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Demand Forecasting in the Early Stage of the Technology's Life Cycle Using a Bayesian Update

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Abstract: The forecasting demand for new technology for which few historical data observations are available is difficult but essential to sustainable development. The current study suggests an alternative forecasting methodology based on a hazard rate model using stated and revealed preferences of consumers. In estimating the hazard rate, information is initially derived through conjoint analysis based on a consumer survey and then updated using Bayes' theorem with available market data. To compare the proposed models' performance with benchmark models, the Bass model, the logistic growth model, and a Bayesian approach based on analogy are adopted. The results show that the proposed model outperforms the benchmark models in terms of pre-launch and post-launch forecasting performances.

Keywords: demand forecasting; conjoint analysis; Bayesian update; broadband internet service; hazard rate model

1. Introduction

From the viewpoints of a company and a government, the forecasting demand for new technologies is essential to their sustainable development. Among the many forecasting models, Bass [1] type models are widely used to analyze demand and diffusion in industrial engineering, policymaking, and marketing. Yet such models depend on historical time series data, which limits their usefulness for the forecasting demand for newly introduced technology.

A second forecasting methodology, discrete choice forecasting (choice-based diffusion models), has been used to forecast the demand for technologies for which there is limited historical data, such as low-earth-orbit mobile satellite service [2], next-generation large-screen televisions [3], dynamic random access memory [4] and photo-voltaic (PV) solar cells [5]. With this methodology, future choice probabilities regarding newly introduced technology can be estimated using the stated preference (SP, hereafter) approach. However, studies such as Bass et al. [6] and Morwitz [7] showed that there exists a difference between forecasts by SP data and the actual purchase since respondents in some conditions overstate and in other conditions understate actual purchase rates. Thus it is important to note that revealed-preference (RP, hereafter) data are generally supplementary to SP data, so that the weakness of SP data can be compensated for by RP data [8]. A key role for RP data in combined SP-RP analyses lies in providing more robust parameter estimates for the demand forecasting of newly introduced technology, which increase the confidence in predictions.

In this paper, we introduce an alternative method of forecasting the new technology demand that uses RP data as well as SP data. This method employs a hazard function, conjoint analysis, and Bayesian update. We derive a prior distribution of a hazard function using conjoint analysis with stated preference data, and we then update that prior distribution with available RP data using Bayes' theorem. The marginal contribution of this study is to derive accurate forecasts for new technology and products with a short history using conjoint analysis with SP data and Bayesian updating with RP data. To our knowledge, the Bayesian update of the utility function and choice probability estimated from the conjoint analysis is the new approach in the field of forecasting research. There are many products and technologies which are in the early stages of the product life cycle. Especially as the market for information and communications technology grows rapidly, new technologies and services are introduced more frequently. This phenomenon indicates that demand forecasting for newly introduced technologies is essential for survival in the competitive market, for investment decision making, for marketing, and for setting policies. Another key contribution of this study is that the proposed model can be applied to new technologies and products in other countries.

We employ benchmark models, the Bass model, the logistic growth model, and analogy model to compare the goodness-of-fit and forecasting performance. To estimate the forecasting models, 23 yearly data of South Korea's broadband Internet service were collected. The data set used for this analysis is suitable for a comparison of the proposed models with benchmark models as the market is saturated. The results of this study can provide the advantage or disadvantage of the proposed model.

The remainder of this study is structured as follows. Section 2 reviews the literature on forecasting models. Section 3 is devoted to a description of the forecasting models which are proposed in this study. In Section 4, the proposed model is applied to the broadband internet service market. The goodness-of-fit and forecasting performance of the proposed model are measured and compared with benchmark models. The concluding section presents the study's theoretical implications and concluding remarks.

2. Literature Review

Diffusion models including Bass-type models and choice-based diffusion models have been utilized to take into account various situations. These models address, among other things, (1) replacement purchasing and repeat purchasing [9–12]; (2) supply restriction [13]; (3) and diffusion at the brand level [14]. Diffusion models, however, have some limitations when forecasting the demand for new technology because they usually depend on historical time series data. Heeler and Hustad [15] and Srinivasan and Mason [16] suggested that ten years or more of data is required for determining coefficients, which can then be used for determining diffusion and sales in later years. Previous research such as that of Srinivasan and Mason [16] has demonstrated that stable and robust parameter estimates can only be obtained if data include the peak of the non-cumulative adoption curve. Therefore, most of the published forecasting applications of new technology forecasting models have been mainly concerned with describing the diffusion patterns and at best generating one step ahead or two steps ahead forecasts [17]. However, it is not clear whether such forecasts will be helpful to policy makers.

In the meantime, researchers have long struggled to develop forecasts for newly introduced technology. Bass et al. [6] mentioned that, "the most critical forecast is the forecast prior to technology launch." Conducting pre-launch purchase intent surveys is useful for determining the initial penetration levels of innovations. In Morrison [18], Jamieson and Bass [19], Hsiao et al. [20], and Islam [5] used this approach to forecast the trial purchase of new technology. A consumer-based approach can play a role as a helpful tool but needs to be used with adjustment and not be used by itself. Most individuals do not know what they will like in advance, and as a result, some people try to guess what they think the interviewer wants to hear [21]. In the case of a consumer survey, there is no valid reason to assume that the result from one group is the same as that from the next group. Thus, a consumer-based approach, generally, does not provide useful information for long-term projections [21]; alternative methods must be considered.

A Bayesian framework is useful for the demand forecasting of new technology with a short history, in which we wish to incorporate various data sources for demand predictions prior to a technology launch, and later update those predictions as data become available. Given the importance of forecasts before or shortly after the launch, methodologies that allow a researcher to incorporate exogenous information and update this information optimally as data become available have an important place in diffusion research [22]. Talukdar et al. [23] highlight the advantages of the Bayesian method in forecasting the technology demand, where the gains of the Bayesian methods are greatest at the early stage of technology introduction, when forecasts are often the most valuable.

Most of the Bayesian models for demand forecasting follow an approach using prior information derived from the diffusion of previously introduced technologies [23,24]. Many technologies, however, do not have analogous technologies that can be served as a suitable reference because they are only evolving technologically and as a business. Therefore, previous Bayesian models for demand forecasting have limitations when there are no analogous technologies. Beyond previously introduced technologies, studies should focus on bringing in auxiliary information to provide sufficient data to estimate reliably. In this study, this auxiliary information includes using data on consumers' stated-preference.

