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

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TEMEP Discussion Paper No. 2009:03

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

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April 15, 2009

Abstract

Forecasting demand for new technology for which few historical data observations are available is difficult but essential to successful marketing. The current study suggests an alternative forecasting methodology based on a hazard rate model using stated and revealed preferences. In estimating the hazard rate, information is derived initially through conjoint analysis based on a consumer survey and then updated using Bayes' theorem with available market data. Based on the results of the empirical analysis, the model described here can significantly improve demand forecasting for newly introduced technologies.

Keywords: demand forecasting, conjoint analysis, Bayesian update, telematics service

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1. Introduction

Forecasting demand for new technologies is essential to succeeding in the marketplace. It provides important information for decision making regarding such things as optimal time to market, pricing, and investment. Among the many forecasting models, Bass type models are used widely to analyze demand and diffusion in such fields as industrial engineering, policymaking, and marketing. Yet such models depend on historical time series data, which limits their usefulness for forecasting demand for newly introduced technology.

A second forecasting methodology, discrete choice forecasting (choice-based diffusion models) has been used to forecast demand for technologies for which there is limited historical data, such as low-earth-orbit mobile satellite service (Jun et al., 2000), next-generation large-screen television (Lee et al., 2006), and dynamic random access memory (Kim et al., 2005). With this methodology, future choice probabilities regarding newly introduced technology can be estimated using the stated preference (SP, hereafter) approach. However, such studies as Bass et al. (2001) and Morwitz (1997) showed that there exists difference between forecasts by SP data and 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 by RP data (Louviere and Hensher, 2001). A key role for RP data in combined SP-RP analyses lies in providing more robust parameter estimates for demand forecasting of newly introduced technology, which increase confidence in predictions.

In this paper we introduce an alternative method of forecasting new technology demand that uses RP data as well as SP data. This method employs a hazard function, conjoint analysis, and Bayesian update. We arrive at 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.

To illustrate, we apply the proposed model to South Korea's telematics service[2] market, a market that was launched in 2002[3]. Telematics service was first launched with simple services such as location search in the automobile industry. These days coupling with fast development of information and communications technology, telematics service providers are now enlarging their business by presenting new services in areas

[2] Telematics is an amalgamation of the words "telecommunication" and "informatics." In the automobile industry, telematics refers to the provision of two-way voice and data communication between the vehicle and information service providers. (Nam et al., 2005)

[3] SK Telecom, one of the biggest mobile carriers in South Korea, was the first to launch the telematics service.

such as traffic information, emergency response, roadside assistance, and entertainment (Nam et al., 2005).

2. The Model

The proposed method involves five steps:

1. Employ the hazard function (a function that is widely used in diffusion research).
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 shows the estimation steps in flow chart.

