature on discrete choice models that consider status-quo bias.

2.1.1 Multinomial Logit Choice Model

Assume a situation in which a respondent chooses one alternative from a choice set that includes several alternatives. Based on random utility theory, the utility of an individual n by obtaining alternative j in a choice set of C_n can be defined as follows:

$$U_{nj} = V_{nj}(w_n, x_j) + \varepsilon_{nj} = \beta_n x_j + \varepsilon_{nj} . \tag{2.1}$$

U_{nj} is the respondent's utility by obtaining alternative j, and it can be divided into two parts: the deterministic utility V_{nj}, and the stochastic term ε_{nj}. The deterministic utility—affected by the respondent's personal characteristics, w_n, and attributes of alternatives, x_j—is a component that can be observed by the researcher.

Each respondent chooses an alternative that gives him or her the highest utility. In this case, the choice probability that a consumer chooses alternative j is defined by way of equation (2.2):

$$P_{nj} = \Pr(U_{nj} > U_{nk}\ \forall k \neq j) = \Pr(\varepsilon_{nk} - \varepsilon_{nj} < V_{nj} - V_{nk}, \forall k \neq j) . \tag{2.2}$$

This probability occurs in a case where the alternative j has a higher utility than any other alternative within the choice set.

If we assume that each distribution of the stochastic term ε_{nj} follows an independent and identically distributed (i.i.d.) Gumbel (type-I extreme value) distribution, the choice probability is calculated as per equation (2.3) and simply expressed as a closed form of equation (2.4) (McFadden, 1973; Train, 2009).

$$P_{nj} = \int \left(\prod_{k \neq j} e^{-e^{-(\varepsilon_{nk} + V_{nk} - V_{nj})}} \right) e^{-\varepsilon_{nk}} e^{-e^{-\varepsilon_{nk}}} d\varepsilon_{nk} \tag{2.3}$$

$$P_{nj} = \frac{\exp(V_{nj})}{\sum_{i=1}^{J} \exp(V_{ni})}, \quad j = 1, \cdots, J \tag{2.4}$$

This is called a multinomial logit choice model, and it has the advantage of leading to a closed form of choice probability.

The marginal willingness to pay (MWTP) for the q^{th} attribute is the amount a consumer is willing to pay in order to maintain the same utility level when the quantity or quality of the q^{th} attribute changes; MWTP is calculated as per equation (2.5):

$$MWTP_{x_q} = -\frac{\partial U / \partial x_q}{\partial U / \partial x_{price}} = -\frac{\beta_q}{\beta_{price}}, \tag{2.5}$$

where x_{price} and β_{price} are the variable and estimated parameter of the price attribute, respectively, and x_q and β_q are the variable and estimated parameter of the q^{th} attribute, respectively.

In addition, equation (2.6) shows the relative importance (RI) of the q^{th} attribute when making a purchase decision. Here, the part-worth of attribute k, $part-worth_k$, can be obtained by multiplying β_k by the difference-range of the suggested maximum and minimum levels of attribute k.

$$RI_q\left(\%\right) = \frac{part-worth_q}{\sum_{k=1}^{K} part-worth_k} \times 100 \tag{2.6}$$

With respect to considering respondent heterogeneity, the multinomial logit choice model has a limitation. As seen in equation (2.2), for the same respondent n, the effect derived from simply adding respondent-specific variables on both the left-hand and right-hand sides of the utility is canceled out. Therefore, in order to reflect a respondent's socio-demographic characteristics—such as income, gender, and age—interaction terms between the socio-demographic variables and attributes are frequently used. For example, Lee and Cho (2009) use the rank-ordered logit choice model, which is similar to the multinomial logit choice model, except that alternatives are ranked in order of preference, with several interaction terms. They consider certain socio-demographics of respondents, including gender, age, marital status, ownership of passenger car, and distance driven per year, along with several vehicle attributes. The interaction terms have been broadly used in previous research (Kim et al., 2006; Ahn et al., 2006; Ewing and Sarigollu, 1998).

2.1.2 Mixed Logit and Generalized Multinomial Logit Models

Although the multinomial logit choice model has a closed form, it cannot adequately reflect consumer heterogeneity; it also has an unrealistic independence of irrelevant alternatives (IIA) property that assumes that the ratio of two alternatives' choice probabilities will not be affected by changes to the attributes of other irrelevant alternatives. These limitations can be overcome by using a mixed logit choice model that reflects the heterogeneity of individual preferences by imposing a distribution on parameters and showing random taste variations.

The mixed logit choice model assumes that β_n follows normal distributions with the mean b and the variance W for the population, and that the stochastic terms also follow i.i.d. Gumbel distributions. The utility of respondent n in choosing j alternative among J number of alternatives can be expressed as per equation (2.7):

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n x_j + \varepsilon_{nj}, \ \beta_n \sim N(b, W) \ . \tag{2.7}$$

While the above multinomial logit choice model sets the β coefficients as fixed parameters, the mixed logit choice model assumes the β coefficients are random parameters that have distributions generated by the heterogeneity of respondents. The probabilities of the mixed logit choice model are the integrals of standard logit probabilities over a density of parameters (Train, 2009), and they can be expressed as:

$$P_{nj} = \int L_{nj}\left(\beta\right) f\left(\beta\right) d\beta , \tag{2.8}$$

where $L_{nj}\left(\beta\right)$ is the standard logit probability:

$$L_{nj}\left(\beta\right) = \frac{e^{V_{nj}(\beta)}}{\sum_{i=1}^{J} e^{V_{ni}(\beta)}} \tag{2.9}$$

and $f\left(\beta\right)$ is the probability density function of β .

In examples of mixed logit choice models, Koo et al. (2012) and Hong et al. (2012) find that the variance of parameters assumed to be normal or log-normal distributions are statistically significant. The degree of variance can be interpreted as the degree of heterogeneity.

A more flexible form rendered by additionally incorporating scale heterogeneity is the generalized multinomial logit (G-MNL) choice model (Fiebig et al., 2010; Greene, 2011).

The G-MNL choice model assumes β_n, as in equation (2.10):

$$\beta_n = \sigma_n \beta + \left[\gamma + \sigma_n \left(1 - \gamma\right)\right] \eta_n, \tag{2.10}$$

where γ is a scalar parameter, $\eta_n \sim MVN\left(0, \Sigma\right)$ is a random vector, and σ_n is the individual-specific scale. σ_n is defined as:

$$\sigma_n = \exp\left(\bar{\sigma} + \theta z_n + \tau v\right), \tag{2.11}$$

where $v \sim N\left(0,1\right)$ is scalar, and the normalized constant $\bar{\sigma}$ is $-\ln\left(\frac{1}{N}\sum_{i=1}^{N}\exp\left(\tau v_i\right)\right)$.

Depending on the value of γ, G-MNL can be of either the G-MNL-I type—where $\beta_n = \sigma_n \beta + \eta_n$ when γ =1—or the G-MNL-II type—where $\beta_n = \sigma_n \left(\beta + \eta_n\right)$ when γ =0. In addition, when $\sigma_n = 1$, the G-MNL is identical to the mixed logit choice model, and when $\sigma_n = 1$ and $\mathrm{var}\left(\eta_n\right) = 0$, it collapses to the multinomial logit choice model.

Basically, flexible forms of the multinomial logit choice model are useful in describing consumer heterogeneity in the status quo. However, to explain in greater detail the reasons for that heterogeneity, another hierarchy that breaks down each parameter is needed. A specific description of the hierarchical multinomial logit choice model that considers the status-quo effect is given in Chapter 3.

2.1.3 Discrete Choice Models that Incorporate the Status-Quo Alternative

Because incorporating the conditions of a respondent's status quo as a socio-demographic feature, as shown above, has limitations, discrete choice models that directly consider the status-quo effect are suggested. Haaijer et al. (2001) argue that including a "no-choice option" or "own-choice alternative" in the choice set is necessary, because it provides a more realistic situation for respondents and is useful in deriving better predictions of market penetration. Dhar (1997) provides an overview of why and when respondents may generally choose the no-choice option; he states that "respondents may choose the no-choice when none of the alternatives appears to be attractive, or when the decision-maker expects to find better alternatives by continuing to search" (p. 216). Dhar also shows that adding an attractive alternative to an already-attractive choice set increases the preference for the no-choice option, and that adding an unattractive alternative to that choice set decreases the preference for it. This implies that when alternatives resemble each other in terms of preference level, consumers will choose the no-choice more frequently than when there is a clearly dominant or unattractive profile in the choice set. Therefore, respondents can choose a no-choice or status-quo alternative, due not only to logical comparisons of attribute levels, but also to the composition of the choice set they face at that time. To overcome such an uncontrolled effect, Haaijer et al. (2001) proposes a model that adds an extra constant for the status-quo alternative.

The multinomial logit choice model with an extra constant for the status-quo option is represented as per equation (2.12):

$$
\begin{aligned}
P\left(c_j\right) &= \frac{\exp\left(\beta X_j\right)}{\exp\left(ASC_{sq} + \beta X_{sq}\right) + \sum_j \exp\left(\beta X_j\right)} \\
P\left(c_{sq}\right) &= \frac{\exp\left(ASC_{sq} + \beta X_{sq}\right)}{\exp\left(ASC_{sq} + \beta X_{sq}\right) + \sum_j \exp\left(\beta X_j\right)}
\end{aligned}
, \qquad (2.12)
$$

where $P\left(c_{sq}\right)$ represents the choice probability of the status quo, while $P\left(c_j\right)$ represents the choice probabilities of the other alternatives. Depending on the sign of the estimated parameter, ASC_{sq}, the status-quo effect can be interpreted as being either positive or negative.

Vermeulen et al. (2008) confirms the results of Haaijer et al. (2001), through the use of an optimal design test. In addition, Scarpa et al. (2005) extends the multinomial logit choice model to a mixed logit choice model that features a status-quo alternative; they find that the mixed logit choice model with an extra constant for the status quo performs best. Subsequent studies by Scarpa et al. (2005) and Meyerhoff (2009) compare four kinds of model specifications: two multinomial logit choice models and two mixed logit choice models, with each pair containing one model with an extra constant and one that does not. Their results align with those of Scarpa et al. (2005).

Although recent research efforts to incorporate a status-quo alternative into conventional choice sets are encouraging, those studies do not consider specific status-quo conditions or the interaction between the status quo and new alternatives, as shown in Figure 1. Rather, they simply capture status-quo bias with respect to the survey selection process. Thus, it is inappropriate to use the simple form of equation (2.12) to incorporate several characteristics of the status-quo effect, with respect to semi-durable products.

2.2 New-Product Adoption Process at the Individual Level

Various studies on the new-product adoption process at the individual level have been conducted; among the models to arise from those studies, one of the most famous is the diffusion model developed by Bass (1969). The diffusion model incorporates two influences: internal and external. As shown in equation (2.13) below, it is assumed that new adopters are influenced by external effects p, such as advertisements, and internal effects q, such as the word-of-mouth effect from consumers who have already purchased the product. The variables $n(t)$, $N(t)$, and m represent the number of net adopters at time t, the number of cumulative adopters until time t, and the market potential, respectively. After introducing the Bass diffusion model, hundreds of variations have been derived to forecast the sales of durable goods (Meade and Islam, 2006; Mahajan et al., 1990).

$$\frac{dN(t)}{dt} = n(t) = \left(p + q\frac{N(t)}{m}\right)\left(m - N(t)\right) \tag{2.13}$$

While a majority of the model variations focus on macro-level sales growth, some studies use an individual-level adoption model to account for consumer heterogeneity. It is worthwhile to review individual-level adoption models to determine differences from the model that will be proposed in Chapter 3.

Chatterjee and Eliashberg (1990) assume consumers are risk-averse and heterogeneous in the amount of information they receive prior to adopting an innovation. Because consumers become more certain when they have more information, heterogeneity can explain differences in the timing of product adoption across consumers. From this perspective, the researchers derive a pattern of aggregate sales.

Horsky (1990) considers the heterogeneity of wage and price as major diffusion factors. The number of consumers who can potentially adopt an innovation—which is referred to as “market potential”—is assumed to be proportional to their income. With this model, if the market potential does not vary in terms of time, the model is identical to the Bass diffusion model.

Song and Chintagunta (2003) assume that, for an innovative product, consumer heterogeneity and a forward-looking quality are major diffusion factors. Their model, based on dynamic utility maximization vis-à-vis choice behavior, is used to explain the diffusion process and offers companies a variety of marketing implications.

Lee et al. (2006) forecast sales of large-screen TVs by combining discrete choice analysis and a Bass diffusion model. They estimate consumer preferences for large-screen TVs by using conjoint analysis. With the estimation of the total number of large-screen TV sales through the use of the Bass diffusion model, they calculate a diffusion curve for each TV type, based on choice-probability information derived from previous discrete choice analysis.

Cho (2007) develops a dynamic micro-level diffusion model under the assumption that price, technological improvement, network externality, various consumer expectations, discount rate of consumer utility, and waiting cost are important factors that explain the diffusion process. By considering consumer heterogeneity with those factors, a diffusion pattern derived from the economic perspective of consumer behavior fully explains the Bass diffusion model.

Although these studies explain the dynamic adoption process in a variety of ways, they usually require time-series, revealed-preference data to facilitate estimations of the diffusion process. Additionally, in some cases, diffusion occurs within a short time, and so it is difficult to explain lacks of price drops or technology improvement.

Another famous model is the technology acceptance model (TAM) introduced by Davis (1986). The TAM adopts the theory of reasoned action (TRA; Ajzen and Fishbein, 1980) to explain the causal relationship between users' perceptions of product usefulness and attitudes, intentions, usage behavior, and ease of use (Yousafzai, et al., 2007). Davis assumes an attitude inclined toward product use; it mainly determines actual use behavior and is a function of "perceived usefulness," which is defined as "the degree to which an individual believes that using a particular system would enhance his or her job performance" (p. 26), and "perceived ease of use," which is defined as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (p. 26). Several meta-analyses and review papers on TAM (e.g., Chuttur, 2009; Yousafzai et al., 2007; Sharp, J.H., 2007; King and He, 2006) outline a variety of related studies.

However, generally speaking, both the diffusion model and TAM are appropriate to the analysis of category-level adoption behavior, rather than that at the brand level—that is, it is difficult, for example, to compare the intention to use word processor software provided by Microsoft (MS) versus that from Apple. Also, simulating how attribute changes affect adoption patterns is not easy; therefore, in the current study, the discrete choice model introduced in the previous chapter is more appropriate to modeling consumer behavior vis-à-vis new-product adoption.

2.3 Research Purpose

The current study differs from previous studies, in three key respects.

First, the model suggested in this study estimates consumer preference and choice probabilities for new products or services more accurately than previous models, by reflecting the effect of the consumer status quo. In previous discrete choice models like the multinomial logit or generalized multinomial logit choice models, the heterogeneity of respondents can be explained through the use of interaction terms or by assuming parameter distribution. In this case, the attributes of the products currently owned by respondents are treated as if they were individual level demographic variables. However, doing so cannot fundamentally explain why consumers stay in the status quo—namely, why they choose the no-choice option—nor can it consider the case where a consumer does not purchase new products.

Previous research addresses this problem by using, within surveys, a choice set that includes the status quo (i.e., no-choice option), to consider the particularity of behavior wherein a respondent chooses the status quo, or by using an additional alternative specific constant to represent the status-quo option. However, previous studies that have included status-quo options in their choice sets are limited in comparison to the current study, in that they do not consider how the status-quo alternative can affect new-product adoption.

Second, I introduce the concept of obsolescence, wherein it is assumed that the consumer’s utility of a currently owned product will decrease as time passes. The use of this concept can provide a dynamic choice probability over time and serve as an explanation for the diffusion of innovation. Previous diffusion models that are considered extensions of the Bass model have used macroscopic-level analysis, which is not rigorously based on economic theory. Therefore, such diffusion models are limited in their ability to analyze diffusion patterns in terms of product characteristics at the brand level. Although micro-level models that explain macroscopic diffusion at the individual level have been proposed to overcome this limitation, they are also limited in their ability to forecast very new products. These kinds of research generally hinge on the use of revealed-preference data, because it requires time-series data to estimate diffusion patterns. In other words, it is not possible to estimate the diffusion patterns of unreleased, new products, or to explain why certain products have diffused within a short time in the absence of technical improvements or price drops.

On the other hand, a choice model that considers obsolescence—one of which is proposed newly in this research—would have advantages in forecasting the changing choice probability patterns of unreleased new products, by using only cross-sectional stated-preference data. Moreover, such a model has an advantage in its ability to explain the diffusion of products in general: it need not consider changes to other attributes.