3. The Model

SP data are useful to estimate the demand for innovations with new attributes or features. However, the issue depends on whether models estimated from SP data yield valid and reliable inferences and predictions of real market behavior. Bass et al. [6] showed that there exists a difference between forecasts by SP data and actual purchases. Thus, it should be noted that RP data are generally supplementary to SP data so that the weakness of SP data can be compensated for by RP data [8]. A significant role for SP data in combined SP-RP analyses lies in data enrichment; that is, providing more robust parameter estimates for the demand forecasting of newly introduced innovations, which increase the confidence in predictions.

Therefore, this study introduces an alternative method of forecasting the innovation demand that uses RP data as well as SP data. This method employs a hazard function, conjoint analysis, and Bayesian update. The proposed method involves five steps like Figure 1:

1. Employ the hazard function.
2. Estimate the hazard function exogenously using conjoint analysis with stated preference data from consumers.
3. Recalibrate the alternative-specific constant.
4. Update the parameters of the hazard function using Bayes' theorem with revealed preference data in the market.
5. Forecast the demand for the newly introduced technologies reflecting the updated hazard function.

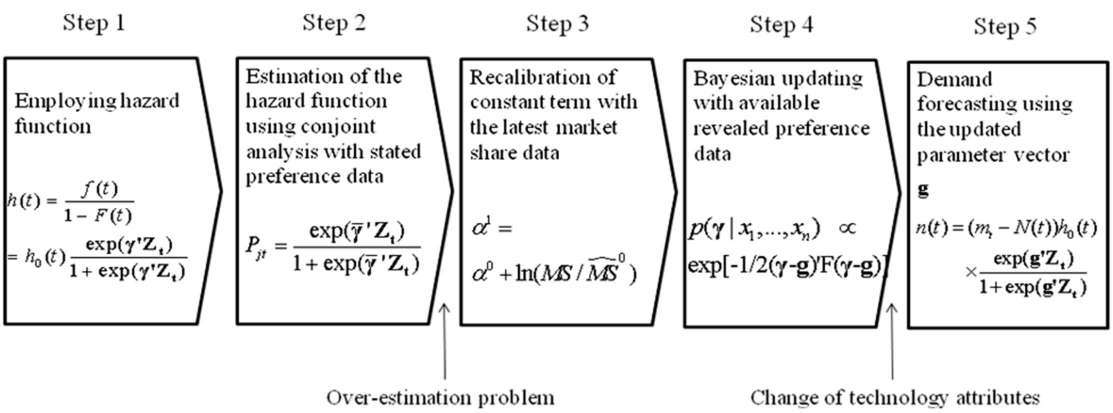

Figure 1. Flow chart of estimation steps.

3.1. Step 1

The proposed forecasting model is based on the hazard rate. The hazard rate $h(t)$ is defined as the probability that an event will take place at time t conditional on it not having taken place before t. Given the event of technology adoption, the hazard rate means the conditional probability that the consumer adopts a new technology in time t, as follows:

$$h(t) = \frac{f(t)}{1 - F(t)} \tag{1}$$

where $f(t)$ is the unconditional probability that the consumer will adopt the new technology at time t, and $1 - F(t)$ is the probability that the consumer will not adopt the new technology before t.

Recently, the proportional hazard model and the log-logistic hazard model have been widely used, according to the diffusion literature [25]. The proportional hazard model is decomposed into the alternative specific component and time component. Alternative to the proportional hazard model, the log-logistic hazard model allows the relative probabilities of adoption to change through time. This can be accomplished by allowing time-varying alternative characteristics to affect adoption probabilities [26]. Therefore, we employ the log-logistic hazard model with time-varying alternative characteristics as the basis of the forecasting model:

$$h(t) = \frac{f(t)}{1 - F(t)} = h_0(t)\frac{\exp(\gamma' Z_t)}{1 + \exp(\gamma' Z_t)} \tag{2}$$

where γ is a vector of coefficients. This study defines Z_t as a vector of new technology attributes at time t.

3.2. Step 2 and Step 3

In most applications, the hazard rate is estimated using time series data. However, it is difficult to estimate the hazard rate of a new technology when a limited number of data observations are available, and thus this study estimates the hazard rate parameters exogenously from survey data. For the estimation, this study employs conjoint analysis, a method which marketing researchers often apply to analyze consumer preferences regarding the attributes of a new technology [3].

The consumer utility function is derived using a random utility theorem with contingent ranking results. (Ranking data are suitable for ordinal preference and produce more information regarding consumers than choice-based data [7].) Although a rank-ordered logit model is generally used for estimating the utility function from a ranking survey [27], this study uses a mixed logit model, which captures preference variation by introducing a stochastic term into the coefficients. Afterward, the estimated distributions of coefficients are used as the prior distributions for Bayesian updating, and are then updated with available RP data using Bayes' theorem.

The utility U_{ijt} that the ith respondent would obtain by adopting the jth alternative at time t consists of the alternative-specific constant utility αT_{jt}, deterministic component $\beta' X_{jt}$, and stochastic part ε_{ijt} as follows:

$$U_{ijt} = \alpha T_{jt} + \beta' X_{jt} + \varepsilon_{ijt} \tag{3}$$

The alternative-specific constant term is added in the utility function to capture the average effect of the unobserved factors of each alternative [28]. $T_{jt} = 1$ if a respondent chooses the jth alternative, and otherwise, $T_{jt} = 0$. This study assumes that ε_{ijt} follows an independent and identical extreme value distribution and parameters α and β follow the normal distribution.

As the respondent ranks the alternatives as $j = 1, 2, 3, ..., J$ for a total of J alternatives, the probability with such a ranking is defined as follows:

$$\text{Prob}_i(U_{i1t} > U_{i2t} > ... > U_{iJt}|\alpha, \beta) = \prod_{j=1}^{J} \frac{\exp(\alpha T_{jt} + \beta' X_{jt})}{\sum_{k=j}^{J} \exp(\alpha T_{kt} + \beta' X_{kt})} \tag{4}$$

Denote the parameters $\begin{pmatrix} \alpha \\ \beta \end{pmatrix}$ and the variables $\begin{pmatrix} T \\ X_t \end{pmatrix}$ as parameter vector γ and variable vector Z_t, respectively. Like many cases of a mixed logit model, the distributions of γ can be specified as the normal distribution. The choice probability is formulated as:

$$L_i = \int (\prod_{j=1}^{J} \frac{\exp(\gamma' Z_{jt})}{\sum_{k=j}^{J} \exp(\gamma' Z_{kt})})\phi(\gamma|b, W)d\gamma \tag{5}$$

where $\phi(\gamma|b, W)$ is the normal density with mean b and covariance W. This study adopts the same procedure as Train [28] for the Bayesian estimation. (This study calculates the probability of the individual's sequence of rankings, which is used in the Metropolis-Hastings (MH) algorithm, instead of the probability based on the response of the most preferred choice in Train [28].)