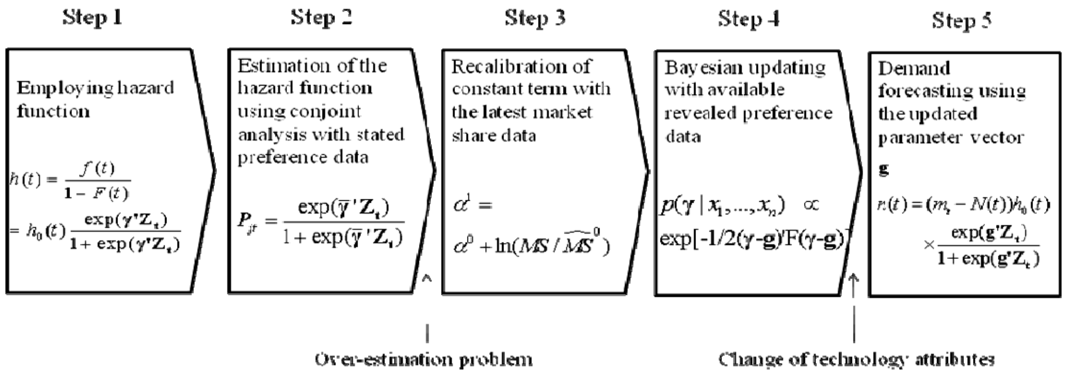


Figure 1. Flow chart of estimation steps

2.1. Hazard Rate Model

The proposed forecasting model is based on failure time, or hazard rate, specifications. The hazard rate $h(t)$ is defined as the probability an event will take place at time t conditional on its not having taken place before t. This study looks specifically at the event of technology adoption. The hazard rate is expressed in terms of 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 (survivor function).

In literatures on innovation diffusion, for reasons such as convenience, a desire to retain analytical parsimony, and facilitation of interpretation and parameter estimation, hazard rate, $h(t)$, has been typically formulated as $h(t)=a$ (external-influence diffusion model), $h(t)=bF(t)$ (internal –influence diffusion model), or $h(t)=(a+bF(t))$ (mixed-influence diffusion model) where a and b are treated as model coefficients or parameters (Mahajan and Peterson, 1985). Each of these versions results in a diffusion curve the parameters of which possess both theoretical and practical interpretations and implications (Mahajan and Peterson, 1985).

Recently the proportional hazard model and the log-logistic hazard model are widely used, according to the diffusion literature (Rose and Joskow, 1990). The proportional hazard model is decomposed into alternative specific component and time component. It is written as $h(t)=h_o(t)\exp(\mathbf{X\beta})$, where $h_o(t)$ is the baseline hazard function which specifies the evolution of the hazard rate over time and $\mathbf{X}$ are fixed alternative characteristics.

Alternative to the proportional hazard model, 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 (Hannan and McDowell, 1984). Therefore we have employed the log-logistic hazard model with time-varying alternative characteristics as the basis of the forecasting model:

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

where $\boldsymbol{\gamma}$ is a vector of coefficients. this study defines $\mathbf{Z_t}$ as a vector of new technology attributes at time t. The hazard rate will monotonically increase, decrease, or remain constant as $\boldsymbol{\gamma}'\mathbf{Z_t}$ is greater than, less than, or equal to zero, respectively.

Defining m_t, $n(t)$, and $N(t)$ respectively 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 $N(t)=m_t F(t)$. Therefore, the expected number of adopters at time t from Eq. (2) is given by

$$n(t) = (m_t - N(t))h_0(t)\frac{\exp(\boldsymbol{\gamma}'\mathbf{Z_t})}{1+\exp(\boldsymbol{\gamma}'\mathbf{Z_t})} \tag{3}$$

2.2. Modeling Consumer Utility

In most applications the hazard rate is estimated using time series data from the subject. Yet it is difficult to estimate the hazard rate of a new technology when only a limited number of data observations is available, and thus this study estimates the hazard rate parameters exogenously from static survey data. For the estimation, this study employs conjoint analysis, a method marketing researchers often use to analyze consumer preferences regarding attributes of a new technology (Lee et al., 2006).

The consumer utility function is derived using a random utility theorem with contingent ranking results[4] from the survey responses. Although it is standard practice to use a rank-ordered logit model to estimate the utility function from a ranking survey (Calfee et al., 2001), 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 then updated with available early-stage RP data using Bayes' theorem.

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

$$U_{ijt} = \alpha T_{jt} + \boldsymbol{\beta}'\mathbf{X_{jt}} + \varepsilon_{ijt} \tag{4}$$

The alternative-specific constant term is added in the utility function to capture the average effect of unobserved factors of each alternative (Train, 2003). $T_{jt} = 1$ if a

[4] Ranking data are suitable for ordinal preference and produce more information about consumers than choice-based data (Louviere and Hensher, 2001).

respondent chooses the j th alternative and $T_{jt} = 0$ if otherwise. This study assumes that stochastic utility ε_{ijt} follows an independent and identical extreme value distribution and that parameters α and $\boldsymbol{\beta}$ are distributed normally across the population with a mean vector and a variance-covariance vector.