Third, I analyze consumer preference in a situation where related product categories exist. Under the current circumstances, when a variety of ICT products interface with each other, the status quo of one category can have a strong influence on purchases among other product categories. In the current study, consumer preference with a consideration of the status-quo effect across product categories is analyzed through the use of a bivariate multinomial probit (MNP) model.

Chapter 3. Model Specification

In this chapter, I propose a discrete choice model that considers a respondent's status quo and the relationship between the status quo and newly suggested alternatives. Above all, I examine several factors that affect the status-quo utility level, and then separately examine other factors that affect the utility levels of new alternatives. I then combine these examinations to show the components of the proposed choice model. Thereafter, I suggest an expanded model that covers the case where there are multi-product categories that affect mutual choices. A schematic detailing the concepts inherent in the proposed model is shown in Figure 2.

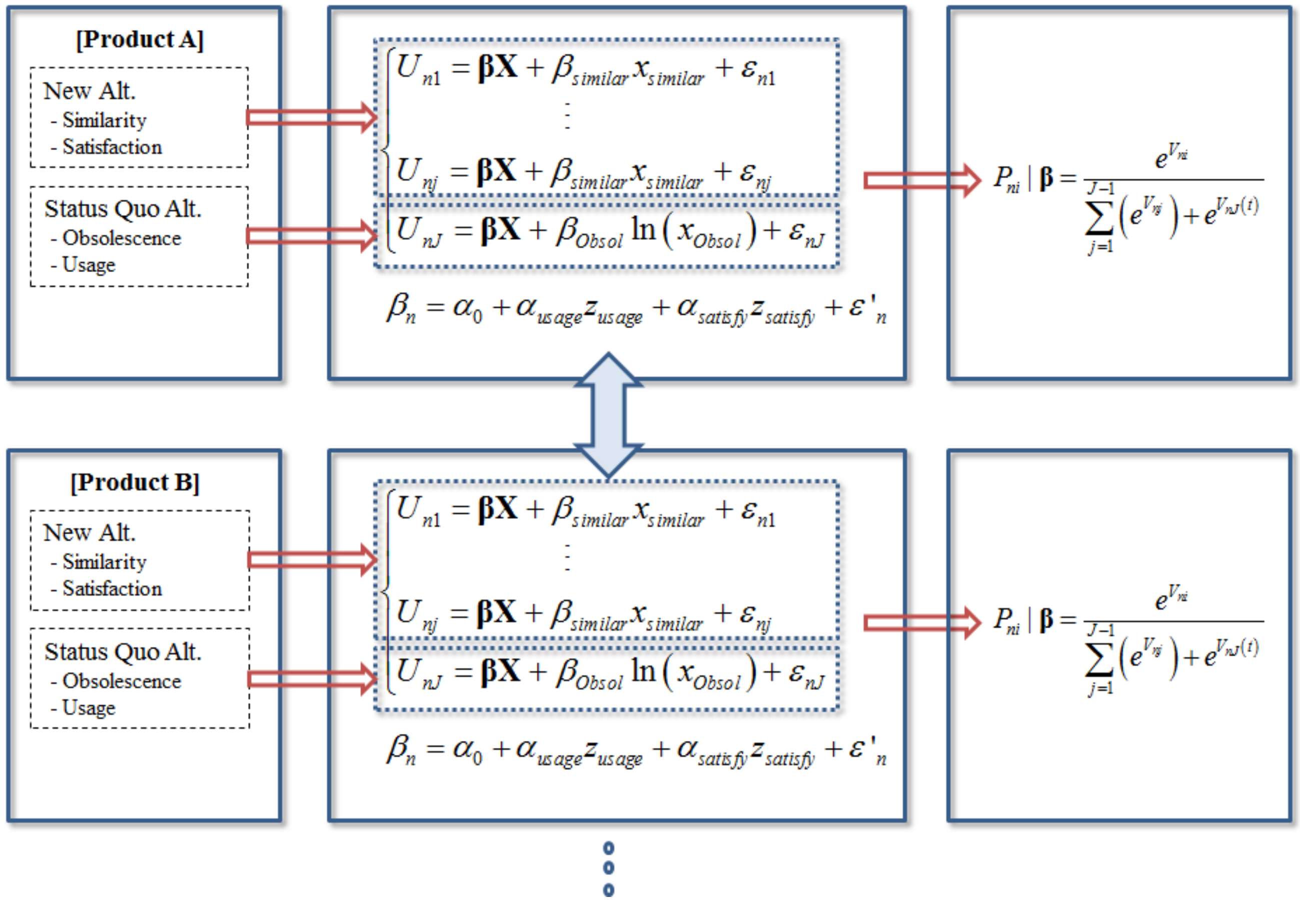


Figure 2. Schematic illustrating the concepts inherent in the proposed discrete choice model, including the status-quo effect

3.1 Modeling for Single-Product Category Case

3.1.1 Modeling Utility Function of the Status-Quo Alternative

Why do consumers purchase new products? There could be a number of reasons, but "a product currently in use becomes old," as the saying goes, is one of the most important reasons we have encountered. Particularly, in the case of semi-durable products, obsolescence has an important role. For instance, although the representative specification of digital cameras—which bear several attributes, such as weight, zoom ratio, and video-recording features—have not changed as time passes, many other parts become obsolete: a lagging shutter-release function, on account of long-term use; wear and tear in camera appearance; and other factors that researchers may find difficult to observe. The physical obsolescence of such products reduces the consumer utility of a currently owned alternative and provides motivation to purchase a new alternative.

However, physical obsolescence is not the only factor to reduce the consumer utility of a currently owned product. Following Kahneman and Tversky (1979)—who examine the psychological factors that affect a consumer's decision-making process—some studies have examined such factors. Arkes and Blumer (1985) and Arkes and Ayton (1999) examine the sunk-cost effect: although the money already paid by the consumer is a "sunk cost," it nonetheless influences future decision-making vis-à-vis the purchase of products or services, because of consumers' natural waste-aversion tendencies (Arkes, 1996).

Gourville and Soman (1998) explains why the sunk-cost effect reduces over time, in so-called payment depreciation. In other words, the product purchased with amount of money k at time t_0 generates a psychological value that exceeds k right after trading, due to the sunk-cost effect or endowment effect. However, the value decreases over time and is finally perceived as resembling a free good; at this point, the waste-aversion tendency no longer informs decisions to retain already-owned products.

Gourville and Soman assume that the potential hedonic impact (psychological value) of a payment x at time t is $V_t(x) = V_0(x) \times e^{-at}$, although it is an arbitrary function, and show that the payment depreciation effect occurs significantly over time.

Similarly, in equation (3.1) below, $V_J(t)$ represents a respondent's observable utility in keeping his or her status quo J, and $x_{Obsol}(t)$ represents the number of elapsed months at time t following the product purchase—the latter of which is a proxy variable for product obsolescence.

$$V_J(t) = \overline{V}_J - \beta_{Obsol} \ln\left(x_{Obsol}(t)\right) \tag{3.1}$$

$$\beta_{Obsol} = \alpha_0 + \alpha_{usage} z_{usage} + \boldsymbol{\alpha}'\mathbf{z} \tag{3.2}$$

$V_J(t)$ assumes a form wherein the status-quo utility is reduced over time monotonically and the size of the reduction is reduced over time,[3] while $\overline{V}_J$ is the utility of the status-quo alternative right after purchase. In equation (3.2), β_{Obsol}, a coefficient of the obsolescence variable, can be influenced by the personal characteristic variable vector $\mathbf{z}$, such as income, education, gender, or average use level ($\boldsymbol{\alpha}$ is a vector of coefficients to be estimated). Especially, I will focus on how the usage level, z_{usage}, accelerates obsolescence.

3.1.2 Modeling Utility Function of the New Alternatives

A consumer can experience more utility when a new alternative and the currently owned product are similar; conversely, a consumer can experience more utility when those items are *not* similar. The consumer choice model and consumer psychology research show that similarity affects choice among alternatives, but usually in different ways (Suk, 2008).

Consumer choice model research that emphasizes competition and substitution among alternatives shows that the choice probability of an alternative is lower when an alternative's attributes are more similar to those of the other alternative (Manrai, 1995; Kannan and Wright, 1991; Chintagunta, 1992). However, in another way, the results of

[3] In general, with the exponential functions that are often used, we can assume $V_J(t) = \overline{V}_J e^{-\alpha t}$ $\forall \alpha > 0$. However, we do not use this kind of form, because there is a problem wherein the utility increases over time when $\overline{V}_J$ is negative for $\alpha > 0$.

consumer psychology research vis-à-vis heuristic decision-making suggest that preference increases for similar products (Loken and Ward, 1990). From this perspective, the current study assumes that the similarity between new alternatives and respondents' currently owned products may have a positive or negative influence; Suk (2008) organizes the related research and proposes that such a similarity can have a positive or negative effect, depending on the degree of intimacy with the alternative.

For a means of defining and measuring similarity, it is worthwhile to mention the work of Lee (2010), which explains the similarity-index literature as follows. Tversky (1977) argues that a similarity between two alternatives is directly proportional to the number of attributes that the two alternatives share, and inversely proportional to the number of attributes on which the two alternatives differ. Though Tversky's concept is supported by consumer research (i.e., Lefkoff–Hagius and Mason, 1993; Ratneshwar and Shocker, 1991), it bears a disadvantage, in that a similarity can be explained only when the attribute level is discrete. For example, in the case of the image stabilization and manual manipulation functions of digital cameras, similarities between two cameras can be decided based on whether or not they have those properties, but it is difficult to apply such a process to continuous variables like the number of pixels, zoom range, and so on. To overcome this limitation, a similarity measurement method was proposed that examines the difference level in continuous variables (Fewster and Buckland, 2001; Bijmolt et al., 1998; Digby and Kempton, 1987). For example, a Euclidean distance is used in equation (3.3) to index dissimilarity among alternatives; it includes continuous variables, where x_{ik} and x_{jk} represent the levels of *k* attribute among alternatives *i* and *j*, respectively.

$$d_{ij} = \left[\sum_{k=1}^{r} \left(x_{ik} - x_{jk} \right)^2 \right]^{1/2} \tag{3.3}$$

However, because the Euclidean measurement has a disadvantage—wherein it is considerably influenced by the scale of an attribute—a normalization that divides into the standard deviation of the attribute level is needed. In this research, I will follow the Mahalanobis distance (Mahalanobis, 1936), shown in equation (3.4), to index the similarity of continuous variables.

$$d_{ij} = \left[\sum_{k=1}^{r} \frac{\left(x_{ik} - x_{jk} \right)^2}{s_k^2} \right]^{1/2} \tag{3.4}$$

In the current study, similarities between new alternatives and the status quo are considered a factor that affects the utility of choosing new alternatives, as in equation (3.5).

$$V_j = \boldsymbol{\beta}\mathbf{X} + \beta_{similar} x_{similar} \tag{3.5}$$

$$\beta_{similar} = \alpha_0 + \alpha_{satisfy} z_{satisfy} + \boldsymbol{\alpha}'\mathbf{z} \tag{3.6}$$

In equation (3.6), $\beta_{similar}$, a coefficient of the obsolescence variable, can be influenced by the personal characteristic variable vector $\mathbf{z}$, such can comprise income, education, gender, or average satisfaction level ($\boldsymbol{\alpha}$ is a vector of coefficients to be estimated). Especially, I will focus on the satisfaction level vis-à-vis a currently owned product, $z_{satisfy}$. Previous studies have analyzed how satisfaction or a closeness of products influences choice (Horsky et al., 2006; Suk, 2008).

3.1.3 Discrete Choice Models that Incorporate a Status-Quo Alternative

In order to consider a status-quo alternative, it is assumed that the net utility a consumer gains when he or she purchases a new product is represented by the utility difference between a new product and a currently owned product. That is, if U_{nJ} represents consumer n's utility from the status-quo alternative J—and U_{nj} represents consumer n's utility from a new product j $(1 \le j \le J-1)$—then the net utility derived from purchasing a new product j, $\tilde{U}_{nj}$, is as shown in equation (3.7):

$$\tilde{U}_{nj} = U_{nj} - U_{nJ}. \quad (3.7)$$

The choice probability that decision-maker n will choose one alternative i among new alternatives, as well as his or her status quo, is calculated as per equation (3.8):

$$\begin{aligned} P_{ni} &= \Pr\left\{\tilde{U}_{ni} > \tilde{U}_{nj},\ where\ 1 \le j \le J,\ and\ j \ne i\right\} \\ &= \Pr\left\{\left(V_{ni} + \varepsilon_{ni}\right) - \left(V_{nJ} + \varepsilon_{nJ}\right) > \left(V_{nj} + \varepsilon_{nj}\right) - \left(V_{nJ} + \varepsilon_{nJ}\right),\ where\ 1 \le j \le J,\ and\ j \ne i\right\} \end{aligned}. \quad (3.8)$$

Equation (3.8) can be modified as in equation (3.9) by substituting $V_{ni} - V_{nJ}$ for $\tilde{V}_{ni}$ and assuming $\tilde{\varepsilon}_{ni} = \varepsilon_{ni} - \varepsilon_{nJ}$ follows an i.i.d. Gumbel distribution.

$$P_{ni} = \Pr\left\{\tilde{V}_{ni} + \tilde{\varepsilon}_{ni} > \tilde{V}_{nj} + \tilde{\varepsilon}_{nj}\right\} \quad (3.9)$$

$$\begin{aligned} where\ & \tilde{V}_{ni} = V_{ni} - V_{nJ},\ \tilde{V}_{nj} = V_{nj} - V_{nJ}, \\ & \tilde{\varepsilon}_{ni} = \varepsilon_{ni} - \varepsilon_{nJ} \sim i.i.d.\ Gumbel\ distribution \\ & \tilde{\varepsilon}_{nj} = \varepsilon_{nj} - \varepsilon_{nJ} \sim i.i.d.\ Gumbel\ distribution \end{aligned}$$

Equation (3.9) has the same formula as a conventional multinomial logit choice model and is based on the random utility model; thus, the choice probability function can be calculated as in equation (3.10) (McFadden, 1973; Train, 2009):

$$P_{ni} = \frac{e^{\tilde{V}_{ni}}}{\sum_{j=1}^{J} e^{\tilde{V}_{nj}}}, \tag{3.10}$$

and it can be rewritten as equations (3.11a) and (3.11b):

$$P_{ni} = \frac{e^{V_{ni}-V_{nJ}}}{\sum_{j=1}^{J} e^{V_{nj}-V_{nJ}}} = \frac{e^{V_{ni}}e^{-V_{nJ}}}{e^{-V_{nJ}}\left(\sum_{j=1}^{J-1}\left(e^{V_{nj}}\right)+e^{V_{nJ}}\right)} = \frac{e^{V_{ni}}}{\left(\sum_{j=1}^{J-1}\left(e^{V_{nj}}\right)+e^{V_{nJ}}\right)} \tag{3.11a}$$

$$P_{ni} = \frac{e^{V_{ni}-V_{nJ}}}{\sum_{j=1}^{J} e^{V_{nj}-V_{nJ}}} = \frac{e^{V_{ni}-V_{nJ}}}{\left(\sum_{j=1}^{J-1}\left(e^{V_{nj}-V_{nJ}}\right)+1\right)}. \tag{3.11b}$$

Equation (3.11a) shows the proposed choice probability that consumer n will choose alternative i; it is similar to the standard choice probability that considers the status quo as one of the choice options. Otherwise, equation (3.11b), as the other modified form of equation (3.11a), can be interpreted as adding a no-choice alternative to the net utility choice situation. Since equation (3.11a) more closely resembles the conventional form, it will be used hereafter.

In combination with the obsolescence effect described in equation (3.1), equation (3.11a) can be shown as equation (3.12):

$$P_{ni} = \frac{e^{V_{ni}}}{\left(\sum_{j=1}^{J-1} \left(e^{V_{nj}} \right) + e^{\bar{V}_J - \beta_{Obosl} \ln\left(x_{Obsol} \right)} \right)}. \tag{3.12}$$

3.1.4 Hierarchical Bayesian Multinomial Logit Choice Model that Incorporates a Status-Quo Alternative

In order to reflect consumer heterogeneity more flexibly, the use of a mixed logit choice model is more appropriate than that of the logit formula in equation (3.12). The choice probability is modified to equation (3.13), where L_{ni} is identical to equation (3.12) and β has a distribution that resembles that of equation (3.14).

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta, \tag{3.13}$$

$$\text{where} \quad f(\beta) \sim N(b, \Sigma). \tag{3.14}$$

It is too complicated to use a classical estimation method, such as maximum likelihood estimation. Bayesian estimation has the advantages of avoiding complicated calculations of integration in equation (3.13) and overcoming both the initial point problem and the global maximization problem (Edwards and Allenby, 2003). Moreover, the results of Bayesian estimation are as easy to interpret as classical estimation results (Train and Sonnier, 2005).