To derive the choice probability for a new technology, this study sets the consumer's utility from the technology in time t as follows:

$$U_{it} = \gamma' Z_t + \varepsilon_{it} \tag{6}$$

In Equation (6), we assume that ε_{it} follows the independent and identical type I extreme value distribution, which leads to a logit form for the choice probability as follows:

$$P_{jt} = \frac{\exp(\gamma' Z_t)}{1 + \exp(\gamma' Z_t)} \tag{7}$$

In forecasting, the alternative-specific constant T should be adjusted because unobserved factors are different for the forecast area compared with the estimation sample [28]. Moreover, it is well known that the stated intentions of consumers can overstate the actual purchase behavior [5]. Thus, an iterative process is used to adjust the constant with a market share from the forecast area. Defining MS, $\overline{MS^0}$, and α^0, respectively, as the latest market share in the forecast area, the predicted market share, and the estimated mean of individual alternative-specific constants, an effective adjustment process is derived by:

$$\alpha^1 = \alpha^0 + \ln(MS/\overline{MS^0}) \tag{8}$$

where the superscript 0 indicates the starting value in the iterative process. The process is repeated until the forecasted market share is sufficiently close to the actual market share.

3.3. Step 4 and Step 5

The distributions of the attribute coefficients and the adjusted alternative-specific constant are employed as prior information. The prior distributions of parameters γ can be updated with an available RP data set $\{x_1, x_2, x_3, ..., x_n\}$ as follows:

$$p(\gamma|x_1, ..., x_n) = \frac{f(x_1|\gamma)...f(x_n|\gamma)g(\gamma)}{\int_\gamma f(x_1|\gamma)...f(x_n|\gamma)g(\gamma)d\gamma} \tag{9}$$

where $p(\cdot)$ is the posterior probability density function (pdf) for the parameter vector γ given the sample, $g(\gamma)$ is the prior pdf for the parameter vector γ, and $f(x_1|\gamma)...f(x_n|\gamma)$ is the likelihood function.

For demand forecasting, m_t, $n(t)$, and $N(t)$ are defined as the total market potential, the noncumulative number of adopters at time t, and the cumulative number of adopters before t, $n(t) = m_t f(t)$ and $N(t) = m_t F(t)$. Accordingly, the expected number of adopters at time t from Equation (2) is given by:

$$n(t) = (m_t - N(t))h_0(t)\frac{\exp(\gamma' Z_t)}{1+\exp(\gamma' Z_t)} \tag{10}$$

To apply the Bayesian update to the log-logistic hazard model, Equation (10) is transformed into linear form by adding an error term u_t that follows the normal distribution.

$$\ln\left(\frac{n(t)}{h_0(t)(m_t - N(t)) - n(t)}\right) = \gamma' Z_t + u_t \tag{11}$$

Given the prior normal distributions of parameter vectors by conjoint analysis and RP data sets, $Z_t(=\begin{pmatrix} T \\ X_t \end{pmatrix})$ and $Y_t(=\ln(\frac{n(t)}{h_0(t)(m_t - N(t)) - n(t)}))$, the posterior distribution of the parameters follows the multivariate normal distribution by Bayes' theorem as follows (See Zellner [29] for details on estimating the posterior pdf):

$$p(\gamma \big| Z_t, Y_t) \propto \exp\left[-1/2(\gamma - g)'\mathrm{F}(\gamma - \mathrm{g})\right] \tag{12}$$

where:

$$\begin{aligned}
&g = (C^{-1} + \overline{S}^{-1} Z_t' Z_t)^{-1} (C^{-1}\overline{\gamma} + \overline{S}^{-1} Z_t' Z_t \hat{\gamma}) \\
&F = C^{-1} + \overline{S}^{-1} Z_t' Z_t \\
&\hat{\gamma} = (Z_t' Z_t)^{-1} Z_t' Y_t \\
&\overline{S} = n^{-1}(Y_t - Z_t\hat{\gamma})'(Y_t - Z_t\hat{\gamma}) \\
&\overline{\gamma}: \text{ prior mean} \\
&C: \text{ prior covariance matrix}
\end{aligned}$$

This posterior pdf of parameter vector γ, which combines prior information with the available finite sample, serves as a basis for inferring the demand forecasts of the new technology. Therefore, it is possible to forecast the diffusion of a new technology using the hazard model of Equation (10) and the updated parameter vector g as follows:

$$n(t) = (m_t - N(t))h_0(t)\frac{\exp(g' Z_t)}{1+\exp(g' Z_t)} \tag{13}$$

where Equation (13) includes a dynamic structure that reflects the change of technology attributes over time t.

3.4. The Performance Measures

In most forecasting situations, accuracy is treated as the overriding criterion for selecting a forecasting method [30]. In this study, "goodness of fit" and "forecast accuracy" are measured. "Goodness of fit" refers to how well the forecasting model is able to reproduce the data that are already known, that is, the in-sample performance. On the other hand, "forecast accuracy" refers to the accuracy of the future forecast. In general, forecast accuracy is measured as the out-of-sample performance based on forecasting the data in the hold-out period using only information from the fitting period.

Even though many measures of "goodness of fit" and "forecasting accuracy" have been proposed, two measures are defined in this study, namely, the mean absolute percentage error (MAPE, hereafter) and the Bayesian information criterion (BIC, hereafter). As measure of "goodness of fit" and "forecasting accuracy," most textbooks recommend the MAPE [31,32] as the primary measure in the following manner:

$$\frac{\sum_{t=1}^{L} \frac{\left|N_t - \hat{N}_t\right|}{N_t}}{L} \times 100 \tag{14}$$

where $\hat{N}_t$ is estimated using actual data, N_t, for L observation periods. The MAPE measures the average forecast errors over lead times from one to L time.

The MAPE, however, may point us away from the best forecasting model, because different forecasting models have different numbers of parameters. In general, adding variables to a model improves the fit to the data [33]. The BIC penalizes the loss of degree of freedom that occurs when forecasting models have more parameters. The BIC places a premium on achieving a given fit with a smaller number of parameters per observation as follows:

$$\log\left(\frac{\sum_{t=1}^{L} (N_t - \hat{N}_t)^2}{L}\right) + \frac{K \log L}{L} \tag{15}$$

where K is the number of parameters.