As the i th respondent ranks the alternatives as $j = 1, 2, 3, 4, ..., J$ for a total of J alternatives at time t, the probability with such ranking is defined as follows:

$$Prob_i(U_{i1t} > U_{i2t} > ... > U_{iJt} \mid \alpha, \boldsymbol{\beta}) = \prod_{j=1}^{J} \frac{e^{\alpha T_{jt} + \boldsymbol{\beta}' \mathbf{X}_{jt}}}{\sum_{k=j}^{J} e^{\alpha T_{jt} + \boldsymbol{\beta}' \mathbf{X}_{jt}}} \tag{5}$$

Denote the parameters $\begin{pmatrix} \alpha \\ \boldsymbol{\beta} \end{pmatrix}$ and the variables $\begin{pmatrix} T \\ \mathbf{X_t} \end{pmatrix}$ as parameter vector $\boldsymbol{\gamma}$ and variable vector $\mathbf{Z_t}$, respectively. In most applications that have actually been called mixed logit, the distributions of $\boldsymbol{\gamma}$ can be specified to be normal with mean *b* and covariance *W*. The choice probability under this density becomes

$$L_i = \int (\prod_{j=1}^{J} \frac{e^{\boldsymbol{\gamma}' \mathbf{Z_{jt}}}}{\sum_{k=j}^{J} e^{\boldsymbol{\gamma}' \mathbf{Z_{jt}}}}) \phi(\gamma \mid b, W) d\gamma \tag{6}$$

where $\phi(\gamma \mid b, W)$ is the normal density with mean *b* and covariance *W* which are parameters to be estimated. This study adopts the same procedure as in Train (2003) for Bayesian estimation of parameters. The only change is that this study should calculate the probability of the individual's sequence of rankings, which is used in Metropolis-Hastings (MH) algorithm, instead of the probability based on response of most preferred choice in Train (2003). The specific estimation procedure is described in Train (2003, pp. 302-306).

2.3. Bayesian Updating with Available Sales Data

To derive the choice probability for a new technology, this study considers only one alternative i.e. one technology. Thus, the consumer's utility from the technology in time

t as follows:

$$U_{it} = \boldsymbol{\gamma}'\mathbf{Z}_{\mathbf{t}} + \varepsilon_{it} \tag{7}$$

In Eq. (2.10), we assumes that ε_{it} follows the independent and identical type I extreme value distribution. This assumption leads to a simple binomial logit form for the choice probability as follows:

$$P_{jt} = \frac{\exp(\boldsymbol{\gamma}'\mathbf{Z}_{\mathbf{t}})}{1+\exp(\boldsymbol{\gamma}'\mathbf{Z}_{\mathbf{t}})} \tag{8}$$

Note that the choice probability has the same form as the log-logistic hazard rate of Eq. (2).

In forecasting, it is useful to adjust the alternative-specific constant T to reflect the fact that unobserved factors are different for the forecast area or year compared with the estimation sample (Train, 2003). Moreover, it is well known that the stated intentions of consumers overstate actual purchase behavior (Bass et al., 2001). An iterative process is used to adjust the constant with market share data 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 is derived by

$$\alpha^1 = \alpha^0 + \ln(MS / \overline{MS^0}) \tag{9}$$

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.

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

$$p(\boldsymbol{\gamma} \mid x_1, \ldots, x_n) = \frac{f(x_1 \mid \boldsymbol{\gamma}) \ldots f(x_n \mid \boldsymbol{\gamma}) g(\boldsymbol{\gamma})}{\int_{\gamma} f(x_1 \mid \boldsymbol{\gamma}) \ldots f(x_n \mid \boldsymbol{\gamma}) g(\boldsymbol{\gamma}) d\boldsymbol{\gamma}} \tag{10}$$

where $p(.)$ is the posterior probability density function (pdf) for the parameter vector $\boldsymbol{\gamma}$ given the sample information set, $g(\boldsymbol{\gamma})$ is the prior pdf for the parameter vector $\boldsymbol{\gamma}$, and $f(x_1 \mid \boldsymbol{\gamma}) \ldots f(x_n \mid \boldsymbol{\gamma})$ is the likelihood function.

