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A Forecasting Model Incorporating Replacement Purchase: Mobile Handsets in South Korea's Market

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A Forecasting Model Incorporating Replacement Purchases: Mobile Handsets in South Korea's Market

Running Title: A Forecasitng Model Incorporating Replacement Purchases

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Abstract

The paper introduces a replacement forecasting model that operates at the brand level and overcomes limitations of existing models. The model (1) consists of a diffusion model and a time series model; (2) separately identifies the diffusion of first-time purchases and that of replacement purchases; (3) reflects brands' competitive factors affecting product diffusion; and (4) characterizes consumers' different replacement cycles. The model is applied to South Korea's mobile handset market. The model performs well in terms of its fit and forecasting when compared with other forecasting models incorporating replacement and repeat purchases. The usefulness of the model stems from its ability to describe complicated environments and its flexibility in including multiple factors that drive diffusion in the regression analysis.

Key words: Forecasting; Replacement; Diffusion model; Mobile handset market

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I. Introduction

Forecasting models for new product are based on models from the fields of biology, epidemiology, and ecology (Linton, 2002). Mansfield (1961) suggested an alternative forecasting model that follows a new product's simple logistic growth, representing word-of-mouth effects. Bass (1969) offered analytical and empirical evidence for the existence of an S-shaped pattern of diffusion by suggesting a general model that reflects innovative and imitative factors. Simple though it may be, the Bass model has been used widely to analyze demand and diffusion in such fields as economics, management, policy, and marketing. The Bass model has been improved upon to reflect replacement purchasing and repeat purchasing (Bayus et al., 1989; Olson and Choi, 1985; Hahn et al., 1994; Danaher et al., 2001); competition between different products (Eliashberg and Jeuland, 1986); and diffusion at the brand level (Parker and Gatignon, 1994; Krishnan et al., 2000); among other things.

As Parker (1992) suggests, first-time adopters make their purchase only at the beginning of a product's life, and therefore replacement and repeat purchases become important factors over the long run in the diffusion of most products. Given that many products' replacement cycles become ever shorter and that consumer preferences will change, consideration of replacement purchases by existing users becomes a fair assumption for analyzing diffusion of both durable and nondurable products.

Forecasting models that take into account replacement and repeat purchases have a long history in the economic literature. Representative examples are Dodson and Muller (1978), Lilien et al. (1981), and Mahajan et al. (1983), which incorporate consumers' subsequent purchase behavior as well as their first-time purchase behavior. Yet such models are hampered by some limitations. First, some of them limit the research focus to nondurable products, such as pharmaceuticals (e.g., Lilien et al., 1981; Hahn et al., 1994). Next, although Bass and Bass (2001) and Bayus et al. (1989) propose models that apply to durable technology products (such as personal computers and color television sets), those models are limited in that they neglect to account for firms' strategies that affect consumers' subsequent purchase behavior. Next, most research taking into account replacement and repeat purchases applies only to a category, and not to particular brands, even though product diffusion at the brand level is an important issue given the severe competition that characterizes most industries. Another drawback of existing models is that they do not separately identify first-time purchases and replacement purchases, and instead use only aggregate sales data. Finally, the existing models do not estimate the replacement purchase rate, which may vary over consumers' different replacement cycles.

The purpose of the current study is to present a new forecasting model that accounts for replacement purchases, that overcomes the aforementioned limitations, and that discusses an application involving a durable consumer product. The proposed model is applied to South Korea's mobile handset market. This application is believed suitable for verifying our forecasting model because South Korea's mobile communication services market has become saturated, and demand for mobile handsets caused by the need for replacement has maintained the mobile handset market's growth. For the mobile handset application, we compare our proposed model's fit and forecasting performance with that of other forecasting models incorporating replacement and repeat purchases to verify its effectiveness.

The next section of the paper depicts the suggested model's conceptual and analytical underpinnings. Section three describes the data and the empirical analysis of the diffusion of South Korea's mobile handset market, followed by comparisons with other forecasting models that account for replacement and repeat purchases. The concluding section presents the study's theoretical implications and suggested extensions.