3.5. The Benchmark Models

None of these performance measures provide a good basis of comparison as to the gains in accuracy obtained by a specific forecasting model. For making such a comparison, some existing methods against which the performance of the proposed methods can be compared should be defined. As the existing models, this study selects a Bayesian approach based on analogy, the Bass model, and the logistic model.

The Bass model reflects the innovation and imitation factors. The parameter p refers to the innovation factor that reflects the impact of activities such as advertising and promotion on adoption. Similarly, the parameter q refers to the imitation factor that captures the communication internal to the social system. The Bass model is as follows:

$$\frac{dN(t)}{dt} = [p + \frac{q}{m}N(t)][m - N(t)] \tag{16}$$

where $N(t)$ is the cumulative number of adopters at time t and m is the size of the potential adopters. On the other hand, the logistic growth model consists of parameters that refer to the first adoption and diffusion speed. The logistic growth model is as follows:

$$N(t) = \frac{m}{1 + \exp\{-(a + bt)\}} \tag{17}$$

where a and b are parameters. In estimating the Bass model and the logistic growth model with little market data, the number of potential adopters, m, is given by expert judgment due to the loss of the degree of freedom.

A Bayesian approach based on analogy (Analogy, hereafter) is the methodology used in previous Bayesian research for demand forecasting such as in studies by Lilien et al. [34] and Talukdar et al. [22]. To estimate Analogy, a two-step approach is suggested. The first step is to forecast the sales of the new technology prior to entry, with the forecasts based on previously introduced technologies. The second step is to update these forecasts once sales data are available using Bayesian regression. Given that the logistic growth model is employed, the parameters a and b of the logistic growth model are initially estimated using the historical time-series data of similar technologies, and then the estimated parameters will be updated if the sales data of the new technology are available.

4. Empirical Results

4.1. Survey Data

A survey of 500 respondents was conducted in 2005 in South Korea. The 500 respondents consisted of people living in metropolitan (Seoul, 186 respondents), urban (Daejeon, 232 respondents), and rural (the countryside, 82 respondents) regions. The interview method used was the face-to-face interview to guarantee the reliability of the conjoint survey. This study created a set of attributes and levels to use in composing the alternative cards describing the various types of broadband Internet service in accordance with a conjoint survey. The monthly price, technology type, additional service, instability, and transmission speed were chosen as the main attributes to use in the survey. Table 1 presents the attributes of broadband Internet service and their levels.

Table 1. Attributes and attribute levels used in the case of the broadband Internet service market.

Attributes	Level
Price (U.S. dollars/month)	20, 40, 60
Access Technology	xDSL, Satellite, Cable, wireless LAN, Powerline communication
Additional Service	AMR, TV service, VoIP, None
Breaking times for an hour (times per hour)	0, 2, 4
Transmission speed (Mbps)	1, 5, 15, 30

The technology type includes xDSL, satellite, cable, wireless LAN, and power line communication. Of course, each technology type is characterized not only by type, price, and instability, but also by attributes such as power efficiency, wire or wireless, existence of extra devices, and so forth. However, including all these attributes in the analysis exponentially increases the number of conjoint cards, so we have designed the technology type attribute as a sort of aggregate that includes characteristics other than price, additional service, instability, and transmission speed. To ensure that respondents realize the aggregate nature of the variable, we trained the interviewers so that they understood which attributes the aggregate includes and could explain it to respondents in detail.

The monthly price level ranged from US$20 to US$60, roughly corresponding to market prices from 1999 to 2005. The additional services include AMR, TV service, VoIP, and None, which are bundling services provided by service providers with broadband Internet service. The instability attribute is measured by breaking times for an hour, roughly corresponding to the technology level in 2006. Finally, the transmission speed contains four values ranging from 1 Mbps to 30 Mbps.

The values for the five attributes yield many permutations of hypothetical alternatives. However, this study used fractional factorial design to reduce the number of alternatives and finally arrived at 25 alternative cards. The 25 alternative cards are divided into five sub-alternative card sets consisting of five cards each. This subset of combinations, called an orthogonal array, enables the valid estimation of the importance of attributes without burdening the respondents with the task of evaluating all possible combinations.

4.2. Revealed Preference Data

The study uses quarterly data for three types of broadband Internet services in South Korea. Although many types of broadband Internet service exist in the South Korean market, this study considers the two alternatives that dominate the market, xDSL and cable, plus a total Internet service that is defined by aggregating the number of subscribers of xDSL, cable, wireless LAN, and satellite.

The observation period used for the model's estimate stretches from the fourth quarter of 1999 to the second quarter of 2005. The subscriber data for each service alternative and total Internet service are reported by South Korea's Ministry of Information and Communication [35]. Figure 2 shows the actual number of subscribers in South Korea's broadband Internet service market.

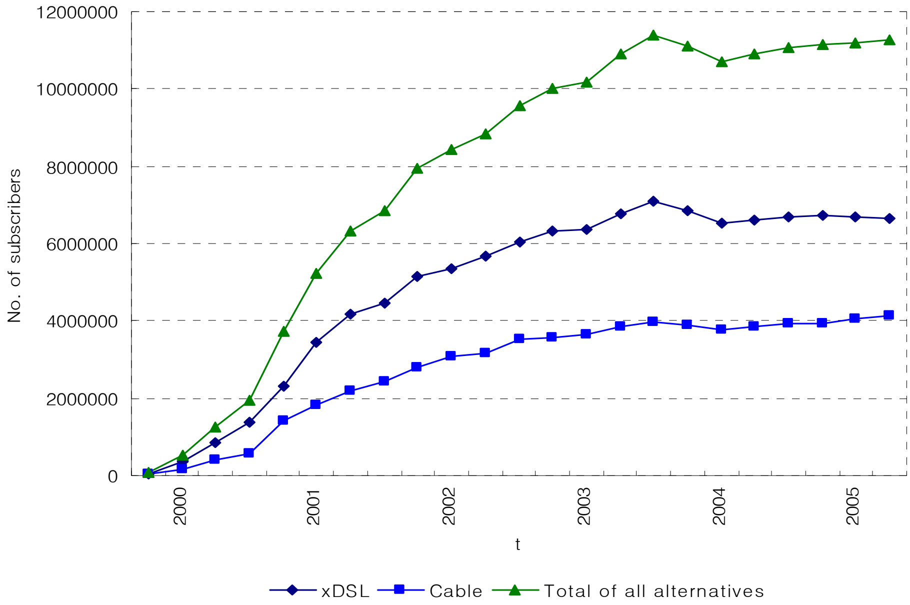

Figure 2. The diffusion of broadband Internet services.