Taking another step, β can be assumed to have the covariates $\mathbf{z_n}$, in what is called the HB multinomial logit choice model (Allenby and Rossi, 2006), as follows:

$$\beta_n = \Gamma \mathbf{z_n} + \zeta_n, \qquad \zeta_n \sim N(0, \Sigma), \tag{3.15}$$

where Γ is the matrix of coefficients that relate β_n to the value of $\mathbf{z_n}$, $\mathbf{z_n}$ is the vector of covariates that account for observed heterogeneity, and ζ_n is an unobserved heterogeneity component that is assumed to be the multivariate normal distribution (Allenby and Ginter, 1995). The covariates can include respondent demographics.

Dong (2007) points out how the HB method has empirical advantages: it provides a natural way of obtaining individual level inference, and inferences vis-à-vis the function of the parameters are easier to acquire. Bayes's theorem, shown in equation (3.16), serves as the base of the Bayesian estimation procedure.

$$P(\theta | Y) = \frac{P(\theta) \times P(Y | \theta)}{P(Y)}, \tag{3.16}$$

where Y and θ represent observed data and the parameters to be estimated, respectively. $P(\theta)$ is the assumed distribution of unknown parameters, also called the prior distribution; $P(Y | \theta)$ is the likelihood function that indicates the distribution of the data conditional on the parameters; and $P(\theta \mid Y)$ is the updated prior distribution by the likelihood, also called the posterior distribution. Because $P(Y)$ is made a constant so as to make the posterior a probability distribution, equation (3.16) is written simply as $P(\theta \mid Y) \propto P(\theta) \times P(Y \mid \theta)$.

Choi (2009) provides a sound description of a Bayesian estimation procedure that uses the Markov chain Monte Carlo (MCMC) Gibbs sampler, which consists of the three steps shown in equation (3.17):

$$\begin{aligned} &\Gamma \mid \Sigma, \beta_n \\ &\Sigma \mid \beta_n, \Gamma . \\ &\beta_n \mid \Gamma, \Sigma \end{aligned} \tag{3.17}$$

The prior distributions of Γ and Σ are assumed to be normal and inverse-Wishart distributions, respectively. Their conditional distributions can be denoted as follows:

$$\Gamma \mid \Sigma, \beta_n, Z \ \ \forall n = \gamma \mid \Sigma, \beta, Z \ \ \forall n \sim Normal\left(\gamma^*, S\right), \tag{3.18}$$

where

$$\beta = \left(\beta_1', \beta_2', \ldots, \beta_n', \ldots, \beta_N'\right)' \tag{3.19}$$

$$\gamma^* = S\left(Z^{*\prime}\left(I \otimes \Sigma^{-1}\right)\beta\right) \tag{3.20}$$

$$S = \left(Z^{*\prime}\left(I \otimes \Sigma^{-1}\right)Z^*\right)^{-1} \tag{3.21}$$

$$Z^* = \left(z_{l=1} \otimes I, z_{l=2} \otimes I, ..., z_{l=n} \otimes I\right); \qquad (3.22)^4$$

and

$$\Sigma \mid \beta_n, \Gamma \ \ \forall n \sim \textit{Invert Wishart}\left(K+N, \left(KI+N\bar{S}\right)/\left(K+N\right)\right), \qquad (3.23)$$

where $\bar{S} = \left(1/N\right)\sum_n \left(\beta_n - \Gamma z_n\right)\left(\beta_n - \Gamma z_n\right)'$ and K represents the number of random variables.

[4] I is the identity matrix and $\otimes$ indicates the Kronecker product.

3.2 Modeling for the Multi-Product Category Case

In this section, unlike the previous single-product category case, it is assumed that each respondent makes choices with respect to purchasing a smart phone and smart TV (or pad) while considering the additional utility derived from the ability of these two products to “talk” to each other. The method previously used for a single-product category has limitations: it does not reflect recursive choice behavior, nor can it assume any correlation between the smart phone and smart TV (or pad) choices. To overcome this limitation, a recursive model that includes multivariate dependent variables is required, to analyze the comprehensive choice behavior related to the use of two different device types.

There are several approaches by which one can incorporate multi-choice behavior. The first approach uses incorporating structural equations, as pioneered by Muthén (1979). He sought to propose a generalized multivariate probit (MVP) model that applies the structural equations of utilities by using maximum likelihood estimation and then generalized least squares (Muthén, 1983). Similar and more recent research has been conducted by Golob and Regan (2002), who analyze the adoption probability of seven information technologies in the trucking industry while assuming simultaneous choices and free correlations among the alternatives. Zhang et al. (2008) and Erdem and Chang (2012) each sought to apply a dynamic structural model in a simultaneous-choice situation. Among the several related studies, Burgette and Nordheim (2010) provide an estimation method for unordered and simultaneous selection, and it is the most relevant study in terms of the choice situation and analytical purpose of the current study. Therefore, I will follow the study of Burgette and Nordheim, providing the *R* code for a bivariate MNP model while using a Bayesian estimation method.

In the study of Burgette and Nordheim, it is assumed that each respondent i makes a first choice Y_{i1} for a smart phone from $p_1 + 1$ alternatives, and then makes a second choice Y_{i2} for a smart TV (or pad) from p_2 alternatives, given the former choice Y_{i1}. Because a researcher cannot observe responses for more than one pair of outcomes, with the first choice $s_0, s_1, ..., s_{p_1}$ and the second choice $r_0, r_1, ..., r_{p_2}$, the sample space can be described as:

$$S = \left\{ \left(s_0, r_j, *, ..., * \right), \left(s_1, *, r_j, *, ..., * \right), ..., \left(s_{p_1}, *, *, ..., *, r_j \right) : j \in \left\{ 0, 1, ..., p_2 \right\} \right\}, \quad (3.24)$$

where * indicates an unobserved response.

The MNP model can be applied to the sample space of equation (3.24). The latent utility of each respondent i, U_i, is assumed to have a length $p_1 + (p_1 + 1) p_2$, since one alternative from each choice is set as a base alternative, in order to make matters simpler and to make the equation identifiable. The utility U_i is partitioned into two parts: length p_1 represents the utility from smart phones and length $(p_1 + 1) p_2$

represents the utility from smart TVs (or pads) while considering the connected benefit of smart phones. The index 0 denotes the base alternative; therefore, if the first part of utility U_i is fully negative, the respondent will choose the base alternative.

The vector of the actual choice of respondent i is represented by $Y_i = (Y_{i1},\ Y_{i2})'$. Under the assumption of rationality, each respondent will choose the alternative that maximizes his or her utility U_i. Equation (3.25), below, shows that the choice is stepwise; hence, the maximization of utility occurs in two steps.

$$
\begin{aligned}
Y_{i1} &= \begin{cases} \operatorname{argmax}_{k_1 \in \{1,\ 2,\ \cdots,\ p_1\}} U_{i,k_1}^{Phone} & \text{if} \quad \max_{k_1 \in \{1,\ 2,\ \cdots,\ p_1\}} U_{i,k_1}^{Phone} > 0 \\ 0 & \text{otherwise} \end{cases} \\
Y_{i2} &= \begin{cases} \operatorname{argmax}_{k_2 \in \{1,\ 2,\ \cdots,\ p_2\}} U_{i,k_2}^{Y_{i1}} & \text{if} \quad \max_{k_2 \in \{1,\ 2,\ \cdots,\ p_2\}} U_{i,k_2}^{Y_{i1}} > 0 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{3.25}
$$

$U_{i,k}^{Phone}$ represents respondent i's utility for alternative k_1 while considering only the attributes of smart phones, while $U_{i,k}^{Y_{i1}}$ represents respondent i's utility for the alternative k_1 of smart TVs (or pads), based on the selected smart phone. If Y_{i1} or Y_{i2} is 0, this means the respondent has chosen the base alternative.

In the current study, the utility U_i is assumed to be linear with a multivariate normal error, as follows:

$$U_i = X_i\beta + \varepsilon_i\,,\quad \varepsilon_i \sim N(0,\ \Sigma)\,. \tag{3.26}$$

The discrete choice model that incorporates the multivariate normal error is the MVP model (Train, 2009). In equation (3.26), X_i is a matrix of attribute levels with covariates; and β is a vector of the parameters to be estimated, which will be interpreted as the marginal utilities of each attribute. $\Sigma = \{\sigma_{ij}\}$ is the variance–covariance matrix of error, where all the diagonal elements are assumed to be 1 for identification. Since the model consists of two steps in making choices, the matrix X_i is partitioned into two diagonal parts, as per equation (3.27):

$$X_i = \begin{bmatrix} I_{p1} \otimes x'_{i1} & 0 \\ 0 & I_{(p_1+1)p_2} \otimes x'_{i2} \end{bmatrix}. \tag{3.27}$$

The vector x_{i1} represents covariates for the first choice (i.e., of a smart phone), while the vector x_{i2} relates to the final choice outcome involving the selection of a smart TV (or pad). From the above equations, the likelihood of outcome can be derived as follows:

$$L(Y \mid \beta, \Sigma) \propto |\Sigma|^{-\frac{n}{2}} \prod_{i=1}^{n} \int_{Y_i} \exp\left(-\frac{1}{2} \sum_{i=1}^{n} (U_i - X_i\beta)' \Sigma^{-1} (U_i - X_i\beta) \right) dU_i \tag{3.28}$$

The parameters β and Σ are also estimated via the Bayesian approach. The prior of each parameter is set, based on the IVD prior specification (Imai and Van Dyk, 2005). In this specification, the covariance Σ is set to a $(p_1+(p_1+1)p_2)\times(p_1+(p_1+1)p_2)$ matrix with $\sigma_{kk}=1$ for identification, and the reducing parameters are to be estimated. Given the degrees of freedom ν of Σ and for the prior scale matrix S of Σ, the prior distributions of β and Σ are specified as follows:

$$\beta \sim N(\beta_0,\ B_0^{-1}) \ \text{ and } \ p(\Sigma) \propto |\Sigma|^{-\frac{\nu+P+1}{2}} \left(\prod_{i=1}^{p_1+2} tr(S\Sigma^{-1}) \right)^{-\nu}, \tag{3.29}$$

where β_0 and B_0^{-1} are the prior mean and variance of β and $P = p_1+(p_1+1)p_2$, respectively.

The variance–covariance matrix can be divided into four sections, as shown in Figure 3. In this figure, the black squares correspond to covariance within the smart phone decision, the medium gray squares to covariance within the smart TV (or pad) decision, the light gray rectangles the correlation between smart phones and smart TVs (or pads), and the white regions the unidentifiable parameters.

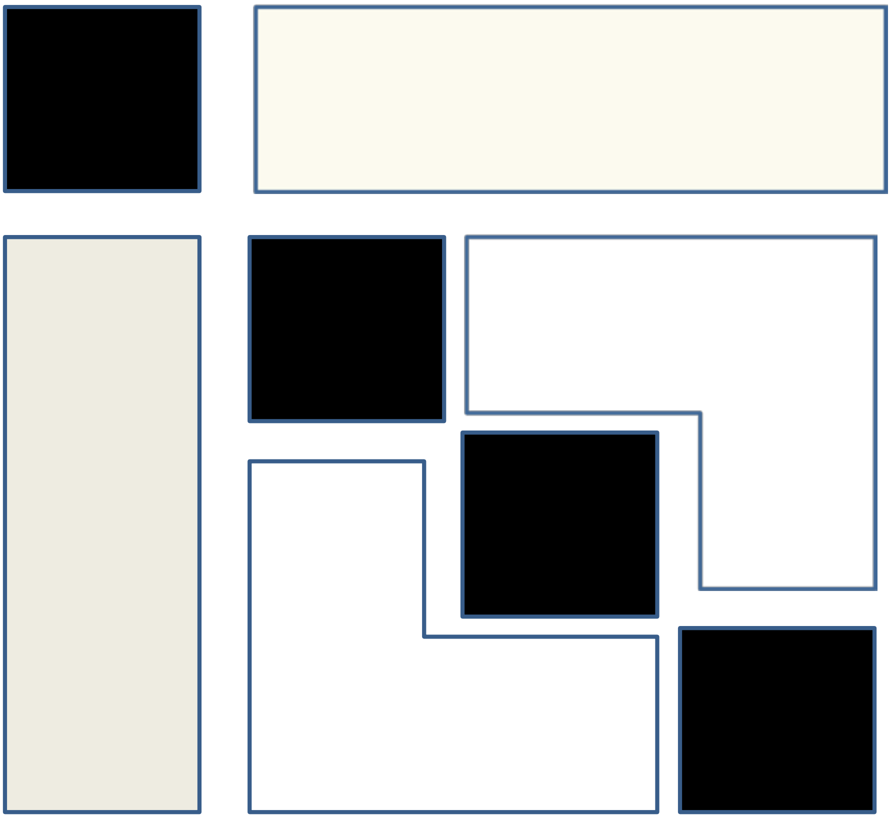


Figure 3. Sub-partitions of the variance–covariance matrix

Chapter 4. Empirical Analysis

4.1 Survey Design and Data Description

For the empirical analysis, a face-to-face conjoint survey was conducted by a specialized research company, Gallup Korea, of 1,003 respondents in South Korea. The respondents were chosen via purposive quota sampling, based on their region of residence and income. Descriptive statistics of these respondents' characteristics are listed in Table 1.

The survey touched on three smart devices: smart phones, smart pads, and smart TVs. First, a smart phone is a mobile phone that has an OS for installing and running applications; at the same time, it is possible to use a smart phone to connect to the internet through Wi-Fi and a third-generation or fourth-generation (4G) communication standard. The iPhone (made by Apple) and Galaxy (made by Samsung Electronics) series smart phones are popular in the market. Second, a smart pad is a mobile tablet PC that has an OS for installing and running applications. Generally, it is larger in size than a smart phone. The iPad (made by Apple) and Galaxy Tab (made by Samsung) series smart pads are, again, popular in the market. In the smart phone and pad markets, MS has recently tried to join the Windows Mobile (W/M) OS. Third, a smart TV is an extended-concept device, in that it has an OS for installing and running applications and connects to the internet to watch video on demand (VoD). The smart TV market has not yet matured. Apple and Google are trying to become involved in this market, while other TV manufacturers—such as Samsung Electronics and LG Electronics—are producing smart TV prototypes.

Table 1. Socio-demographics of respondents

Respondent characteristics		Number of respondents	Ratio
Gender	Male	502	50.05%
	Female	501	49.95%
Age	20–29	256	25.52%
	30–39	267	26.62%
	40–49	291	29.01%
	50–59	189	18.84%
Region	Seoul	380	37.89%
	Busan	160	15.95%
	Daegu	115	11.47%
	Incheon	120	11.96%
	Gwangju	83	8.28%
	Daejeon	85	8.47%
	Kyunggi-do	60	5.98%
Average income (thousands of KRW per month)	<2,500	69	6.88%
	2,500–3,499	250	24.93%
	3,500–4,499	303	30.21%
	4,500–5,499	227	22.63%
	>5,499	154	15.35%

Note: KRW = South Korean won

The survey was executed in three steps. At the beginning, a questionnaire asked respondents for their demographic data and information pertaining to their use of smart devices, including usage and satisfaction level. Then, a conjoint survey for each smart device was conducted. Finally, conjoint surveys were conducted for multi-product categories, i.e., choosing smart phones and smart pads simultaneously. Specific information captured by way of this survey is described in the next section.

4.1.1 Single-Product Category Case

4.1.1.1 Conjoint Survey for Smart Phones

Table 2. Attributes and attribute levels of smart phones, gathered via the conjoint survey

Attributes	Levels		
OS	iOS	Android	W/M
Screen size (inches)	3	4	5
4G availability	Not available	Available	
Weight (grams)	100	150	200
Delay (seconds)	Fast (1)	Normal (5)	Slow (10)
Price (KRW)	600,000	900,000	1,200,000

Note: KRW = South Korean won

The first smart device examined was the smart phone. I assumed the use of three OS—namely, iOS (provided by Apple), Android (provided by Google), and W/M (provided by MS)—along with other important attributes used to choose a smart phone, such as screen size, 4G availability, weight, performance (i.e., transmission delays), and price. The attribute levels used in the conjoint survey are listed in Table 2. For specific descriptions of each attribute or attribute level, see Appendix A.