To apply the Bayesian update to the log-logistic hazard model, Eq. (3) is transformed into linear form as follows:

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

This procedure is commonly used to generate the estimating equation by adding an error term u_t assuming that the error term is normally and independently distributed, each with zero mean and common variance σ^2.

Given the prior normal distributions of parameter vectors by conjoint analysis and RP data sets, $\mathbf{Z_t}\ (= \begin{pmatrix} T \\ \mathbf{X_t} \end{pmatrix})$ and $\mathbf{Y_t}\ (= \ln(\frac{n(t)}{h_0(t)(M_t - N(t)) - n(t)}))$, the posterior distribution of the parameters follows the multivariate normal distribution by Bayes' theorem as follows:[5]

$$p(\boldsymbol{\gamma} \mid \mathbf{Z_t}, \mathbf{Y_t}) \propto \exp[-1/2(\boldsymbol{\gamma}\text{-}\mathbf{g})'\mathrm{F}(\boldsymbol{\gamma}\text{-}\mathbf{g})] \tag{12}$$

where

$\mathbf{g} = (\mathbf{C}^{-1} + \overline{\mathbf{S}}^{-1}\mathbf{Z_t}'\mathbf{Z_t})^{-1}(\mathbf{C}^{-1}\overline{\boldsymbol{\gamma}} + \overline{\mathbf{S}}^{-1}\mathbf{Z_t}'\mathbf{Z_t}\hat{\boldsymbol{\gamma}})$

$\mathbf{F} = \mathbf{C}^{-1} + \overline{\mathbf{S}}^{-1}\mathbf{Z_t}'\mathbf{Z_t}$

$\hat{\boldsymbol{\gamma}} = (\mathbf{Z_t}'\mathbf{Z_t})^{-1}\mathbf{Z_t}'\mathbf{Y_t}$

$\overline{\mathbf{S}} = n^{-1}(\mathbf{Y_t} - \mathbf{Z_t}\hat{\boldsymbol{\gamma}})'(\mathbf{Y_t} - \mathbf{Z_t}\hat{\boldsymbol{\gamma}})$

$\overline{\boldsymbol{\gamma}}$: prior mean

$\mathbf{C}$: prior covariance matrix

This posterior pdf of parameter vector $\boldsymbol{\gamma}$, which combines prior information

[5] See Zellner (1971, ch. 8) for details on estimating the posterior pdf.

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 Eq. (3) and the updated parameter vector $\mathbf{g}$ as follow:

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

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

3. Empirical Results

3.1. Estimation of Individual Utility Function

The model is applied to the telematics service market in South Korea, in which such services as navigations, traffic information, and emergency assistance are available. Data for the conjoint analysis were obtained from 500 South Korean citizens in July 2005 using face-to-face interviews. The variables for the service attributes consist of the following: contents of provided services, data transmission accuracy, penetration rates, price of telematics service, and areas covered by telematics service. Table 1 presents the attributes of telematics service and their levels for conjoint analysis. The values for the five attributes yield 108 hypothetical alternatives ($3\times 2\times 3\times 3\times 2 = 108$), but we reduced the number of alternatives to 16 by means of an orthogonal test. To reduce the burden on respondents, we divided the 16 alternatives into four sets of four alternatives. The alternative of not subscribing to telematics was presented with each set. Therefore the total number of observations available for estimation is 10,000 (500 respondents × 20 alternatives).