To estimate Analogy as a benchmark model, the telephone subscribers and cable television subscribers of OECD members, which consist of 30 countries, were collected. The collected observation period stretches from the first quarter of 1975 to the fourth quarter of 1998 for the telephone subscribers. For the cable television subscribers, however, the observation period depends on the introduction time of each country's cable television service. The subscriber data for the telephone and cable television are reported by International Telecommunication Union (ITU)'s World Telecommunication Indicators. The telephone subscribers and the cable television subscribers are used for the prior information of xDSL and cable Internet service, respectively.

4.3. Estimation Results

For conjoint analysis, the variables for the attributes of Internet service include the monthly price (PRICE), technology type (XDSL, SATELLITE, CABLE, WLAN, and PLC), breaking times for an hour (INSTABILITY), and transmission speed (SPEED). Throughout the mixed logit estimation procedure, the estimated means and standard deviations of the coefficients of the consumer utility function are shown in the upper part (Prior) of Table 2. These means and standard deviations are prior information, which will be updated using Bayes' theorem with available subscriber data. All estimates except those of INSTABILITY and PRICE are significant with a significance level of 5%. As expected, the signs of all estimated means except those of PRICE and INSTABILITY are positive, which means that the consumer utility increases for a low price, high stability, and high speed.

To recalibrate the alternative-specific constant, the iterative process is operated with the penetration rate data of each service in 1999Q4. This process adjusts the overestimation derived from consumers' overstated intention. The adjusted alternative-specific constant is reported in Table 2.

The number of potential subscribers of each service is given by the saturated point of its service diffusion to update the parameters of the forecasting model. If the subscriber data, level of service attributes, and market potential are known, the parameters of the hazard model can be updated using Bayes' theorem. To simplify the model, this study assumes that the baseline hazard function $h_0(t)$ remains constant over time, as estimated by Hannan and McDowell [26]: $h_0(t) = 1$. The three estimates of each parameter relate to an estimation region that increases in steps of four quarters from 1999Q4 to 2002Q3. The bottom part of Table 2 depicts the estimated mean and deviation for the posterior distributions of the coefficients. As a result of Model 1, the estimated standard deviations of the posterior distributions are less than those of the prior distributions. This phenomenon again shows that Bayesian updating reduces the uncertainty of future diffusion.

Table 2. Estimated prior and posterior distributions of the diffusion parameters (broadband Internet service).

	Variable	xDSL		Cable		Total of All Alternatives	
		Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Prior	Alternative-specific constant (ASC)	0.0044 [−3.2350] †	0.0028	0.0001 [−3.1258]	0.0001	−0.0088 [−2.5000]	0.0484
	PRICE	−0.0020	0.0001	−0.0020	0.0001	−0.0020	0.0001
	INSTABILITY	−0.0169	0.0504	−0.0169	0.0504	−0.0169	0.0504
	SPEED	0.0077	0.0042	0.0077	0.0042	0.0077	0.0042
Poste-rior	ASC (4) * ASC (8) ASC (12)	−7.5680 −10.2512 −10.3513	3.52×10^{-28} 5.83×10^{-30} 2.22×10^{-31}	−8.5254 −9.5000 −12.6000	3.51×10^{-31} 4.63×10^{-32} 2.58×10^{-32}	−10.2548 −10.8541 −11.5740	0.0152 0.0069 3.51×10^{-31}
	PRICE (4) PRICE (8) PRICE (12)	−0.4682 −0.0024 −0.0008	9.98×10^{-5} 5.25×10^{-22} 6.41×10^{-32}	−0.4775 −0.0009 −0.0010	9.99×10^{-5} 9.98×10^{-5} 5.67×10^{-32}	−0.4938 −0.0001 −0.0007	9.98×10^{-5} 9.98×10^{-5} 5.67×10^{-32}
	INSTABILITY (4) INSTABILITY (8) INSTABILITY (12)	0.3926 0.199 0.1667	0.0207 0.0195 3.69×10^{-32}	0.2852 0.1585 0.2403	0.0286 0.0197 3.25×10^{-32}	0.3689 0.1974 0.2129	0.0203 0.0197 3.25×10^{-32}
	SPEED (4) SPEED (8) SPEED (12)	0.0679 0.0502 0.0617	0.003 0.0025 4.76×10^{-32}	0.1006 0.04 0.0575	0.0038 0.0029 6.42×10^{-32}	0.074 0.01 0.0027	0.0035 0.0029 6.42×10^{-32}

*: The number in a parenthesis indicates quarterly data used for Bayesian update; †: The number in a bracket indicates the alternative-specific constant adjusted by recalibration.

4.4. Goodness of Fit and Forecasting Accuracy

In this section, using the first four (or eight or twelve) quarters of data, the parameters of each model are estimated. In estimating the proposed model, the market potential for each service is given. To measure the goodness of fit, the values of the MAPE and BIC are computed for the calibration periods.

To help set the stage for the fitting results that follow, this study examines the absolute performance of each model within the three calibration periods (four, eight, and 12 quarters). Table 3 includes a summary of the results for the model fitting of the four forecasting models applied to three services (xDSL, cable, total of all alternatives). In terms of the MAPE value, the proposed model fits quite well in terms of calibration, and in general, the Bass model and the logistic model produce bigger MAPE values than those of the proposed model.

In the right-hand column of Table 3, however, the logistic model produces the lowest BIC over the fitting region. This phenomenon indicates that the logistic model has a small squared error in the later region of the observation period relative to the proposed model. This comes from the fact that the actual value and the estimated value in the later region of diffusion are bigger than those in the early region. For example, the 5 percent of the MAPE in the early region of diffusion is different from the 5 percent of the MAPE in the later region of diffusion. The 5 percent of the MAPE in the later region of diffusion means that there is a great deal more BIC than that in the early region. This result shows that the proposed model has a better fitting performance in the early region of the observation period.

The additional data set used to estimate the models does not improve the goodness of fit. Given that the MAPE and BIC values are similar across the observation periods, this study represents that the calibration periods should not be related to the fitting performance.

Table 3. Goodness-of-fit measures for broadband Internet service.