Table 3. Status quo of respondents' smart phones

Attributes	Level	Frequency	Ratio
OS	iOS	101	15.19%
	Android	564	84.81%
	W/M	0	0.00%
Screen size (inches)	size ≤ 3.5	109	16.39%
	3.5 < size ≤ 4.0	289	43.46%
	4.0 < size ≤ 4.3	163	24.51%
	4.3 < size	104	15.64%
4G availability	3G	561	84.36%
	4G	104	15.64%
Weight (grams)	≤130	372	55.94%
	130 < weight ≤ 140	173	26.02%
	>140	122	18.35%
Delay (seconds)	Fast (1)	219	32.93%
	Normal (5)	387	58.20%
	Slow (10)	59	8.87%

A total of 665 respondents (66.3%) have any type of smart phone. Of course, in order to consider a respondent's status quo, it is important to know what kind of smart phone a respondent has. Some examples of specifications of smart phones holding high market shares are provided to help respondents, and respondents were asked to provide information on their smart phones' specifications. Descriptive statistics pertaining to the physical specifications of the respondents' smart phones are shown in Table 3.

Table 4. Purchase time, satisfaction, use time, and network effect for smart phones of respondents

		Frequency	Ratio
Smart phone purchase time	Jan. 2010–June 2010	42	6.32%
	July 2010–Dec. 2010	101	15.19%
	Jan. 2011–June 2011	189	28.42%
	July 2011–Dec 2011	190	28.57%
	Jan. 2012–Apr. 2012	143	21.50%
Satisfaction	Very dissatisfied	1	0.15%
	Dissatisfied	15	2.26%
	Normal	147	22.11%
	Satisfied	475	71.43%
	Very satisfied	27	4.06%
Smart phone use time (minutes)	<60	141	21.20%
	60–119	259	38.95%
	120–179	122	18.35%
	180–239	72	10.83%
	240–300	43	6.47%
	>300	28	4.21%
Smart phone OS used by acquaintances (average)	1. iOS	30.51%	
	2. Android	64.76%	
	3. W/M	4.73%	

Other information related to smart phone use behavior is shown in Table 4. Knowledge of purchasing time, user satisfaction, and use time is important in analyzing the status-quo effect, as is knowledge of how many acquaintances use the same OS smart phone.[5]

Smart Phone Attributes	Smart Phone A	Smart Phone B	Smart Phone C	Status Quo
1. OS	iOS	Android	W/M	keep using Current Smart Phone
2. Screen Size (inches)	3	5	5	
3. 4G availability	Not Available	Not Available	Available	
4. Weight (grams)	100	100	150	
5. Delay (seconds)	Fast (1)	Normal (5)	Slow (10)	
6. Price(KRW)	600,000	900,000	600,000	
Most preferred alternative				

Figure 4. Choice set of smart phone conjoint survey

Figure 4 provides an example of a choice set used in the conjoint survey. Three OS types of new smart phones are provided, along with a status-quo option. A respondent can choose a new smart phone A, B, or C, or continue to use his or her current smart phone.

[5] In many cases, in what is called the network effect (Katz and Shapiro, 1985), a consumer obtains higher utility from a product when the number of other users consuming the product increases.

4.1.1.2 Conjoint Survey for Smart Pads

The second smart device examined here is the smart pad. I assume for this device the same OSs as for smart phones: iOS, Android, and W/M; I also consider other important attributes in choosing a smart pad, such as screen size, weight, performance (transmission delay), and price.

Table 5. Attributes and attribute levels of smart pad conjoint survey

Attributes	Attribute levels		
OS	iOS	Android	W/M
Screen size (inches)	7	9	11
Weight (grams)	400	700	1,000
Delay (seconds)	Fast (1)	Normal (5)	Slow (10)
Price (KRW)	500,000	750,000	1,000,000

The attribute levels used in the conjoint survey are shown in Table 5. For specific descriptions of each attribute or attribute level, see Appendix B. A total of 197 respondents (19.6%) have any type of smart pad. To consider a respondent’s status quo, it is important to know what kind of smart pad he or she has. Some examples of specifications of smart pads holding high market shares are provided to help respondents, and respondents were asked to provide information on their smart pads’ specifications. Descriptive statistics pertaining to the physical specifications of the respondents’ smart pads are shown in Table 6.

Table 6. Status quo of respondents' smart pads

	Level	Frequency	Ratio
OS	iOS	86	43.65%
	Android	111	56.35%
	W/M	0	0.00%
Screen size (inches)	7.0	52	26.40%
	7.7	17	8.63%
	8.9	15	7.61%
	9.7	86	43.65%
	10.1	27	13.71%
Weight (grams)	300–399	68	34.52%
	400–499	16	8.12%
	500–599	25	12.69%
	600–699	60	30.46%
	700–800	28	14.21%
Delay (seconds)	Fast (1)	87	44.16%
	Normal (5)	105	53.30%
	Slow (10)	5	2.54%

Other information related to smart pad use behavior is listed in Table 7. An understanding of purchase time, user satisfaction, and use time is important in analyzing the status-quo effect, as is knowledge of how many acquaintances are using the same OS smart pad.

Table 7. Purchase time, satisfaction, use time, and network effect for smart pads of respondents

		Frequency	Ratio
Smart pad purchase time	Jan. 2010–June 2010	6	3.05%
	July 2010–Dec. 2010	21	10.66%
	Jan. 2011–June 2011	55	27.92%
	July 2011–Dec. 2011	67	34.01%
	Jan. 2012–Apr. 2012	48	24.37%
Satisfaction	Very dissatisfied	1	0.51%
	Dissatisfied	4	2.03%
	Normal	25	12.69%
	Satisfied	154	78.17%
	Very satisfied	13	6.60%
Smart pad use time (minutes)	<60	25	12.69%
	60–119	49	24.87%
	120–179	66	33.50%
	180–239	26	13.20%
	240–300	24	12.18%
	>300	7	3.55%
Smart Pad OS used by acquaintances (average)	1. iOS	45.00%	
	2. Android	51.51%	
	3. Other (W/M, Bada OS)	3.49%	

Figure 5 provides an example of a choice set used in the conjoint survey. Three OS types of new smart pads are provided, along with a status-quo option. A respondent can choose a new smart pad A, B, or C, or continue to use his or her current smart pad.

Smart Pad Attributes	Smart Pad A	Smart Pad B	Smart Pad C	Status Quo
1. OS	iOS	Android	W/M	keep using Current Smart Pad
2. Screen Size (inches)	9	11	11	
3. Weight (grams)	1,000	1,000	700	
4. Delay (second)	Fast (1)	Slow (10)	Fast (1)	
5. Price (KRW)	750,000	1,000,000	500,000	
Most preferred alternative				

Figure 5. Choice set of smart pad conjoint survey

4.1.1.3 Conjoint Survey for Smart TVs

Table 8. Attributes and attribute levels of smart TV conjoint survey

Attributes	Levels		
OS	iOS	Android	Others (domestic)
Screen size (inches)	30	40	50
Internet search	Not available		Available
Application level	Low		High
Price (KRW)	1,000,000	2,000,000	3,000,000

The last smart device examined in this study is the smart TV. I assume three different OSs: iOS, Android, and other domestic manufacturers' OSs, such as those of Samsung Electronics or LG Electronics. Other important attributes assessed in choosing a smart pad—such as screen size, Internet search function, and level of applications—are also considered. The attribute levels used in the conjoint survey are shown in Table 9. For specific descriptions of each attribute or attribute level, see Appendix C.

A total of 225 respondents (22.4%) have any type of smart TV. To consider a respondent's status quo, it is important to know what kind of smart TV he or she has. Respondents provided information on the specification of their smart TVs, and descriptive statistics thereof are shown in Table 9.

Table 9. Status quo of respondents' smart TVs

		Frequency	Ratio
Manufacturer	Samsung	142	63.11%
	LG	83	36.89%
Screen size (inches)	<30	1	0.44%
	30–39	5	2.22%
	40–49	178	79.11%
	50–59	39	17.33%
	60–69	2	0.89%
Internet search availability	Internet search available	222	98.67%
	Internet search not available	3	1.33%
Number of available applications	High	109	48.66%
	Low	116	51.34%

Other information related to smart TV use behavior, such as purchase time or use time, is provided in Table 10.

Table 10. Purchase time and use time for smart TVs of respondents

		Frequency	Ratio
Smart TV purchase time	Jan. 2010–June 2010	8	3.56%
	July 2010–Dec. 2010	8	3.56%
	Jan. 2011–June 2011	44	19.56%
	July 2011–Dec. 2011	98	43.56%
	Jan. 2012–Apr. 2012	67	29.78%
Smart TV use time per week (minutes)	<500	7	3.11%
	500–999	62	27.56%
	1,000–1,499	75	33.33%
	1,500–1,999	62	27.56%
	2,000–2,499	14	6.22%
	>2,500	5	2.22%

Figure 6 provides an example of a choice set used in the conjoint survey. Three OS types of new smart TVs are provided, along with a status-quo option. A respondent can choose a new smart TV A, B, or C, or continue to use his or her current smart TV.

TV Attributes	TV A	TV B	TV C	Status Quo
1. OS	iOS	Android	Others	keep using Current Smart TV
2. Screen Size (inches)	40	50	50	
3. Internet search availability	Available	Not available	Not available	
4. Available Applications	Low	High	High	
5. Price (KRW)	2,000,000	3,000,000	2,000,000	
Most preferred Alternative				

Figure 6. Choice set of smart TV conjoint survey

4.1.2 Multi-Product Category Case

To gather information on and analyze consumer choice behavior within a multi-product category, the questionnaire asked about two choice sets: one for a smart phone and one for a smart pad or smart TV. Before responding, several characteristics relating to the concurrent use of smart devices with the same OS are proposed, such as sharing purchased applications, sharing documents and photos easily through a cloud service, and lowering the learning cost that is incurred when starting to use a different OS. A total of 139 respondents (13.9%) own both a smart phone and a smart pad; 168 (16.7%) respondents own both a smart phone and a smart TV.

Note that, for the sake of simplicity, in the case of smart phone and smart pad selection, we examined only two OSs—namely, iOS and Android. Other attributes and the attribute levels presented to the respondents were the same as those in the single-product category case.

4.2 Estimation Results

4.2.1 Single-Product Category Case

4.2.1.1 Empirical Research on Smart Phones

For the smart phone case, equation (4.1) shows the utility of respondent n in choosing an alternative j:

$$
\begin{aligned}
U_{nj} = {} & \beta_{OS\_iOS} x_{OS\_iOS} + \beta_{OS\_Android} x_{OS\_Android} + \beta_{Size} x_{Size} + \beta_{4G} x_{4G} \\
& + \beta_{Weight} x_{Weight} + \beta_{Delay} x_{Delay} + \beta_{Price} x_{Price} + \beta_{Obsol} \ln\left(x_{Obsol}\right) \\
& + \beta_{Same\_OS} x_{same\_OS} + \beta_{Diff\_Size} x_{Diff\_Size} + \beta_{Diff\_Size^2} x_{Diff\_Size^2} \\
& + \beta_{Network} x_{Network} + \varepsilon_{nj}
\end{aligned} \quad . \qquad (4.1)
$$

$where\ \varepsilon_{nj} \sim i.i.d.\ Gumbel\ \ distribution$

The variables x_{OS_iOS} and $x_{OS\_Android}$ indicate whether a smart phone uses iOS or Android as an OS. The variables x_{Size}, x_{4G}, x_{Weight}, x_{Delay}, and x_{Price} represent screen size, the 4G communication standard, weight, performance explained in terms of delay time in opening a website, and the price of a smart phone, respectively. While these are basic variables, the others are included in order to reflect a respondent's status-quo effect in making a choice. The variable x_{Obsol} represents the obsolescence effect of an already-owned smart phone. The amount of time for which a respondent uses the owned smart phone on a monthly basis serves as the value of x_{Obsol}. To reflect the phenomenon whereby the amount of obsolescence effect decreases as the use time increases, I take the log transformation as the obsolescence variable.

On the topic of similarity, Lefkoff–Hagius and Mason (1993) show that physical characteristics bear the greatest influence in a consumer's ability to distinguish similarity among products, although they may also consider product benefits and product image. Of the various variables that can be used to define similarity, objective differences in terms of the basic attributes of a smart phone are considered, based on the findings of Lefkoff–Hagius and Mason (1993). However, among the observed attributes, x_{4G}, x_{Weight}, x_{Delay}, and x_{Price} always have some effect—either positive or negative—on utility as they increase. In other words, respondents prefer a smart phone that is 4G-ready, lighter, faster, and cheaper; therefore, differences in terms of these variables do not indicate dissimilarity, but rather performance inferiority or superiority. However, the remaining variables—i.e., OS and size—are thought to be proxy variables that measure similarity. In particular, because the OS generally captures differences in terms of brand and service, it is possible to roughly incorporate other factors that affect similarity, as derived from the OS similarity variable. I assume the variables x_{same_OS} and x_{Diff_Size} represent the similarity between the status quo and new alternatives. x_{same_OS} indicates whether or not a smart phone alternative has the same OS[6], x_{Diff_Size} indicates the degree of dissimilarity in terms of screen size, and $x_{Diff\_Size^2}$ is a square term of x_{Diff_Size}.

The final variable, $x_{Network}$, represents the direct network effect of the smart phone OS. In other words, the variable indicates what proportion of a respondent's acquaintances use the same OS. The value of $x_{Network}$ can differ across respondents, and each alternative can have a different OS. The coefficient βs refer to the marginal effect of each attribute, and are assumed to have a distribution that incorporates consumer heterogeneity. The coefficients of β_{Size}, β_{Weight}, β_{Delay}, β_{Price}, β_{Obsol}, and $\beta_{Network}$ are assumed to have positive or negative signs, while the other coefficients are assumed to be in a normal distribution.

In addition, to analyze the effect of the status-quo option's use or satisfaction level, the hierarchical structure for β of the k^{th} attribute is assumed to relate to the coefficients as follows:

$$\beta_{n,k} = \alpha_{intercept,k} + \alpha_{usage,k} z_{n,usage} + \alpha_{satisfy,k} z_{n,satisfy} + \varepsilon'_n$$
$$where\ \varepsilon'_n \sim N\left(0, V_\beta\right) \qquad (4.2)$$

[6] The dummy variables for OS, 4G, and the same OS are effects-coded; their base levels are MS OS, 3G, and different OS, respectively.

The variables $z_{n,usage}$ and $z_{n,satisfy}$ are demographic variables that indicate use and level of satisfaction with respondent n's owned smart phone, respectively. $\alpha_{intercept,k}$ is an intercept of $\beta_{n,k}$, and α_{usage} and $\alpha_{satisfy}$ are the related coefficients for each demographic variable as noted—that is, for the normally distributed βs, their means are dependent on the respondent characteristics, and their variance–covariance matrix is V_{β}.

The Bayesian estimation method is used. Among 50,000 iterations, the initial 30,000 iterations are discarded as burn-in draws for convergence; I use the remaining 20,000 iterations to calculate the mean and the standard deviation of parameters. The estimation results of the means and standard deviations (i.e., the square root of the diagonal elements of V_{β}) for normally (or log-normally) distributed βs are shown in Table 11.

Table 11. Estimation results for smart phones, via an HB mixed logit choice model

Parameters	Mean of β			Standard deviation
	$\alpha_{intercept}$	α_{usage}	$\alpha_{satisfy}$	
β_{OS_iOS}	15.324** Base: MS OS (–7.380**)			28.605**
	12.459*	0.164	0.191	
$\beta_{OS\_Android}$	–7.944** Base: MS OS (–7.380**)			37.277**

	–1.991	–0.351*	–0.332	
β_{Size}		8.654**		113.149**
	–12.892	–1.124*	–22.893**	
β_{4G}		6.058**		24.439**
		Base: 3G (–6.058**)		
	3.863	–0.078	0.786	
β_{Weight}		–4.562**		24.200**
	1.509	–0.055	3.077**	
β_{Delay}		–52.797**		213.532**
	0.644	0.751	15.530**	
β_{Price}		–63.285**		101.115**
	–5.535	0.122	–8.955**	
β_{Obsol}		–57.727**		60.460**
	–4.126	–0.859**	–9.519**	
β_{Same_OS}		16.547**		13.570**
		Base: different OS (–16.547**)		
	7.204**	0.163*	1.888**	
β_{Diff_Size}		–12.196**		21.558**
	1.262	0.212	–4.058**	
$\beta_{Diff\_Size^2}$		5.955**		7.948**
	15.144**	0.054	–2.652**	
$\beta_{Network}$		36.103**		30.150**
	–9.696**	0.394*	10.240**	

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

All the means of β are statistically significant at the 95% level—that is, 95% of the draws from each distribution exclude 0. With respect to the OS coefficients, iOS is found to be much preferred over the others. The Android OS could have a smaller preference value than that for iOS, despite the Android smart phone having a higher market share than iOS smart phones in real life; this apparent contradiction may be explained by the fact that the Android higher market share can be explained in terms of other factors. For example, preference driven by the direct network effect or the same OS might actually account for why a large portion of consumers buy Android smart phones.[7]

With respect to the obsolescence effect, its negative effect becomes larger when respondents are satisfied more by the status quo, or use it more. The reason for the negative effect from use level is obvious: a high use level accelerates physical obsolescence. As for satisfaction level, based on the estimation results, consumers satisfied with their currently owned smart phones are sensitive to obsolescence, and so they might be likely to upgrade to a new smart phone sooner than those who are less satisfied with their currently owned smart phones.