II. The Model

The major components of the model are sales to first-time purchasers who try a product initially and sales to replacement purchasers who have purchased a product previously. The basic equation is as follows:

$$n(t) = s(t) + r(t), \qquad (1)$$

where $n(t)$ is the product's total sales at time t, $s(t)$ is sales to first-time purchasers at time t, and $r(t)$ is replacement sales at time t. Eq. (1) is the category-level equation implied by our proposed model. Based on Eq. (1) we suggest a new replacement forecasting model at the brand level.

If we specify the number of brands in the product market as N, the total sales of brand i consist of sales to first-time purchasers and replacement sales as follows:

$$n_i(t) = s_i(t) + r_i(t). \qquad (2)$$

Note that Eq. (2) adds up (across brands) to Eq. (1), where $n(t) = \sum_{i=1}^{N} n_i(t)$,

$s(t)=\sum_{i=1}^{N} s_i(t)$ and $r(t)=\sum_{i=1}^{N} r_i(t)$. In Eq. (2), first-time purchasers at time t determine to adopt the product at time t, and then part of the triers would adopt the product produced by brand i. If $\beta_i(t)$ is brand i's market share in terms of first-time purchases, then $s_i(t)$ is defined as follows:

$$s_i(t)=\beta_i(t)s(t), \tag{3}$$

$$\textit{such that } \sum_{i}^{N}\beta_i(t)=1;$$

$$s(t)=m[F(t)-F(t-1)], \tag{4}$$

where $F(t)$ is the cumulative distribution function of triers of the product up to time t and parameter m indicates the number of potential triers in the product market. To estimate the sales to first-time purchasers, Eq. (4), we must specify the functional form for the underlying cumulative distribution function, $F(t)$. Various forecasting models, such as the original Bass model (Bass, 1969) and a generalized Bass model with marketing-mix variables (Bass et al., 1994), are available for $F(t)$. The number of triers of the product at time t is estimated in Eq. (4) using the forecasting model, and that estimate is applied in Eq. (3). The restriction is added to reflect that the summation of each brand's market share equals 1 for first-time purchasers. We explore this in more detail subsequently.

On the other hand, in diffusion by replacement purchasers at time t, the product users' replacement cycle is reflected in our forecasting model based on the fact that consumers' replacement cycles are not all alike. In the current study, we assume a replacement purchase rate γ_{τ_j} that varies over replacement cycle τ_j ($j=1,2$), provided that $\gamma_{\tau_{3+}}$ is the replacement purchase rate in the case of replacement cycles of more than τ_3 years. Then, $r(t)$ is as follows:

$$r(t)=\gamma_{\tau_1}\sum_{i=1}^{N} n_i(t-\tau_1)+\gamma_{\tau_2}\sum_{i=1}^{N} n_i(t-\tau_2)+\gamma_{\tau_{3+}}\sum_{i=1}^{N} n_i(t-\tau_{3+}). \tag{5}$$

Replacement purchasers may adopt the new products of brand i after taking into consideration multiple specific factors related to brand i. In this study, we assume that consumers' replacement-purchase behavior is affected by the bandwagon effect and marketing-mix such as advertising efforts and price. As proxy variables we use market share data to reflect the bandwagon. Therefore, replacement sales of brand i can be expressed as follows:

$$r_i(t) = \lambda_i(t)\{\gamma_{\tau_1}\sum_{i=1}^{N} n_i(t-\tau_1) + \gamma_{\tau_2}\sum_{i=1}^{N} n_i(t-\tau_2) + \gamma_{\tau_{3+}}\sum_{i=1}^{N} n_i(t-\tau_{3+})\}$$
$$\textit{where } \lambda_i(t) = \zeta_{iband} ms_i(t-1) + \sum_j \zeta_{ij} x_j(t) \quad , \qquad (6)$$

$$\textit{such that } \sum_{i}^{N} \lambda_i(t) = 1$$

where $ms_i(t-1)$ is brand i's market share at time $t-1$, $x_j(t)$ is marketing-mix variables of brand i at time t. In Eq. (6), the parameters ζ represent the effects and magnitudes to which each brand's bandwagon effect and marketing-mix affect replacement sales. The restriction is added to reflect that the summation of each brand's market share equals 1 for replacement purchasers.