(a) xDSL						
Quarterly Data Used for Estimation	**Fitted MAPE**			**Fitted BIC**		
	4	**8**	**12**	**4**	**8**	**12**
The proposed model	**32.78**	**42.44**	**21.58**	11.60	**10.57**	11.63
Bass model	80.19	82.76	62.58	10.72	11.38	11.31
Logistic model	60.79	72.34	72.13	**10.31**	11.05	**11.14**
Analogy	66.33	65.29	58.22	11.35	11.86	11.50
(b) Cable						
Quarterly Data Used for Estimation	**Fitted MAPE**			**Fitted BIC**		
	4	**8**	**12**	**4**	**8**	**12**
The proposed model	**17.71**	47.66	**27.91**	10.66	11.55	11.17
Bass model	59.34	104.30	73.49	9.95	11.20	11.06
Logistic model	46.53	75.74	80.73	**9.85**	**10.87**	**10.91**
Analogy	25.92	**27.46**	35.71	10.03	11.05	11.17
(c) Total internet service						
Quarterly Data Used for Estimation	**Fitted MAPE**			**Fitted BIC**		
	4	**8**	**12**	**4**	**8**	**12**
The proposed model	**29.90**	39.08	**37.98**	11.85	12.33	12.12
Bass model	71.27	88.96	67.74	11.00	11.86	11.77
Logistic model	54.99	77.92	85.69	**10.71**	**11.59**	**11.74**
Analogy	30.72	**33.99**	42.47	11.07	11.84	12.03

The best MAPE or BIC is shown in bold.

Table 4 shows the fit comparison of the out-of-sample forecasts with the benchmark models using the same market data. The MAPE numbers and BIC numbers for each alternative technology over the period of the hold-out sample are calculated to measure the forecasting accuracy of the proposed model and benchmark models. For the forecasts using the first four quarters, for instance, this study forecasts quarter 5 through 23 for each service, and reports the MAPE value in Table 4. Therefore, calibration period 4 (8 or 12) means nineteen-step-ahead (fifteen-step-ahead or eleven-step-ahead) forecasts because the total observation period is 23 quarters.

The results show that the proposed model clearly outperforms the benchmark models such as the Bass model, logistic growth model, and Analogy. The proposed model gives the lowest MAPE value for five out of a total of nine MAPE tests for the forecasting performance. The remaining two best forecasting performances are attained by Analogy. On the other hand, in terms of BIC, the proposed model has the four best forecasting performances. Thus, this study concludes that the proposed model is suitable for demand forecasting with a short history. For policy makers in the industry and public sectors, the proposed model may be the most attractive because accurate forecasts before or shortly after the launch of an innovation are most important to them.

Among the benchmark models, the Bass model also reports the lowest BIC value in three BIC tests. Although the logistic model exhibits a good performance in terms of the goodness of fit of the model, the Bass model outperforms the logistic growth model in terms of the forecasting performance. Generally, the Analogy forecasts are worse than those of the proposed models.

Table 4. The forecasting accuracy of the forecasting models for broadband Internet service.

(a) xDSL						
Quarterly Data Used for Estimation	Forecast MAPE			Forecast BIC		
	4	8	12	4	8	12
The proposed model	**11.97**	**3.56**	2.21	12.05	**11.18**	10.97
Bass model	15.96	6.51	1.90	12.04	11.81	**10.71**
Logistic model	16.26	6.54	**1.87**	**11.69**	11.92	10.90
Analogy	27.09	5.44	2.78	12.52	11.39	11.03
(b) Cable						
Quarterly Data Used for Estimation	Forecast MAPE			Forecast BIC		
	4	8	12	4	8	12
The proposed model	21.20	**7.10**	**2.49**	12.03	**11.35**	**10.45**
Bass model	18.06	12.61	4.42	11.81	11.56	10.91
Logistic model	19.84	12.85	4.68	11.86	11.65	10.95
Analogy	**16.60**	10.43	5.50	**11.69**	11.40	10.93
(c) Total of All Alternative Internet Services						
Quarterly Data Used for Estimation	Forecast MAPE			Forecast BIC		
	4	8	12	4	8	12
The proposed model	17.17	**4.02**	2.90	12.79	**11.67**	11.54
Bass model	17.84	4.65	2.75	**11.96**	11.92	**11.24**
Logistic model	19.55	5.60	3.22	12.75	12.09	11.68
Analogy	**17.14**	7.72	**2.46**	12.61	12.13	11.25

The best MAPE or BIC is shown in bold.

The forecasting results of the proposed model can be founded in Figures 3–5.

A number of important patterns emerge from these figures. This study first discusses the improvement of the forecasting performance as the data used for the estimation increases, as would be expected. In the case using 12 quarterly data to estimate the models, the updated forecasts are very close to the actual quarterly data. Especially, the forecasting results clearly show this phenomenon in all three applications. This result supports the usefulness of Bayesian updating with available market data. It is expected that more data for parameter updating may lead to a more accurate forecasting performance. This pattern is not significantly different according to the three applications.

Most likely, the proposed model over-predicts the actual number of subscribers in the case using a small number of data for Bayesian updating. Especially, the proposed model looks as if it shows the best improvement as the number of observation periods used for the estimation increase.

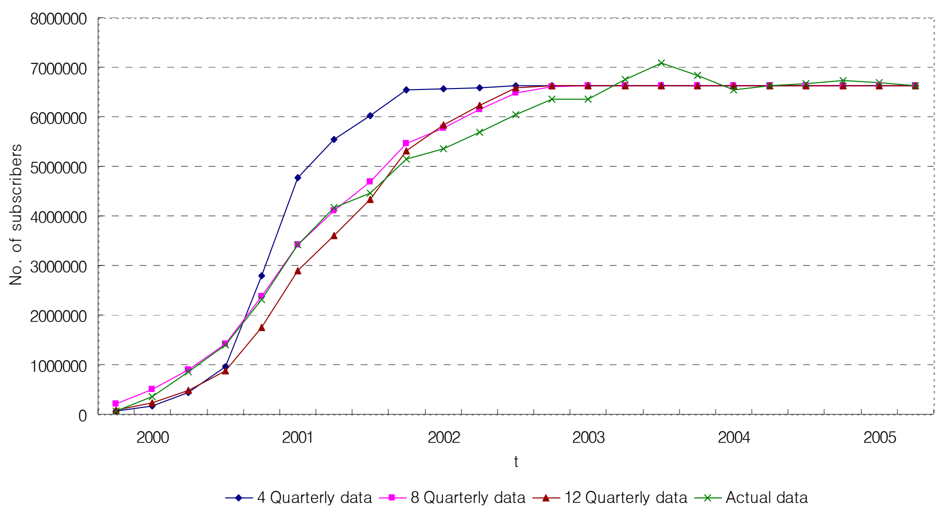

Figure 3. Cumulative subscribers for the xDSL service in South Korea (Observed, fitted, and predicted values with horizons of 4, 8, or 12 quarters).