As for the coefficients related to similarity, the respondents are likely to choose a smart phone that is similar to their current phone in terms of OS and screen size.[8] Based on the estimation results of the alpha, the satisfied respondents are more sensitive to the use of the same OS and a similar size. These findings can be interpreted thus: satisfied consumers are not likely to choose dissimilar alternatives. In addition, satisfied respondents are more sensitive to the prices of new alternatives and less sensitive to the

[7] Without considering such status-quo effects, the coefficient of the Android OS is estimated to be higher than those of iOS and MS OS. Therefore, in order to analyze the pure effect of OS, conventional analysis that does not consider the status-quo effect causes an overestimation for whichever type of smart phone occupies the highest market share.

[8] The respondents monotonically prefer a similar size, given that the domain of x_{Diff_Size} is about [–0.2, 0.2] in the simulation. The slope of preference with respect to similar size, however, decreases in that domain.

network effect.

All the standard deviations (or variances) of parameters are statistically significant at the 95% level. Because the magnitude of the standard deviation is usually relatively large compared to the mean values, it is rational to use the mixed logit choice model, which estimates the distribution of parameters rather than the fixed parameters.

Table 12. Relative importance of attributes for choosing a smart phone

Attributes	Relative importance	Attributes	Relative importance
OS	8%	Price	16%
Size	5%	Obsolescence	41%
4G availability	3%	OS similarity	7%
Weight	1%	Size similarity	2%
Delay	10%	Network effect	8%

Based on equation (2.6), the relative importance of each attribute is calculated, and the results thereof are presented in Table 12. The obsolescence attribute is the most important factor to affect purchasing decisions. Among the status-quo effects, size similarity does not appear to be important in choosing a smart phone, while the importance of OS similarity is thought to be considerable. Among the conventional attributes of a smart phone, price is the most important factor, followed by performance (transmission delay).

To analyze the choice probabilities of several representative smart phones, I assume specific attribute levels, as shown in Table 13. The specifications of smart phones with iOS and Android OSs are similar to the typical smart phone model that actually has a large market share.[9]

Table 13. Base scenario for new smart phone alternatives

	Alternative 1	Alternative 2	Alternative 3
OS	iOS	Android	W/M
Screen size (inches)	3.5	5.3	4.3
4G availability	Not available	Available	Available
Weight (grams)	140	182	182
Delay (seconds)	Fast (1)	Fast (1)	Fast (1)
Price (KRW)	1,200,000	1,200,000	900,000

Using equation (3.16), the choice probabilities can be calculated; the results thereof are shown in Table 14. The first row shows the choice probabilities while not considering status-quo alternatives. In this case, the W/M smart phone has a choice probability similar to that of the iOS smart phone. However, while considering the status-quo option, the choice probabilities dramatically change: the iOS smart phone then has a much higher choice probability than W/M. With the status-quo option, 26.4% of the choice probability for a W/M smart phone decreases, while only 14.5% of the choice probability for an iOS smart phone decreases.

[9] Appropriate assumptions are used for the W/M smart phone specifications, as this product has not yet been introduced to the South Korean market.

Table 14. Choice probabilities of smart phones, based on the base scenario

	iOS smart phone	Android smart phone	W/M smart phone	Status quo
Choice probability while not considering status quo	20.6%	59.1%	20.4%	–
Choice probability while considering status quo	6.1%	32.7%	1.7%	59.6%

While the choice probabilities shown in Table 14 show the current-time situation, Figure 7 shows changes in choice probabilities as time progresses. Such change can be simulated by increasing the level of obsolescence. Up to 10 months from now, one can see that the choice probabilities of the iOS and Android smart phones will have increased relatively quickly; that of the W/M smart phone, on the other hand, is found to increase quickly after 20 months.

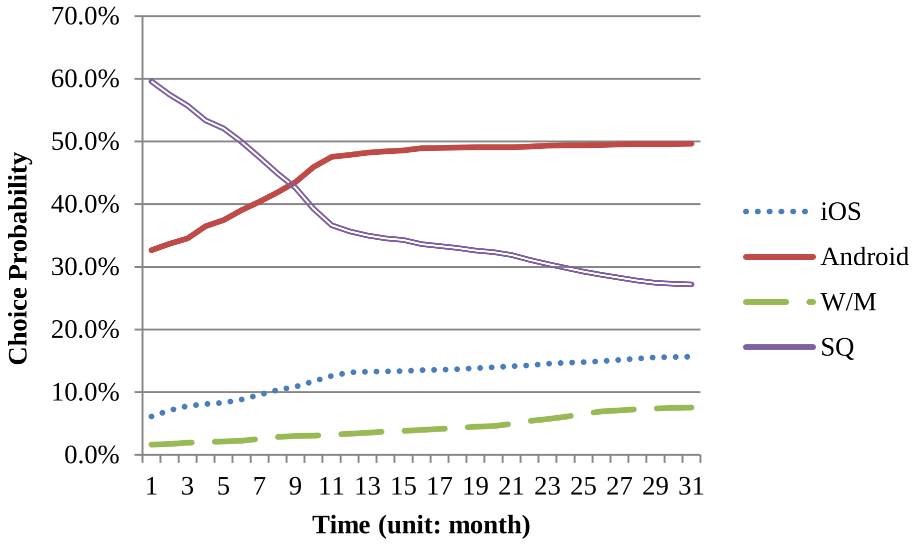
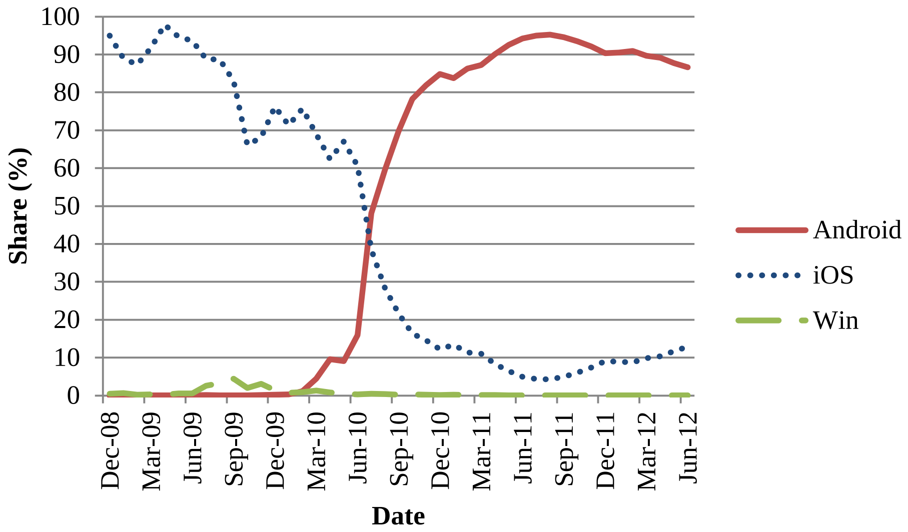


Figure 7. Changes to smart phone choice probabilities, by OS or status quo (SQ)

Figure 8 shows the real market data of mobile OS traffic in South Korea. The iOS had a higher market share in the early stages, because there was no other competitor at that time. However, after the introduction of Android smart phones—made by Samsung, a famous South Korean company—its market share in South Korea has rapidly increased. At the present time, Android holds a market share seven times larger than that of iOS, while W/M holds a very small market share. This scenario closely resembles the descriptive statistics shown in Table 3. Although it is difficult to incorporate every kind of smart phone in the base scenario, the simulated market share shown in Figure 7 seems to roughly approximate the market share calculated through the use of real market data.



Source: StatCounter: http://gs.statcounter.com.

Figure 8. Real-life mobile traffic data in the South Korean market, by OS

4.2.1.2 Empirical Research on Smart Pads

For smart pads, equation (4.3) shows the utility of respondent n choosing alternative j:

$$\begin{aligned} U_{nj} = {} & \beta_{OS\_iOS} x_{OS\_iOS} + \beta_{OS\_Android} x_{OS\_Android} + \beta_{Size} x_{Size} \\ & + \beta_{Weight} x_{Weight} + \beta_{Delay} x_{Delay} + \beta_{Price} x_{Price} + \beta_{Obsol} \ln\left(x_{Obsol}\right) \\ & + \beta_{Same\_OS} x_{same\_OS} + \beta_{Diff\_Size} x_{Diff\_Size} + \beta_{Diff\_Size^2} x_{Diff\_Size^2} \\ & + \beta_{Network} x_{Network} + \varepsilon_{nj} \end{aligned} \qquad (4.3)$$

$$where\ \varepsilon_{nj} \sim i.i.d.\ Gumbel\ distribution$$

All the variables are the same as in the smart phone case, except for the omission of x_{4G}.[10] The variables x_{OS_iOS} and $x_{OS\_Android}$ indicate whether a smart pad has iOS or Android OS. The variables x_{Size}, x_{Weight}, x_{Delay}, and x_{Price} represent screen size, weight, performance (transmission delay), and price of a smart pad, respectively; the other variables related to the status-quo effect are exactly the same as for smart phones. Also, in the smart pad case, the coefficients of β_{Size}, β_{Weight}, β_{Delay}, β_{Price}, β_{Obsol}, and $\beta_{Network}$ are assumed to have positive or negative signs, while the other coefficients are assumed to be in a normal distribution.

In addition, to analyze the effect of the status-quo option usage or satisfaction level, the hierarchical structure for β of the k^{th} attribute is assumed to relate to the coefficients as follows:

$$\beta_{n,k} = \alpha_{intercept,k} + \alpha_{usage,k} z_{n,usage} + \alpha_{satisfy,k} z_{n,satisfy} + \varepsilon'_n \qquad \text{where } \varepsilon'_n \sim N\left(0, V_\beta\right) \quad . \tag{4.4}$$

[10] The variable for distinguishing 3G or 4G is omitted, because more than half of all smart pads sol d have only Wi-Fi functionality, and not 3G or 4G.

The variables $z_{n,usage}$ and $z_{n,satisfy}$ are demographic variables that indicate the use and satisfaction level of respondent n's currently owned smart pad, respectively. $\alpha_{intercept,k}$ is an intercept of $\beta_{n,k}$, and α_{usage} and $\alpha_{satisfy}$ are the related coefficients for each demographic variable as noted.

The Bayesian estimation method is used. Among 80,000 iterations, the initial 50,000 iterations are discarded as burn-in draws for convergence; the remaining 30,000 iterations are used to calculate the mean and standard deviation of parameters. The estimation results of the means and standard deviations (i.e., the square root of the diagonal elements of V_β) for normally (or log-normally) distributed βs are shown in Table 15.

Table 15. Estimation results for smart pads, via an HB mixed logit choice model

	Mean of β			Standard deviation
	$\alpha_{intercept}$	α_{usage}	$\alpha_{satisfy}$	
β_{OS_iOS}		4.135** Base: MS OS (–4.176**)		5.107**
	9.001*	0.105	–1.618	
$\beta_{OS\_Android}$		0.040 Base: MS OS (–4.176**)		7.786**
	7.359	–0.007	–1.856	
β_{Size}		9.954**		11.335**
	–7.748	–0.497**	5.716**	
β_{Weight}		–12.265**		76.450**
	1.796	0.476	9.537**	

β_{Delay}		–35.823**		97.890**
	0.893	–1.375	6.333	
β_{Price}		–30.880**		87.749**
	7.367	0.819	–2.437	
β_{Obsol}		–35.434**		42.986**
	5.041	–0.800*	–5.955**	
β_{Same_OS}		6.569**		10.223**
		Base: different OS (–6.569**)		
	–4.936	0.185	2.346*	
β_{Diff_Size}		–9.943**		52.099**
	1.166	0.202	–3.395	
$\beta_{Diff\_Size^2}$		–0.325		21.420**
	9.613	–0.396	–1.222	
$\beta_{Network}$		11.808**		40.030**
	–15.458**	–0.185	2.386	

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

All the means of β—except those for Android OS—and the square term of dissimilar size statistically exclude 0 at the 95% confidence interval. As for the coefficients for OS, iOS is preferred to the Android OS, and both iOS and Android OS are preferred to the W/M OS.

As expected, the negative effect of the obsolescence effect became large when a respondent used his or her smart pad more frequently. In the case of coefficients related to similarity, respondents are more sensitive to the use of smart phones that are similar to their current phones, in terms of OS and size. In this case, unlike the smart phone, the mean of the coefficients for the square term of different size is not significant, and so we can assume that respondents' utilities monotonically increase when they choose a similar size of smart pad. Respondents who are more satisfied with their current smart pad tend to prefer the same OS more.

All the standard deviations (or variances) of parameters are statistically significant at the 95% level. Because the magnitude of the standard deviation is usually relatively large compared to the mean values, it is rational to use a mixed logit choice model, which estimates the distribution of parameters rather than fixed parameters.

Table 16. Relative importance of attributes in choosing a smart pad

Attributes	Relative importance	Attributes	Relative importance
OS	5%	Obsolescence	50%
Size	2%	OS similarity	6%
Weight	3%	Size similarity	2%
Delay	14%	Network effect	5%
Price	13%		

The relative importance of each attribute is calculated and shown in Table 16. The obsolescence attribute is the most important factor when making a purchasing decision. Among the status-quo effects, size similarity is relatively less important than OS similarity; among conventional attributes of the smart pad itself, price, delay (performance), and OS are thought to be the most important factors.

Table 17. Base scenario for new smart pad alternatives

	Alternative 1	Alternative 2	Alternative 3
OS	iOS	Android	W/M
Screen size (inches)	9.7	10.1	10.1
Weight (grams)	650	575	575
Delay (seconds)	Fast (3)	Fast (3)	Fast (3)
Price (KRW)	1,000,000	1,000,000	1,000,000

To analyze the choice probabilities of several representative smart pads, I assume specific attribute levels, as shown in Table 17. The specifications of smart pads with iOS and Android are similar to the typical smart pad model that actually has a large market share.[11]

Using equation (3.16), choice probabilities can be calculated as shown in Table 18. The first row shows the choice probabilities while not considering status-quo alternatives, while the second row shows the choice probabilities while considering status-quo option. What is interesting is that the choice probability of a W/M smart pad does not change, despite the existence of a status-quo option. It shows that consumers who prefer an iOS or Android smart pad can be distinguished from other consumers who prefer a W/M smart pad. Therefore, consumers who do not prefer W/M smart pads do not want to replace their smart pads with W/M smart pads, even after introducing a W/M smart pad, while the

[11] Appropriate assumptions are used for the W/M smart pad specifications, as this product has not y et been introduced to the South Korean market.

other consumers will replace them with a W/M smart pad upon its release.

Table 18. Choice probabilities of smart pads, based on the base scenario

	iOS smart pad	Android smart pad	W/M smart pad	Status quo
Choice probability while not considering status quo	46.8%	46.1%	7.1%	–
Choice probability while considering status quo	32.5%	29.7%	7.1%	30.7%

From Figure 9, we can predict that the difference in choice probabilities between iOS and Android smart pads will decrease after 15 months; however, these changes in choice probabilities are smaller than those of smart phones.

The respondents' descriptive statistics, as shown in Table 6, show that Android has a slightly higher market share than iOS, while that of W/M is nonexistent. These statistics correspond to the simulated results in Figure 9, which show that the Android and iOS market shares are expected to be almost identical following the launch in South Korea of the W/M smart pad. In terms of what will be the real-life W/M smart pad share, Gartner (2012) forecasts that the market share of the W/M smart pad will be similar to that of the Windows 8 smart pad and that it will occupy an 8.0% share of worldwide smart pad sales in 2013.