The estimated posterior means and variances of the coefficients of the consumer utility function are shown in Table 1. All estimates are significant at 5 percent except for the alternative-specific constant. According to the estimation results, more advanced telematics service, more accuracy, higher penetration rates, lower price, and wider service coverage positively affect the consumer's utility.

Table 1. Parameter estimates of the consumer utility function

Attributes	Level	Mean	Variance
Alternative-specific constant	Subscribing to service 1, Not subscribing to service 0	0.0006 (0.1282)	0.0226 (13.0000)
Provided service	Traffic information service	0[a]	0
	Traffic information service + life information service	0.0193 (3.6455)	0.0123 (1.8771)
	Traffic information service + life information service + remote control and emergency service	0.0569 (4.7344)	0.0565 (2.7715)
Data transmission accuracy	100% accuracy, 80% accuracy	0.0156 (5.6172)	0.0111 (3.0407)
Penetration rate	1%, 25%, 50%	0.0266 (6.3419)	0.0199 (3.1014)
Price (U.S. dollars/month)	10, 30, 50	-0.0099 (-16.4440)	0.0079 (4.0629)
Service coverage	National capital region only	0[a]	0
	National capital region + provinces	0.0351 (8.8202)	0.0349 (4.2803)

Note: t statistics in parentheses. All coefficients except that of the alternative-specific constant are significant at α = 0.05 level.

[a] 0 indicates the base level for dummy coding.

3.2. Estimation of Hazard Rate

3.2.1. Recalibration of Constant

To recalibrate the alternative-specific constant, the iterative process described in section 1.3 is operated with penetration rate data from South Korea's telematics service market in 2005. The adjusted alternative-specific constant derived by the fifth iteration process is –5.5050. Compared with the constant's original value, this result shows that consumers greatly overstate their intentions to subscribe to telematics service. The adjusted consumer utility function is used to forecast the number of telematics subscribers after the other coefficients are updated using Bayes' theorem.

3.2.2. Forecasting the Potential Telematics Service Market

As market potential of telematics service, i.e. m_t in Eq. (3), we consider automobiles with fewer seats than ten, in which telematics terminals are expected to be installed excluding such special cars as vehicle for construction and such large-sized cars as lorry and bus. Hereafter, we define these automobiles as *potential cars*. To estimate the number of potential cars, the Bass model (Bass, 1969) is used. The Bass model consists of the parts explained by the innovation effect (p) and the imitation effect (q) as follows:

$$m_t = p[T - M_{t-1}] + \frac{q}{T} M_{t-1}[T - M_{t-1}] \tag{14}$$

where T is the market ceiling of potential cars and m_t and M_{t-1} are the noncumulative and cumulative number of potential cars at any time.

To estimate the Bass model, we use nonlinear least squares estimation with registration data of potential cars from 1945 to 2005. Table 2 summarizes the estimation results derived via the Bass model. The estimated number of potential cars is used to forecast the number of telematics subscribers.

Table 2. Parameter estimates of Bass model

Variable	Coefficient	*t* value
p	0.0009	0.4381
q	0.2574	10.3251
T	11,680,990	24.3704

Note: All estimates except p are significant at α = 0.01 level.

3.2.3. Bayesian Update

If $n(t)$, $N(t)$, Z_t, and m_t in Eq. (13) are known, the parameters of the hazard model can be updated using Bayes' theorem. To simplify the model, we assume the baseline hazard function $h_0(t)$ remains constant over time as estimated by Hannan and McDowell (1987): $h_0(t) = 1$. Table 3 depicts the estimated mean and deviation for the prior and posterior distributions of the coefficients. The coefficients of such variables as *life information service*, *remote control and emergency service*, and *service coverage* are not updated because those variables indicate unrealized services—that is, they are services that will be available in the future.

The estimated deviations of the posterior distributions are less than those of the prior distributions. That reduction in variance means a reduction in uncertainty, and thus it leads to more accurate forecasts (Stoneman, 2002).