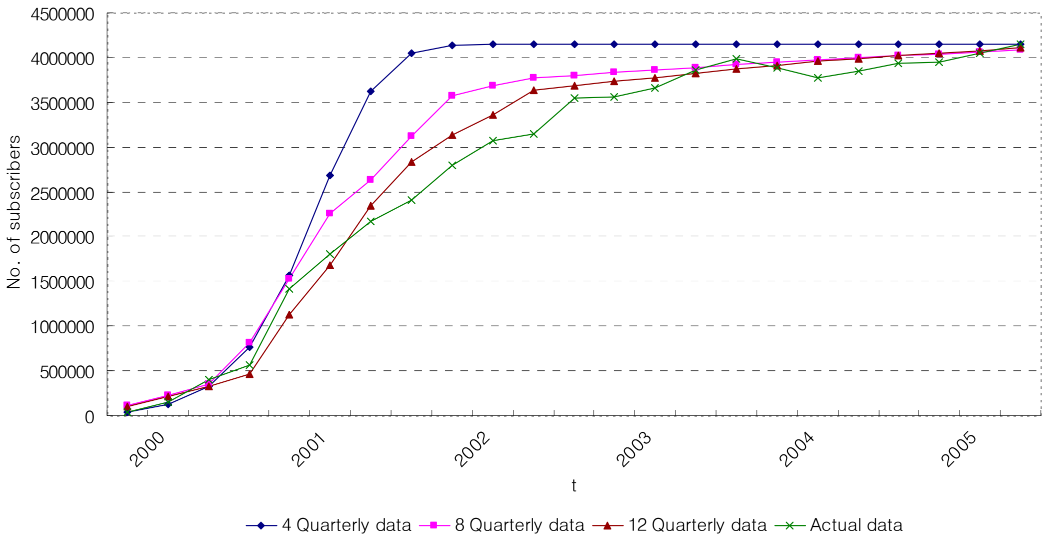

Figure 4. Cumulative subscribers for cable service in South Korea (Observed, fitted, and predicted values with horizons of 4, 8, or 12 quarters).

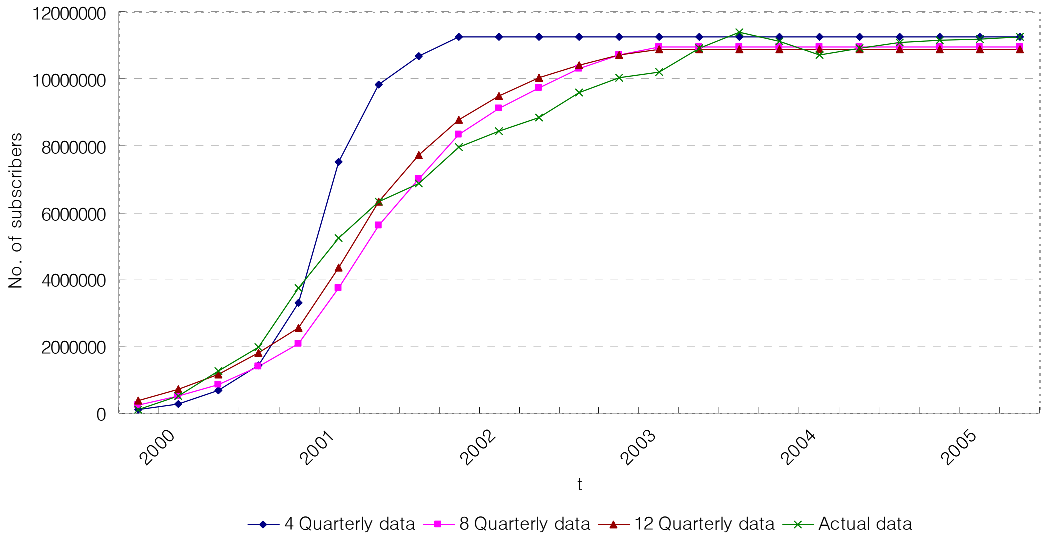

Figure 5. Cumulative subscribers for the total of all Internet services in South Korea (Observed, fitted, and predicted values with horizons of 4, 8, or 12 quarters).

5. Conclusions

New technologies change fast and grow rapidly, and as a result, they are frequently introduced in the market. However, the risk of a market failure increases for newly introduced innovations. One way of controlling these risks is the use of sound explicit models for planning and forecasting new technology. In such environments, Bass-type models, which depend on historical sales data or adopter data, are limited in their ability to forecast the demand for a technology with a short history. This study proposes an alternative forecasting method based on conjoint analysis and Bayes' theorem to forecast the demand for new technologies for which limited market data are available. The method is illustrated using stated preference data gathered from a consumer survey as well as revealed preference data, the latter of which are used to update the hazard rate parameters using Bayes' theorem. We apply the proposed model to the broadband internet service in South Korea, which is saturated and suitable for the forecasting test. The results demonstrate that the combination of a stated preference and revealed preference approach contributes to improving the model's fit.

Many researchers have pointed out that a big difference between forecasts from stated preference data and actual data exists. Therefore, enough revealed preference data are essential for more robust parameter estimates for demand forecasting, which increase the confidence in predictions. Especially, the iterative process for the recalibration of the alternative-specific constant should be used before Bayesian updating with the available data because consumers' stated intentions can overestimate the actual purchase behavior. Using the same calibration period for revealed-preference data, the proposed model outperforms benchmark models.

In actuality, however, a high cost is needed for an analysis of the proposed model because it depends on consumer survey data. On the other hand, a market simulation can be conducted by introducing hypothetical changes in the attribute levels of innovation. Throughout the market simulation, we can observe the changes in the competitive structure of the market and capture the relative importance of factors that affect technology diffusion. The implications of the market simulation may prove important for R&D strategies, industry policymaking, and the management strategies of decision makers. We believe this study provides a basis for practitioners designing a market strategy and academics developing a forecasting model. As the forecasting performance of the proposed model has been proven in this study, future studies will be able to apply the proposed model to a number of technologies and products in other countries. Further researches exploring forecasting with respect to several different technology categories would help determine how well the results presented here can be generalized for other data sets.

Author Contributions: Chul-Yong Lee designed the study, outlined the methodology, developed the model, and estimated the parameters of the model. Min-Kyu Lee reviewed the related literature, interpreted the results, and revised the manuscript. All authors have read and approved the final manuscript.