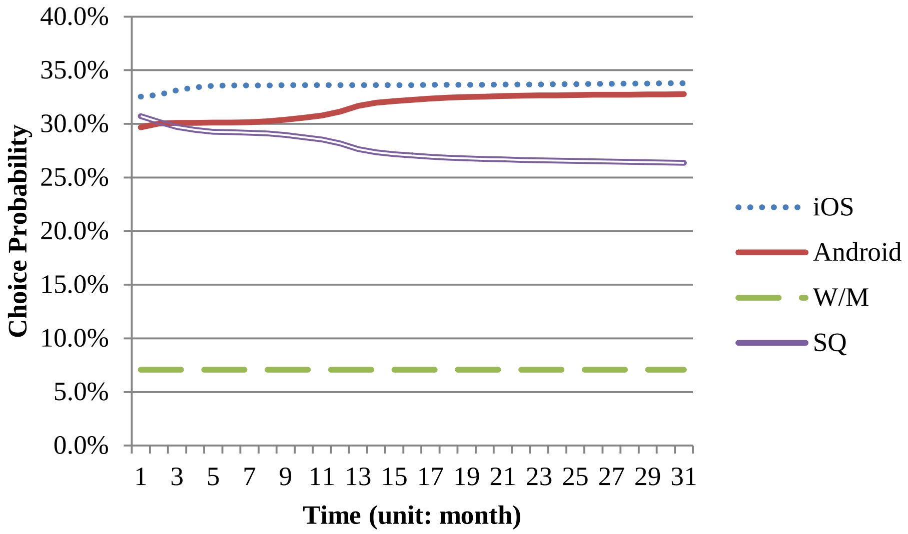


Figure 9. Changes to smart pad choice probabilities, by OS and status quo (SQ)

4.2.1.3 Empirical Research on Smart TVs

For the smart TV case, equation (4.5) shows the utility of respondent n in choosing alternative j.

$$
\begin{aligned}
U_{nj} = {} & \beta_{OS\_iOS} x_{OS\_iOS} + \beta_{OS\_Android} x_{OS\_Android} + \beta_{Size} x_{Size} \\
& + \beta_{Internet} x_{Internet} + \beta_{Application} x_{Application} + \beta_{Price} x_{Price} + \beta_{Obsol} \ln\left(x_{Obsol}\right) + \varepsilon_{nj}
\end{aligned}
\tag{4.5}
$$

$$
where\ \varepsilon_{nj} \sim i.i.d.\ Gumbel\ distribution
$$

The variables x_{OS_iOS} and $x_{OS\_Android}$ indicate whether a smart TV has iOS or Android OS. They are effect-coded with the base alternative of another, domestic OS, such as the Samsung or LG OS. The variables x_{Size}, $x_{Internet}$, $x_{Application}$, and x_{Price} represent smart TV screen size, availability of internet search function, high level of application, and price, respectively. $x_{Internet}$ and $x_{Application}$ are effect-coded with the base alternative of unavailable internet search function and lower level of application, respectively. In the case of a smart TV, the variable for OS similarity is not included, because every smart TV owner has the Samsung or LG OS. There is a large correlation between the variable for OS similarity and the variables indicating OS. Also, in the case of variables relating to different size, because consumers usually likely to have larger screen sizes, it is not appropriate to assume that consumers have preferences for a screen size different from their currently owned smart TVs. Finally, the network effect is thought to be not worthwhile to examine, because a smart TV is fixed within a house and has fewer opportunities to act as tool by which to communicate with others. Therefore, as a status-quo variable, I include only the obsolescence effect, x_{Obsol}.

The coefficients of β_{Size}, $\beta_{Internet}$, $\beta_{Application}$, β_{Price}, and β_{Obsol} are assumed to have positive or negative signs, while the other coefficients are assumed to be in a normal distribution.

Because there are no variables relating to similarity in equation (4.5), the hierarchical structure for β of the k^{th} attribute is assumed to have only a use variable, $z_{n,usage}$, as a covariate, as follows:

$$\beta_{n,k} = \alpha_{intercept,k} + \alpha_{usage,k} z_{n,usage} + \varepsilon'_n \quad . \qquad (4.6)$$
$$where\ \varepsilon'_n \sim N\left(0, V_\beta\right)$$

The Bayesian estimation method is used. Among 50,000 iterations, the initial 30,000 iterations are discarded as burn-in draws for convergence; the remaining 20,000 iterations are used to calculate the mean and standard deviation of parameters. The estimation results of the means and standard deviations (i.e., the square root of the diagonal elements of V_β) for normally (or log-normally) distributed βs are shown in Table 19.

Table 19. Estimation results for smart TVs, via an HB mixed logit choice model

	Mean of β		Standard deviation
	$\alpha_{intercept}$	α_{usage}	
β_{OS_iOS}	–3.566**		15.010**
	Base: Domestic OS (–5.701**)		
	–0.843	–0.201	
β	9.266**		13.790**

	Base: Domestic OS (–5.701**)		
	6.698**	0.190	
β_{Size}	9.280**		15.212**
	3.383	0.169	
$\beta_{Internet}$	8.076**		19.080**
	Base: No internet function (–8.076**)		
	–0.332	0.105	
$\beta_{Application}$	2.826**		15.689**
	Base: Lower level of application (–2.826**)		
	–9.044**	0.056	
β_{Price}	–18.686**		18.698**
	–9.138**	–0.558**	
β_{Obsol}	–16.760**		33.655**
	–10.907*	0.408	

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

All the means of β are statistically significant at the 95% level. With the coefficients for OS—unlike those for the smart phone and smart pad cases—the Android OS is most preferred for smart TVs. In terms of the obsolescence effect, as expected, consumers who spend more time watching TV are sensitive to obsolescence.

All the standard deviations (or variances) of parameters are statistically significant at the 95% level. Because the magnitude of the standard deviation is usually relatively large compared to the mean values, it is rational to use a mixed logit choice model, which estimates the distribution of parameters rather than fixed parameters.

Table 20. Relative importance of attributes in choosing a smart TV

Attributes	Relative importance	Attributes	Relative importance
OS	8%	Application level	3%
Size	18%	Price	27%
Internet availability	8%	Obsolescence	36%

The relative importance of each attribute is calculated and shown in Table 20. The obsolescence attribute is the most important factor to inform a purchase decision; the price and size of a smart TV are also thought to be important. However, endemic characteristics of a smart TV—such as OS, internet availability, and application level—are thought to be relatively less important.

Table 21. Base scenario for new smart TV alternatives

	Alternative 1	Alternative 2	Alternative 3
OS	iOS	Android	Others (domestic)
Size (inches)	40	40	40
Internet availability	Available	Available	Available
Application level	High	High	High
Price (KRW)	2,000,000	2,000,000	2,000,000

To analyze the choice probabilities of several representative smart TVs, I assume specific attribute levels, as shown in Table 21. Among the choice probabilities shown in

Table 22 are some interesting results. Without considering status quo, smart TVs with Android OS are predicted to predominate; however, while considering status quo, its probability largely decreases compared to iOS or other smart TV OSs. In fact, because all the respondents currently owned Samsung or LG OS smart TVs (see Table 9), the market shares for iOS, Android, and other domestic OSs are predicted to be 23.2%, 31.1%, and 45.7%, respectively. That is, in the absence of a consideration status-quo option, the choice probability of an Android smart TV is likely to be overestimated.

Table 22. Choice probabilities of smart TVs, based on the base scenario

	iOS smart TV	Android smart TV	Other-OS smart TVs	Status quo
Choice probability while not considering status quo	24%	65%	11%	–
Choice probability while considering status quo	23.2%	31.1%	6.3%	39.5%

In Figure 10, one can see that there is little change in the choice probabilities. The main reason for the relatively small change would be the longer product lifecycle of a smart TV. Therefore, it can be inferred that the obsolescence effect impacts choice probability relatively less for smart TVs that for smart phones or smart pads.

In summary, through the use of an HB multinomial logit model that incorporates status-quo effects, the hypotheses about obsolescence—i.e., H1 and H3a—are found to be correct. In the cases of hypotheses concerning similarity, H2a is found to be correct for

OS and size similarities, while H3b is correct for OS similarity and only partially correct for size similarity.

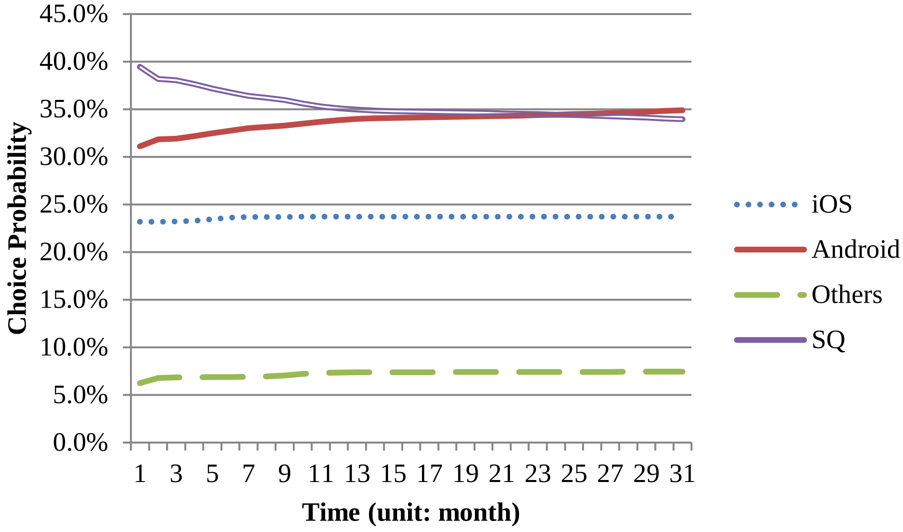


Figure 10. Changes to smart TV choice probabilities, by OS and status quo (SQ)

4.2.2 Multi-Product Category Case

4.2.2.1 Empirical Research on Multi-Product Categories: Smart Phones and Smart Pads

This section examines how consumers' preferences for smart pads differ according to the different types of smart phone OSs. Using equation (3.20), consumer utility for smart phones and smart pads are as follows:

$$
\begin{aligned}
U_{i,k_1}^{Phone} &= \beta_{k_1} + \beta_{Phone,\,Size} x_{Phone,\,Size} + \beta_{Phone,\,4G} x_{Phone,\,4G} + \beta_{Phone,\,Weight} x_{Phone,\,Weight} \\
&\quad + \beta_{Phone,\,Delay\_L} x_{Phone,\,Delay\_L} + \beta_{Phone,\,Delay\_M} x_{Phone,\,Delay\_M} \\
&\quad + \beta_{Phone,\,Price} x_{Phone,\,Price} + \beta_{Phone,\,Obsol} \ln\left(x_{Phone,\,Obsol}\right) \\
&\quad + \beta_{Phone,\,Same\_OS} x_{Phone,\,same\_OS} + \beta_{Phone,\,Diff\_Size} x_{Phone,\,Diff\_Size} \\
&\quad + \beta_{Phone,\,Network} x_{Phone,\,Network} + \varepsilon_i \\
U_{i,k_2}^{Y_{1i}} &= \beta_{k_2} + \beta_{Pad,\,Size} x_{Pad,\,Size} + \beta_{Pad,\,Weight} x_{Pad,\,Weight} + \beta_{Pad,\,Delay\_L} x_{Pad,\,Delay\_L} \\
&\quad + \beta_{Pad,\,Delay\_H} x_{Pad,\,Delay\_H} + \beta_{Pad,\,Price} x_{Pad,\,Price} + \beta_{Pad,\,Obsol} \ln\left(x_{Pad,\,Obsol}\right) \\
&\quad + \beta_{Pad,\,Same\_OS} x_{Pad,\,same\_OS} + \beta_{Pad,\,Diff\_Size} x_{Pad,\,Diff\_Size} \\
&\quad + \beta_{Pad,\,Network} x_{Pad,\,Network} + \varepsilon_i
\end{aligned}
\tag{4.7}
$$

$where\ \varepsilon_i \sim N\left(0, \Sigma\right)$

$U_{i,k}^{Phone}$ represents respondent i's utility for alternative k_1 among several smart phones, while considering only the attributes of smart phones; meanwhile, $U_{i,k}^{Y_{i1}}$ represents respondent i's utility for alternative k_1 among several smart pads, based on the selected smart phone. At this point, unlike the other cases, I consider only two alternatives that have iOS and Android for both smart phones and smart pads. β_{k_1} indicates an alternative-specific constant for a smart phone alternative and β_{k_2} indicates a smart pad alternative. In addition, the variable for delay, which is used as a continuous variable in the single-product category case, is dummy-coded as high-performance or low-delay (x_{Delay_L}) and middle-performance or medium-delay (x_{Delay_M}), with a base of low-performance or high-delay. The other variables are the same as those in the single-product category cases. The estimation results using the Bayesian approach are shown in Tables 23 and 24. From 20,000 iterations, draws of up to 5,000 iterations are discarded as burn-in samples.

Table 23 shows the estimates of β for smart phone selection (first stage). An estimated value refers to the preference for an iOS smart phone compared to an Android smart phone. For example, a value of –3.129 for $\beta_{Phone,\,Size}$ means a respondent is less sensitive to the size of a smart phone when he or she chooses an iOS smart phone, compared to an Android smart phone. Compared to an Android smart phone, a respondent is more sensitive to 4G capability, weight, and the preference for a medium level of delay, and is less sensitive to the size, price, and network effect. In the case of the status-quo effect, there is no significant difference in consumer preference between an iOS and Android smart phone, except in terms of network effect.

Table 23. Estimates of β for smart phone selection (first stage)

Parameter	Mean of β for choosing iOS over Android smart phone
β_{k_1}	14.718**
$\beta_{Phone,\,Size}$	–3.129**
$\beta_{Phone,\,4G}$	5.503**

$\beta_{Phone, Weight}$	–1.656**
$\beta_{Phone, Delay\_M}$	2.756**
$\beta_{Phone, Delay\_L}$	0.648
$\beta_{Phone, Price}$	2.476**
$\beta_{Phone, Obsol}$	0.311
$\beta_{Phone, Same\_OS}$	–0.718
$\beta_{Phone, Diff\_Size}$	0.120
$\beta_{Phone, Network}$	–9.195**

** indicate the posterior estimates are statistically different from zero at 95% level.

While the first stage does not generate distinguished results compared to the analysis of smart phones in the single-product category case, the second-stage results are noteworthy (see Table 24). Table 24 shows how the preference for an iOS compared to an Android smart pad is different, as a function of smart phone selection. The first column contains information pertaining to the situation in which an iOS smart phone is chosen, while the second column contains that for when an Android smart phone is chosen. For example, when respondents choose an iOS over Android smart pad, both the respondents who choose an iOS and Android smart phone in the first stage are more influenced by the obsolescence effect, but the degree of influence is larger for the respondents who choose an iOS smart phone, compared to those who choose an Android smart phone.