Table 3. Estimated prior and posterior distribution of hazard model parameters

Variables	Prior		Posterior	
	Mean	Deviation	Mean	Deviation
Alternative-specific constant	-5.5050	0.0226	-5.5911	0.0225
Life information service	0.0193	0.0123	0.0193	0.0123
Remote control and emergency service	0.0569	0.0565	0.0569	0.0565
Data transmission accuracy	0.0156	0.0111	0.0124	8.6563E-06
Penetration rate	0.0266	0.0199	0.3004	3.6892E-04
Price (U.S. dollars/month)	-0.0099	0.0079	-0.4074	5.6398E-03
Service coverage (national capital region + provinces)	0.0351	0.0349	0.0351	0.0349

3.3. Forecasting Demand for Telematics Service

We forecast the number of telematics subscribers using an estimated hazard rate reflecting changes in attributes of service. The data for changes in attributes of telematics service are collected from the technology roadmap suggested by the Electronics Information Center in South Korea (2004). Figure 2 shows the estimated number of telematics subscribers and actual observations. The mean absolute percentage error (MAPE) value calculated with available data from 2002 to 2005 is 7.85 percent, which indicates good model fit, while the MAPE value prior to the Bayesian update is 74.84 percent.

The government of South Korea expected that subscribers in the South Korean telematics market would total 750,000 in 2005 and rise to 4 million by 2007 (Korea Information Strategy Development Institute, 2005). In actuality, however, the number of telematics subscribers in South Korea in 2005 totaled only 510,000, and our study estimates that the number of subscribers will grow to 1.4 million in 2007 and 4 million in 2009. That result shows a two-year gap between the aim of the government and the estimated results.

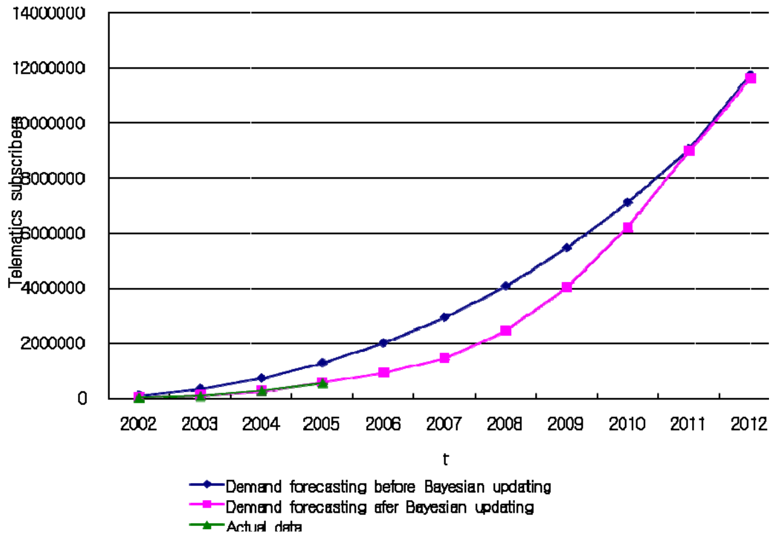
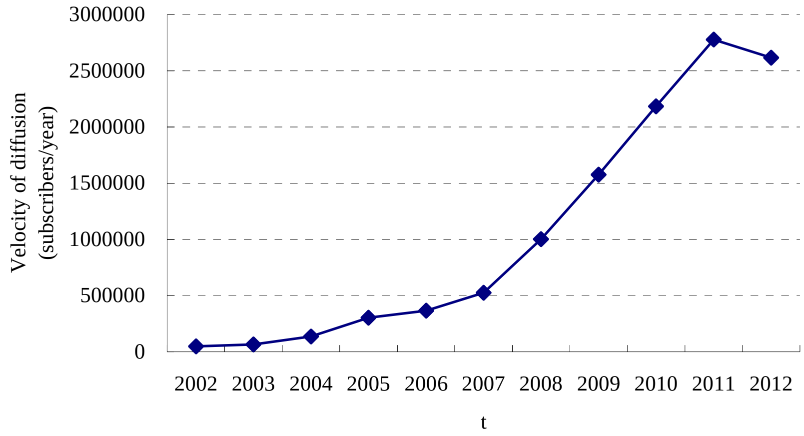