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References

1. Bass, F.M. A new product growth for model consumer durables. *Manag. Sci.* **1969**, *15*, 215–227. [CrossRef]
2. Jun, D.B.; Kim, S.K.; Park, M.H.; Bae, M.S.; Park, Y.S.; Joo, Y.J. Forecasting demand for low earth orbit mobile satellite service in Korea. *Telecommun. Syst.* **2000**, *14*, 311–319. [CrossRef]
3. Lee, J.; Cho, Y.; Lee, J.D.; Lee, C.Y. Forecasting the evolution of demand for the large sized television of next generation using conjoint and diffusion models. *Technol. Forecast. Soc.* **2006**, *73*, 362–376. [CrossRef]
4. Kim, W.J.; Lee, J.D.; Kim, T.Y. Demand forecasting for multigenerational product combining discrete choice and dynamics of diffusion under technological trajectories. *Technol. Forecast. Soc.* **2005**, *72*, 825–849. [CrossRef]
5. Islam, T. Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy* **2014**, *65*, 340–350. [CrossRef]
6. Bass, F.M.; Gordon, K.; Ferguson, T.L.; Githens, M.L. DIRECTV: Forecasting diffusion of a new technology prior to product launch. *Interfaces* **2001**, *31*, S82–S93. [CrossRef]
7. Morwitz, V. Why consumers don't always accurately predict their own future behavior. *Market. Lett.* **1997**, *8*, 57–70. [CrossRef]
8. Louviere, J.J.; Hensher, D.A. *Stated Choice Methods: Analysis and Application*; Cambridge University Press: Cambridge, UK, 2001.
9. Olson, J.; Choi, S. A product diffusion model incorporating repeat purchases. *Technol. Forecast. Soc.* **1985**, *27*, 385–397. [CrossRef]
10. Bayus, B.L.; Hong, S.; Labe, R.P., Jr. Developing and using forecasting models of consumer durables. *J. Prod. Innov. Manag.* **1989**, *6*, 5–19. [CrossRef]
11. Hahn, M.H.; Park, S.; Krishnamurthi, L.; Zoltners, A.A. Analysis of new product diffusion using a four-segment trial-repeat model. *Market. Sci.* **1994**, *13*, 224–247. [CrossRef]
12. Danaher, P.J.; Hardie, B.G.S.; Putsis, W.P. Marketing-mix variables and the diffusion of successive generations of a technological innovation. *J. Market. Res.* **2001**, *38*, 501–514. [CrossRef]
13. Jain, D.; Mahajan, V.; Muller, E. Innovation diffusion in the presence of supply restrictions. *Market. Sci.* **1991**, *10*, 83–90. [CrossRef]

14. Krishnan, T.K.; Bass, F.M.; Kumar, V. Impact of a late entrant on the diffusion of a new product/service. *J. Market. Res.* **2000**, *37*, 269–278. [CrossRef]
15. Heeler, R.M.; Hustad, T.P. Problems in predicting new product growth for consumer durables. *Manag. Sci.* **1980**, *26*, 1007–1020. [CrossRef]
16. Srinivasan, V.; Mason, C.H. Nonlinear least squares estimation of new-product diffusion models. *Market. Sci.* **1986**, *5*, 169–178. [CrossRef]
17. Mahajan, V.; Muller, E.; Wind, Y. *New-Product Diffusion Models*; Kluwer Academic Publishers: Norwell, MA, USA, 2000.
18. Morrison, D.G. Purchase intentions and purchase behavior. *J. Market.* **1979**, *43*, 65–74. [CrossRef]
19. Jamieson, L.F.; Bass, F.M. Adjusting stated intentions measures to predict trial purchases of new products: A comparison of models and methods. *J. Market. Res.* **1989**, *26*, 336–345. [CrossRef]
20. Hsiao, C.; Sun, B.; Morwitz, V.G. The role of stated intentions in new product purchase forecasting. *Adv. Econ.* **2002**, *16*, 11–28.
21. Evans, M.K. *Practical Business Forecasting*; Blackwell Publishers: Oxford, UK, 2003.
22. Putsis, W.P., Jr.; Srinivasan, V. Estimation Techniques for Macro Diffusion Models. In *New Product Diffusion Models*; Mahajan, V., Muller, E., Wind, Y., Eds.; Kluwer Academic Publishers: Boston, MA, USA, 2000.
23. Talukdar, D.; Sudhir, K.; Ainslie, A. Investigating new product diffusion across products and countries. *Market. Sci.* **2002**, *21*, 97–114. [CrossRef]
24. Neelamegham, R.; Chintagunta, P. A Bayesian model to forecast new product performance in domestic and international markets. *Market. Sci.* **1999**, *18*, 115–136. [CrossRef]
25. Rose, N.L.; Joskow, P.L. The diffusion of new technologies: Evidence from the electric utility industry. *RAND J. Econ.* **1990**, *21*, 354–373. [CrossRef]
26. Hannan, T.H.; McDowell, J.M. Rival precedence and the dynamics of technology adoption: An empirical analysis. *Economica* **1987**, *54*, 155–171. [CrossRef]
27. Calfee, J.; Winston, C.; Stempski, R. Econometric issues in estimating consumer preferences from stated preference data: A case study of the value of automobile travel time. *Rev. Econ. Stat.* **2001**, *83*, 699–707. [CrossRef]
28. Train, K. *Discrete Choice Method with Simulation*; Cambridge University Press: Cambridge, UK, 2003.
29. Zellner, A. *An Introduction to Bayesian Inference in Econometrics*; Wiley and Sons: New York, NY, USA, 1971.
30. Makridakis, S.; Wheelwright, S.C.; Hyndman, R.J. *Forecasting: Methods and Applications*; John Wiley & Sons: Chichester, UK, 1998.
31. Hanke, J.E.; Reitsch, A.G. *Business Forecasting*, 5th ed.; Prentice-Hall: Englewood Cliffs, NJ, USA, 1995.
32. Bowerman, B.L.; O'Connell, R.T.; Koehler, A.B. *Forecasting Time Series and Regression: An Applied Approach*; Thomson Books/Cole: Belmont, CA, USA, 2004.
33. Greene, W.H. *Econometric Analysis*, 5th ed.; Prentice-Hall: Upper Saddle River, NJ, USA, 2003.
34. Lilien, G.L.; Rao, A.G.; Kalish, S. Bayesian estimation and control of detailing effort in a repeat-purchase diffusion environment. *Manag. Sci.* **1981**, *27*, 493–506. [CrossRef]
35. Ministry of Information and Communication. *IT Statistical Data*; Ministry of Information and Communication: Seoul, Korea, 2006.