Table 24. Estimates of β for choosing smart pad based on the smart phone selection (second stage)

	Estimate of β for choosing an iOS over Android smart pad given an iOS smart phone	Estimate of β for choosing an iOS over Android smart pad given an Android smart phone
β_{k_2}	0.202	–0.631
$\beta_{Pad,\,Size}$	0.006	–0.123
$\beta_{Pad,\,Weight}$	4.862**	4.554**
$\beta_{Pad,\,Delay\_M}$	4.736**	1.184**
$\beta_{Pad,\,Delay\_L}$	1.722**	1.102**
$\beta_{Pad,\,Price}$	–6.902**	–2.716**
$\beta_{Pad,\,Obsol}$	–2.239**	–0.480*
$\beta_{Pad,\,Same\_OS}$	–0.554	–0.464*
$\beta_{Pad,\,Diff\_Size}$	2.263**	2.353**
$\beta_{Pad,\,Network}$	–0.880	–1.416*

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

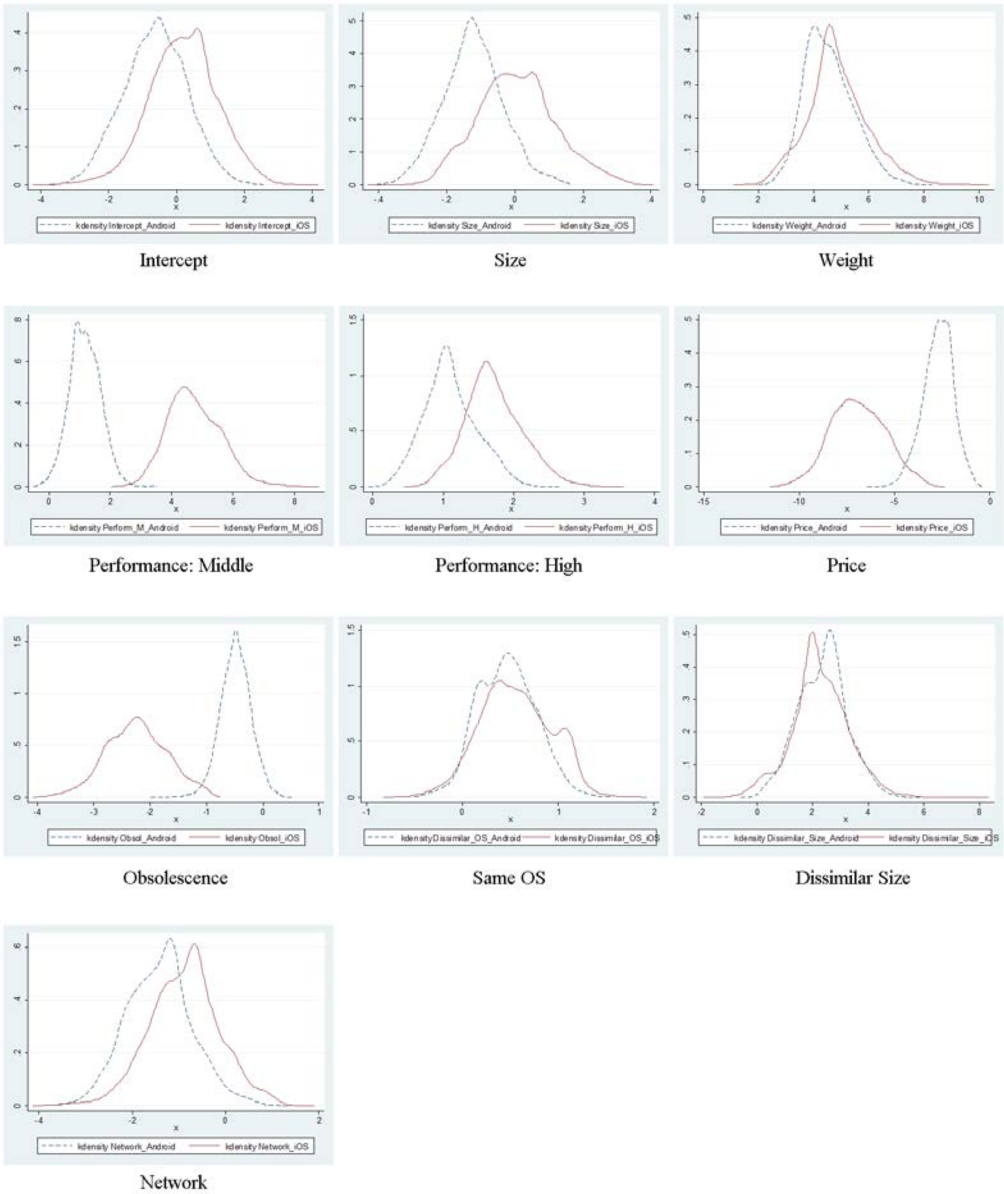


Figure 11. Kernel-density plots of posterior distributions for the β parameters, for choosing an iOS smart pad over an Android smart pad

Figure 11 helps one compare the effect of the first-stage selection by showing kernel-density plots. The dashed-line curves are conditional on the Android smart phone selection, and the solid-line curves are conditional on the iOS smart phone selection. The preference, especially, for middle-level delay, price, and obsolescence can be distinguished.

Table 25 shows the variance–covariance matrix of Σ in equation (4.7). In this case, the variance–covariance matrix is very simple, because I consider only two alternatives. For identification, all diagonal elements are fixed to 1. As expected, an iOS smart pad has a negative correlation when a consumer owns an Android smart phone, but a positive correlation when a consumer owns an iOS smart phone. The correlations are very significantly high, in both cases.

Table 25. Correlation matrix of smart phone and pad alternatives

	iOS smart phone	iOS smart pad for given Android smart phone	iOS smart pad for given iOS smart phone
iOS smart phone	1	–0.923**	0.915**
iOS smart pad for given Android smart phone		1	–
iOS smart pad for given iOS smart phone			1

** indicate the posterior estimates are statistically different from zero at 95% level.

4.2.2.2 Empirical Research on Multi-Product Categories: Smart Phones and Smart TVs

This section shows how consumer preference for smart TVs differs according to the different types of smart phone OS a consumer already uses. Using equation (3.20), consumer utilities for smart phones and TVs are as follows:

$$
\begin{aligned}
U_{i,k_1}^{Phone} = {} & \beta_{k_1} + \beta_{Phone,\,Size} x_{Phone,\,Size} + \beta_{Phone,\,4G} x_{Phone,\,4G} + \beta_{Phone,\,Weight} x_{Phone,\,Weight} \\
& + \beta_{Phone,\,Delay\_L} x_{Phone,\,Delay\_L} + \beta_{Phone,\,Delay\_M} x_{Phone,\,Delay\_M} \\
& + \beta_{Phone,\,Price} x_{Phone,\,Price} + \beta_{Phone,\,Obsol} \ln\left(x_{Phone,\,Obsol}\right) \\
& + \beta_{Phone,\,Same\_OS} x_{Phone,\,same\_OS} + \beta_{Phone,\,Diff\_Size} x_{Phone,\,Diff\_Size} \\
& + \beta_{Phone,\,Network} x_{Phone,\,Network} + \varepsilon_i \\
U_{i,k_2}^{Y_{1i}} = {} & \beta_{k_2} + \beta_{TV,\,Size} x_{TV,\,Size} + \beta_{TV,\,Internet} x_{TV,\,Internet} \\
& + \beta_{TV,\,Application\_H} x_{TV,\,Application\_H} + \beta_{TV,\,Price} x_{TV,\,Price} \\
& + \beta_{TV,\,Obsol} \ln\left(x_{TV,\,Obsol}\right) + \varepsilon_i
\end{aligned}
\tag{4.8}
$$

$$where\ \varepsilon_i \sim N\left(0, \Sigma\right)$$

$U_{i,k}^{Phone}$ represents respondent i 's utility for alternative k_1 among several smart phones while considering only the attributes of smart phones, while $U_{i,k}^{Y_{i1}}$ represents the respondent i 's utility for alternative k_1 among several smart TVs, based on the selected smart phone. I consider three alternatives, in the same manner as for the previous single-product category case. β_{k_1} indicates an alternative-specific constant for a smart phone alternative and β_{k_2} indicates that for a smart TV alternative. Others are as per the previous descriptions of variables. Estimation results generated through the use of the Bayesian approach are shown in Tables 26, 27, and 28. From 40,000 iterations, draws of up to 30,000 iterations are discarded as burn-in samples.

Table 26 shows the estimates of β for smart phone selection (first stage). The estimated values refer to the preference for an iOS or Android smart phone, compared to a W/M smart phone. For example, in the case of $\beta_{Phone,\ Size}$, the preference for a large smart phone screen size is higher for Android phones than for W/M smart phones, but the difference is not significant between iOS and W/M smart phones. In addition, for $\beta_{Phone,\ 4G}$, the preference for 4G availability leads to a preference for these phones, in this order: iOS, W/M, and Android.

Figure 12 helps one compare preference differences vis-à-vis smart phone choice (first stage) by showing kernel-density plots. The dashed-line curves represent Android smart phone selection, and the solid-line curves represent iOS smart phone selection. The variance of preference for an iOS smart phone is usually smaller than that for an Android smart phone.

Table 26. Estimates of β for smart phone selection (first stage)

	Mean of β for choosing iOS over W/M smart phone	Mean of β for choosing Android over W/M smart phone
β_{k_1}	2.327*	–8.759**
$\beta_{Phone,\,Size}$	–0.278	2.454**
$\beta_{Phone,\,4G}$	1.815**	–3.657**
$\beta_{Phone,\,Weight}$	–0.230	0.748
$\beta_{Phone,\,Delay\_M}$	1.645**	–1.449
$\beta_{Phone,\,Delay\_L}$	1.789**	–0.773
$\beta_{Phone,\,Price}$	–0.326**	–0.643**
$\beta_{Phone,\,Obsol}$	–0.794*	–1.430**
$\beta_{Phone,\,Same\_OS}$	0.308	0.255
$\beta_{Phone,\,Diff\_Size}$	–2.907**	–3.407
$\beta_{Phone,\,Network}$	6.432**	16.513**

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

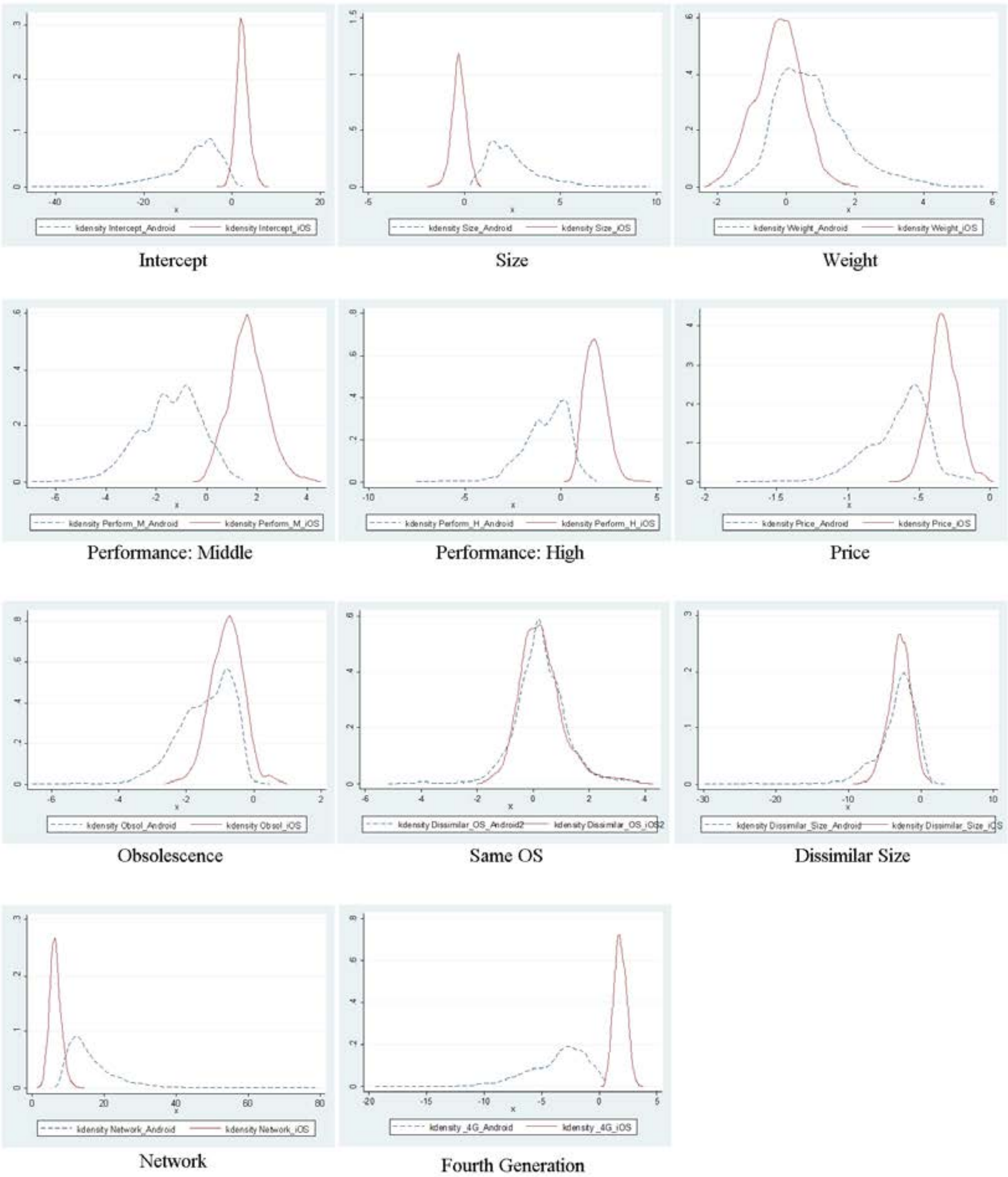


Figure 12. Kernel-density plots of posterior distributions for the β parameters, for choosing an iOS and Android smart phone over a W/M smart phone

Table 27. Estimates of β for choosing an iOS over other-OS smart TVs, based on smart phone selection (second stage)

	Mean of β for choosing iOS over other-OS smart TVs, given iOS smart phone selection	Mean of β for choosing iOS over other-OS smart TVs, given Android smart phone selection	Mean of β for choosing iOS over other-OS smart TVs, given W/M smart phone selection
β_{k_2}	15.631**	113.346**	–1.401
$\beta_{TV,Size}$	–2.660**	–1.784**	–0.733
$\beta_{TV,Internet}$	6.555**	44.960**	2.621**
$\beta_{TV,Application\_H}$	–3.830**	–42.513**	0.622
$\beta_{TV,Price}$	–1.460	–42.436**	0.960
$\beta_{TV,Obsol}$	–8.108**	–271.606**	–0.895

** indicate the posterior estimates are statistically different from zero at 95% level.

Table 27 shows how the preference for an iOS compared to other-OS smart TVs differs as a function of smart phone selection. The first column contains information pertaining to the situation in which an iOS smart phone is chosen, while the second column[12]

[12] The estimates in the second column show a very diffused distribution, except vis-à-vis screen size. Their posterior distributions do not seem to converge well. At this point, it is not appropriate to co mpare the mean values of the posteriors.

contains that in which an Android smart phone is chosen; the last column contains that in which a W/M smart phone is chosen. For example, in the case of β_{Size_TV}, respondents choosing an iOS smart phone are the least sensitive to screen size.

The kernel-density plots are shown in Figure 13. The long dashed-line curves are conditional on W/M smart phone selection, short dashed-line curves are conditional on iOS smart phone selection, and the solid-line curves are conditional on Android smart phone selection.

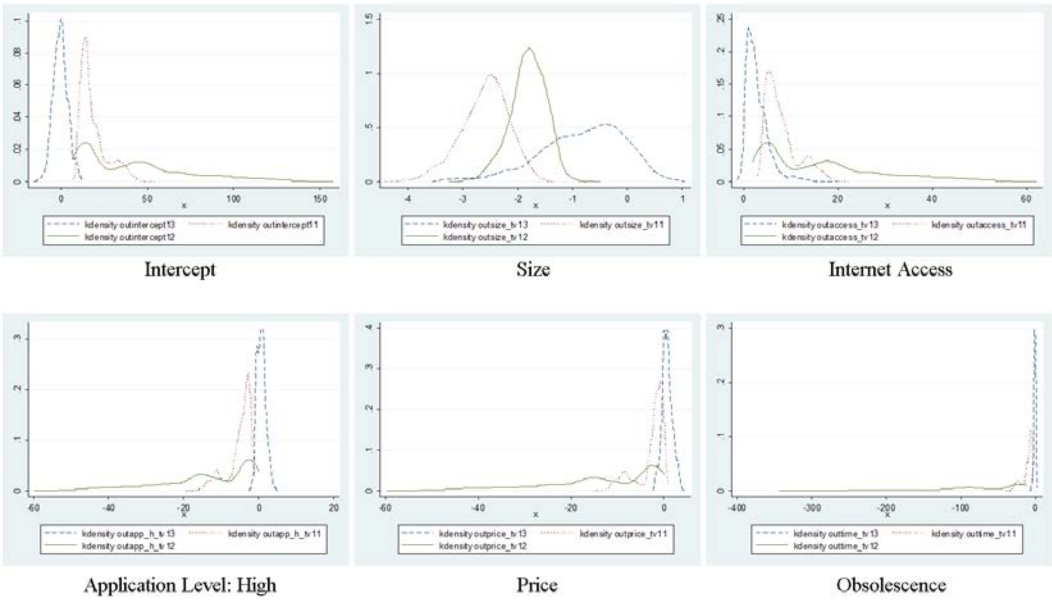


Figure 13. Kernel-density plots of posterior distributions for the β parameters, for choosing an iOS smart TV over other-OS smart TVs

Table 28. Estimates of β for choosing an Android over other-OS smart TVs, based on smart phone selection (second stage)

	Mean of β for choosing Android over other-OS smart TVs, given iOS smart phone selection	Mean of β for choosing Android over other-OS smart TVs, given Android smart phone selection	Mean of β for choosing Android over other-OS smart TVs, given W/M smart phone selection
β_{k_2}	–5.526**	0.804	–1.732
$\beta_{TV,Size}$	1.263**	–0.117	0.135
$\beta_{TV,Internet}$	–0.451	0.311	–1.284
$\beta_{TV,Application\_H}$	–0.532	–0.990	–0.265
$\beta_{TV,Price}$	–0.878	–0.264	0.790
$\beta_{TV,Obsol}$	–0.936	–1.497*	0.359

*, ** indicate the posterior estimates are statistically different from zero at 90% and 95% level, respectively.