Figure 2. Forecast of telematics subscribers

To derive additional information from the forecasts, we employ the concepts of *velocity* and *acceleration* of diffusion suggested by Frank (2004). The velocity of diffusion is an indication of the number of new subscribers per time unit, whereas acceleration looks at the change in the number of new subscribers from time period to time period. As Figure 3 indicates, the maximum velocity of telematics service is expected to be achieved in 2011, and thereafter velocity will gradually decrease as the telematics market is saturated. On the other hand, the forecasted acceleration of the diffusion shows a remarkable increase in 2008 because, in accordance with the telematics roadmap, advanced services such as remote control, emergency service, and wider service coverage will be available. In addition, penetration rate growth may also contribute to the rapid acceleration of the diffusion due to the bandwagon effect. This result is based on the assumption that consumer utility is affected by quality of service and the penetration rate, and thus consumer choice probability regarding telematics service will increase with quality of service and the number of service users. This phenomenon indicates that the acceleration of the telematics diffusion will be changed if advanced service is provided in the marketplace earlier or later than expected.



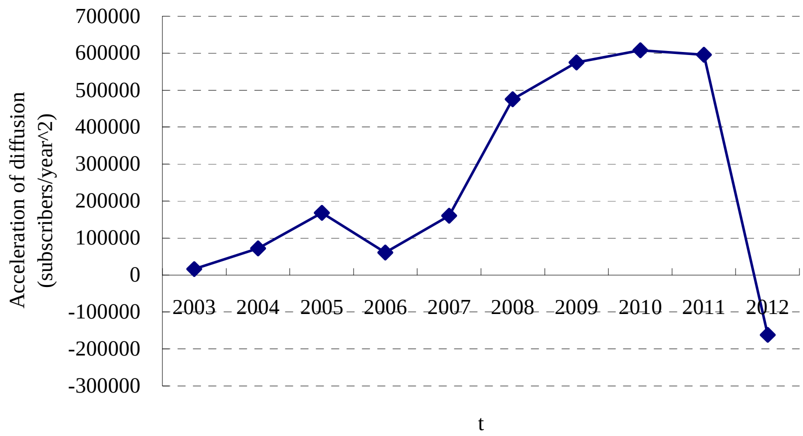


Figure 3. Velocity and acceleration of the diffusion of telematics service

4. Conclusion

As the market for information and communication technology such as the telematics service grows rapidly and new technologies are introduced more frequently, the life cycles of such technologies grow shorter. In environments such as this, Bass-type models, which depend on historical sales data or adopter data, are limited in their ability to forecast demand for a technology with a short history. The paper proposes an alternative forecasting method that relies on conjoint analysis and Bayes' theorem to forecast 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. An exogenous technology roadmap is used to reflect future changes in the attributes of new technologies.

We apply the proposed model to the telematics service in South Korea, which is in the early stage of its diffusion. The results demonstrate that the combination of a stated preference and revealed preference approach contributes to the model's fit, although we could not test forecasting performance of the proposed approach since hold-out data are lacking. We find that the forecasting model described here may be well suited to explaining the diffusion of the sales of a new technology and may generate a more accurate long-run forecast than would be derived by the stated preference approach alone. We believe the paper provides a basis for practitioners designing a market strategy and academics developing a forecasting model.

Further research exploring diffusion and forecasting with respect to several different technology or service categories would help determine how well the results presented here generalize to other data sets. If the proposed model is applied to a technology with long history, forecasting accuracy can be measured by comparing actual data with forecasts of the hold-out period based on information from the fitting period.

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