Table 28 shows how the preference for an Android smart TV compared to other-OS smart TVs differs as a function of smart phone selection. The first column contains information pertaining to the situation in which an iOS smart phone is chosen; the second column, that in which an Android smart phone is chosen; and the last column, that in which a W/M smart phone is chosen. Unlike in the previous case, respondents choosing an iOS smart phone have a higher preference for screen size—that is, iOS smart-phone users are likely to have a larger smart TV for Android OS, but not for iOS. However, a few parameters are statistically significant.

The kernel-density plots are shown in Figure 14. The long dashed-line curves are conditional on W/M smart phone selection; the short dashed-line curves, on iOS smart phone selection; and the solid-line curves, on Android smart phone selection.

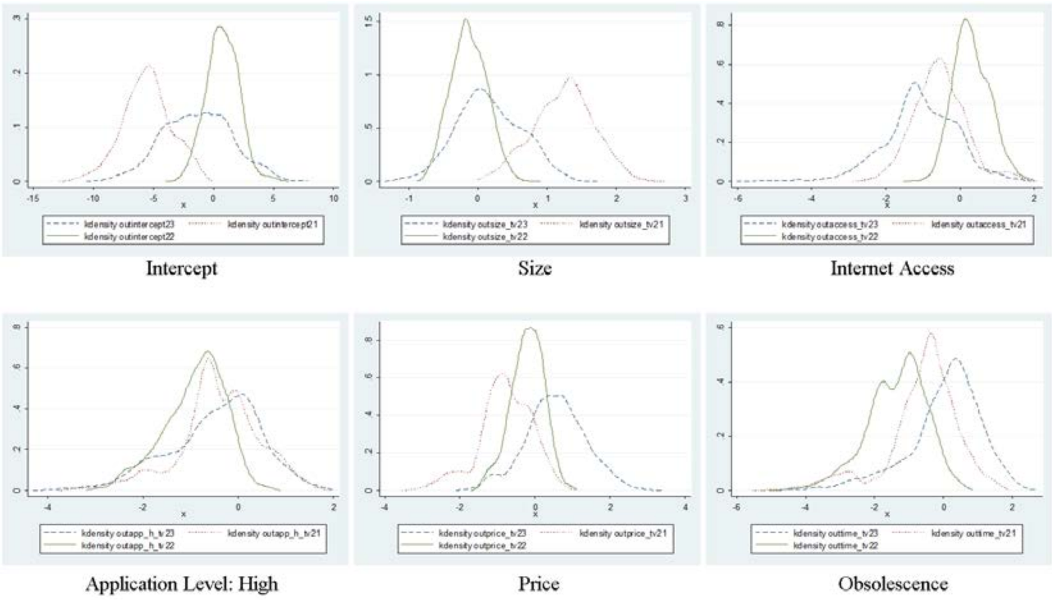


Figure 14. Kernel-density plots of posterior distributions for the β parameters, for choosing an Android smart TV over other-OS smart TVs

Finally, Table 29 shows the variance–covariance matrix of Σ in equation (4.8). For identification, all diagonal elements are fixed to 1. Only three covariances are significant;

the first significant value, 0.691, indicates correlation within smart phone selection. A positive correlation of 69.1% means that compared to a W/M smart phone, both iOS and Android smart phones are likely to be chosen together—in other words, the respondents make a clear distinction between iOS and Android smart phones, and W/M smart phone. The second significant value, –0.849, indicates the correlation between iOS and Android smart TV selections, conditioned on an iOS smart phone selection. A negative correlation of 84.9% shows that an iOS and Android smart TV are on different ends of the preference continuum, at the center of which are other-OS smart TVs; the result is the same when respondents choose an Android smart phone, though the level of negative correlation is smaller. Additionally, we find that there is no significant correlation between iOS and Android smart TVs when respondents choose a W/M smart phone.

In summary, H4 is found to be correct, because there are significantly different coefficient patterns for a smart pad or TV, as a function of smart phone selection.

Table 29. Correlation matrix of smart phone and TV alternatives

			Phone		Smart TV					
					Given W/M phone		Given iOS phone		Given Android phone	
			iOS phone	Android phone	iOS TV	Android TV	iOS TV	Android TV	iOS TV	Android TV
Smart phone		iOS phone	1	0.691**	–0.201	0.504	–0.600	0.619	–0.246	0.227
		Android phone		1	–0.281	0.474	–0.661	0.672	–0.203	0.158
Smart TV	Given W/M phone	iOS TV			1	–0.196	–	–	–	–
		Android TV				1	–	–	–	–
	Given iOS phone	iOS TV					1	–0.849**	–	–
		Android TV						1	–	–
	Given Android phone	iOS TV							1	–0.788**
		Android TV								1

** indicate the posterior estimates are statistically different from zero at 95% level.

Chapter 5. Conclusion

The purpose of this study was to consider the status-quo effect in estimating consumer preference for semi-durable products that are purchased periodically. Because consumers largely depend on their experience with currently owned products and those products' current status when they purchase new products, estimating new alternatives with no consideration of status quo may garner inaccurate results. Especially, among several possible status-quo effects, the obsolescence, similarity, and network effects are treated as major influences in terms of consumer status quo. In addition, I assume consumer preference for a product to be dependent on the status quo of other related products—that is, the status-quo effect is not only influential within the same product category, but also across related product categories.

Three smart devices—namely, smart phones, smart pads, and smart TVs—were selected for empirical analysis here, because they are good examples of semi-durable products that are purchased from time to time; they are also related products that interact with each other. The current study developed a choice model that incorporates a status-quo alternative and considers several status-quo effects.

First, estimations vis-à-vis the three smart devices are generated via the HB multinomial logit choice model. Each parameter is assumed to follow a multivariate normal distribution, while the mean of the multivariate normal distribution has covariates that consist of the use and satisfaction level of currently owned products. For the three devices, the fact that all the parameter variance values and interesting covariates of the multivariate normal distribution are significant suggests that the use of the HB multinomial logit choice model is reasonable. In addition, all the parameters for obsolescence and network effect are significant with expected signs, and similarities between new alternatives and currently owned products tend to positively affect consumer utility. The relative importance of the status-quo effect when choosing a new product is quite considerable—that is, the assumptions proposed earlier in this paper on status-quo effect are supported. I report the mean and variance of β s and their coefficients of covariates, the relative importance of each attribute, and changes in choice probability based on base scenarios.

In summary, the choice probabilities of new products change over time due to the obsolescence effect as well as largely influenced by the status-quo effect. There are several implications from the perspective of demand forecasting, as follows:

· Because the choice probabilities that include a status-quo alternative differ significantly from those that lack one, the proposed model is highly recommended in generating more precise myopic predictions of consumer demand.

· Choice probabilities change over time due to the obsolescence effect. Although the amount of change is small for a product category that tends to feature longer product lifecycles, the ability to predict changes in choice probabilities is nonetheless useful.

· The choice model that does not include a similarity or network effect is likely to overestimate the consumer preference for alternatives that have high market shares. A consumer may choose a certain type of alternative because he or she is familiar with it, or simply because others use the same type of alternative.

Second, two recursive choice models—i.e., those for the smart phone and smart pad, and for the smart phone and smart TV—are estimated via a bivariate MNP model while using the Bayesian estimation method. From the analysis, it is found easily, through the use of kernel-density plots, that consumer preference for various attributes of a smart pad or smart TV differs as a function of which kinds of smart phone the consumers choose. In addition, as an advantage of the probit model, the ability to see correlation across alternatives is useful.

Consequently, it is obviously important to incorporate the status-quo effect into models that examine semi-durable products, to ensure more accurate forecasting results. Additionally, by including the obsolescence effect, the dynamics of choice probability can be analyzed only through the use of cross-sectional survey data. It is also noteworthy that the status-quo effect often extends across multi-product categories. The framework of this research can be generally applied to market analysis vis-à-vis the various high-technology products that are currently pouring into the marketplace. Future research is expected to garner a better understanding of implications, based on status effects.

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Appendix A: Descriptions of Attributes and Attribute Levels from the Smart Phone Conjoint Survey

Table A. Descriptions of attributes and attribute levels from the smart phone conjoint survey

Attributes		Descriptions of attributes and attribute levels	
OS	Description	Depending on OS, the usable applications and downloadable online markets (free/paid) differ	
	Levels	1. iOS	Apple iPhone (3GS, 4, 4S) OS; only the Apple App store (for downloading applications) and iTunes (for interfacing with PCs for file transmissions) are available for use
		2. Android	Google OS; a variety of smart phones and application markets can be used, except the Apple iPhone and App store; no need to use specialized software for file transmission; OS and smart phone providers differ, and so support of OS updates varies
		3. W/M	MS OS; PC Windows is modified for smart phone use, so compatibility with PC is high (editing function of MS Office can be used in the smart phone); fewer applications are available in W/M than in iOS and Android
Screen size	Description	Screen size of smart phone iPhone (3.5 inches), Galaxy S (4.0 inches), Galaxy Note (5.3 inches), Optimus LTE (4.5 inches)	
	Levels	1. 3 inches	Width: 3.5 cm; height: 7 cm
		2. 4 inches	1.7 times the screen size of a 3-inch smart phone
		3. 5 inches	2.7 times the screen size of a 3-inch smart phone

4G availability	Description	- 4G LTE is a more advanced wireless internet service than 3G - 4G LTE's internet speed is 3 times faster than 3G's - LTE devices and plans should be used with 4G LTE service
	Levels	1. 3G Wireless internet access
		2. 4G LTE wireless internet access (3G is available in areas where 4G LTE is not available)
Weight	Description	Weight of smart phone iPhone 3GS (135 g), Galaxy S (118 g), Galaxy Note (183 g)
	Levels	1. 100 g
		2. 150 g
		3. 200 g
Delay	Description	Time taken for a web page (e.g., http://naver.com) to load on the smart phone screen while connecting to the internet via Wi-Fi
	Levels	1. Fast (1 s)
		2. Normal (5 s)
		3. Slow (10 s)
Price	Description	Price of device
	Levels	1. 600,000 KRW
		2. 900,000 KRW
		3. 1,200,000 KRW

Appendix B: Descriptions of Attributes and Attribute Levels from the Smart Pad Conjoint Survey

Table B. Description of attributes and attribute levels from the smart pad conjoint survey

Attributes		Descriptions of attributes and attribute levels	
OS	Description	Depending on OS, the usable applications and downloadable online markets (free/paid) differ	
	Levels	1. iOS	Apple iPad OS; only the Apple App store (for downloading applications) and iTunes (for interfacing with PCs for file transmissions) are available to use
		2. Android	Google OS; a variety of smart pads and application markets can be used, except the Apple iPad and App store; no need to use specialized software for file transmission; OS and smart pad providers differ, and so support of OS updates varies
		3. W/M	MS OS; PC Windows is modified for smart pad use, so compatibility with PC is high (editing function of MS Office can be used in the smart pad); fewer applications are available in W/M than in iOS and Android
Screen size	Description	Screen size of smart pad iPad (9.7 inches), Galaxy Tab (7.0, 7.7, 8.9, or 10.1 inches)	
	Levels	1. 7 inches	3.0 times the screen size of a 4-inch smart phone
		2. 9 inches	5.0 times the screen size of a 4-inch smart phone
		3. 11 inches	7.5 times the screen size of a 4-inch smart phone
Weight	Description	Weight of smart pad iPad2 (610 g), Galaxy Tab 7.7 (370 g), Galaxy Tab 10.1 (575 g)	

	Levels	1. 400 g
		2. 700 g
		3. 1,000 g
Delay	Description	Time taken for a web page (e.g., Naver) to load on the smart pad screen while connecting to the internet via Wi-Fi
	Levels	1. Fast (1 s)
		2. Normal (5 s)
		3. Slow (10 s)
Price	Description	Price of smart pad
	Levels	1. 50,000 KRW
		2. 75,000 KRW
		3. 100,000 KRW

Appendix C: Descriptions of Attributes and Attribute Levels from the Smart TV Conjoint Survey

Table C. Descriptions of attributes and attribute levels from the smart TV conjoint survey

Attributes		Descriptions of attributes and attribute levels	
OS	Description	Depending on OS, the usable applications and downloadable online markets (free/paid) differ	
	Levels	1. iOS	Apple OS; only the Apple App store (for downloading applications) is available for use
		2. Android	Google OS; a variety smart TVs and application markets can be used, except Apple iTV and the App store
		3. Other OS	Domestic manufacturer OS like Samsung or LG OS
Screen size	Description	Screen size of smart TV	
	Levels	1. 30 inches	Width: 66.3 cm; height: 37.3 cm
		2. 40 inches	Width: 88.3 cm; height: 49.7 cm 1.77 times the screen size of a 30-inch TV
		3. 50 inches	Width: 110.4 cm; height: 62.1 cm 2.77 times the screen size of a 30-inch TV
Internet search	Description	Internet search availability on the smart TV screen	
	Levels	1. Internet search available	
		2. Internet search not available	
Applications	Description	Number of available applications on smart TVs	
	Levels	1. High	Smart phone applications and smart TV specialized applications are available

			for use
		2. Low	Only smart TV built-in applications are available for use; additional applications needed to update firmware
Price	Description	Price of smart TV	
	Levels	1. 1 million KRW	
		2. 2 million KRW	
		3. 3 million KRW	

Abstract (Korean)

본 연구의 목적은 소비자가 “현재 보유한 제품 (status quo)”이 새로운 제품 선택에 미치는 영향을 고려하여 주기적으로 구매되는 준내구재 제품에 대한 소비자의 선호를 분석하는 것이다. 소비자들은 일반적으로 새로운 제품을 구매할 때 그들이 현재 보유한 제품의 상태와 이로부터 얻은 경험 등에 크게 영향을 받기 때문에, 새로운 제품들의 비교만으로는 소비자 선호를 정확히 예측하는 것이 힘들기 때문이다. 특히, 본 연구에서는 보유한 제품의 진부화 정도나 새로 구매하고자 하는 제품과의 유사성 등을 현재 보유한 제품이 미치는 주된 영향으로 고려하고 분석하였다. 이와 같은 현재 보유한 제품의 상태를 고려한 선택 모형은 동일한 카테고리 내의 제품 선택뿐만 아니라, 상호 영향을 줄 수 있는 다른 카테고리 제품의 경우에 대해서도 확장이 가능하다.

실증 분석은 세 개의 스마트 기기인 스마트폰, 스마트패드, 스마트TV에 대해서 수행되었다. 우선 계층적 베이지안 (hierarchical Bayesian)을 이용한 다항로짓모형 (multinomial logit model)을 이용하여, 현재 보유한 제품이 새로운 선택에 어떤 영향을 미치는지를 분석하였다. 분석 결과, 새로운 제품을 선택함에 있어서 해당 제품 속성 수준 자체만큼이나 기존에 보유했던 제품의 특성이 선택에 미치는 영향이 큰 것으로 나타났고, 새로운 대안들의 선택확률을 계산함에 있어 현재 보유한 대안을 고려하는 경우와 그렇지 않은 경우에 큰 차이가 있음을 알 수 있었다. 시간에 따른 대안의 선택확률 변화는

진부화 효과가 미치는 영향이 추정되면 시뮬레이션 해 볼 수 있다. 이처럼 시계열 데이터 없이도 시간에 따른 선택확률의 변화를 분석할 수 있는 것은 본 연구의 장점 중 하나이다. 이 외에도, 보다 정밀한 수요 예측을 위한 함의들이 도출되었다. 다양한 카테고리 제품간의 상호 연계성의 관점에서, 현재 보유한 제품이 다른 카테고리의 제품 선택에 미치는 효과를 이변량 다항프로빗 모형 (bivariate multinomial probit model)을 이용하여 분석할 수 있다. 본 연구에서는 이변량 다항프로빗 모형을 이용하여 응답자가 어떤 스마트폰을 선택했는지에 따라서 새로운 스마트패드나 스마트TV의 선택이 어떻게 달라지게 되는지를 분석하였다. 그 차이는 모수 추정 결과를 분포 밀도 (kernel density) 그래프를 통해서 쉽게 식별할 수 있게 하였고, 분산-공분산 행렬을 통해 다른 카테고리의 제품간의 상관관계까지 고려할 수 있도록 하였다.

정리하면, 본 연구는 왜 우리가 선택 모형에서 소비자가 현재 보유한 제품이 새로운 제품의 선택에 미치는 영향을 고려해야 하는 이유를 제시하고, 이를 실증적으로 어떻게 고려하여 분석할 것인지에 대한 분석틀을 제공하는 것에 의의가 있고, 이를 통해 더 정확한 수요 예측 모형을 개발하는데 기여할 것으로 보인다.

주요어 : 소비자 선호, 계층적 베이지안 다항로짓, 이변량 다항프로빗, 현재 상태, 진부화, 유사도

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