The model's final form is derived by combining Eq. (3) and Eq. (6) as follows:

$$\begin{aligned} n_i(t) &= \beta_i(t)s(t) + \lambda_i(t)\{\gamma_{\tau_1}\sum_{i=1}^{N} n_i(t-\tau_1) + \gamma_{\tau_2}\sum_{i=1}^{N} n_i(t-\tau_2) + \gamma_{\tau_{3+}}\sum_{i=1}^{N} n_i(t-\tau_{3+})\} + \varepsilon_i(t) \\ &= \beta_i(t)s(t) + (\zeta_{iband} ms_i(t-1) + \sum_j \zeta_{ij} x_j(t)) \times \\ &\quad \{\gamma_{\tau_1}\sum_{i=1}^{N} n_i(t-\tau_1) + \gamma_{\tau_2}\sum_{i=1}^{N} n_i(t-\tau_2) + \gamma_{\tau_{3+}}\sum_{i=1}^{N} n_i(t-\tau_{3+})\} + \varepsilon_i(t) \end{aligned} \quad , \qquad (7)$$

$$\textit{such that } \sum_{i}^{N} \beta_i(t) = 1, \quad \sum_{i}^{N} \lambda_i(t) = 1.$$

Eq. (7) includes the vector autoregression (VAR) equation's form in which brand i's sales volume is expressed as a linear combination of its lagged value and the lagged values of the sales volume of all other brands in the category. This model is based on the assumption that each brand's sales volume is affected by competing brands' sales volumes, as well as its own previous sales volume. In addition, the above equation is expanded to include other exogenous variables such as marketing-mix variables, as well as lagged endogenous values. A time series model such as VAR, however, is applicable only for short-run forecasting because the forecasts of time series become ever more imprecise as the forecast horizon increase. To overcome nonstationary problem of the time series model, researchers have developed an error correction model (ECM), which uses cointegrated variables to transform variables' short-run equilibrium into long-run equilibrium. In other words, ECM is the methodology that matches economic variables' short-run and long-run behavior by including cointegrated variables with lagged terms as explanatory variables[1].

Our proposed model in Eq. (7) can also be understood as a replacement forecasting model with concepts such as ECM. Instead of ECM's cointegrated variables, our model introduces the variable represented by the diffusion model, which shows the supremacy of its long-run forecast. The diffusion model provides medium- and long-run forecasts, such as an estimate of the ceiling point and estimates of the peak time and sales volume at the peak time (Meade and Islam, 2001). Therefore, our model's structure consists of a diffusion model (the first term of Eq. (7)), which provides long-run information generated by first-time purchasers, and a time series model (the second term of Eq. (7)), which provides short-run information generated by previous users' product replacement. In the next section we will discuss the substantive findings on mobile handset market and the results of model's fit and forecasting performance.

III. Empirical Results

Data Description

The study uses quarterly data for three brands of mobile handsets in South Korea. Although many brands of mobile handsets exist in the South Korean market, we consider the two brands that dominate the market, Samsung Electronics and LG Electronics (denoted as Brand 1 and Brand 2, respectively), plus an additional brand that is defined by aggregating the sales of four other brands and is denoted as Brand 3.

The observation period used for our model's estimate stretches from the first quarter of 2000 to the first quarter of 2005 because of the limitation of available data at the brand level (sales data and the other data at the category level are available from the first quarter of 1995). The subscriber data for mobile communication services and the aggregate sales data for mobile handsets are reported by South Korea's Ministry of Information and Communication (2006) and by National Statistical Office (2006), respectively. The value of domestic profit divided by the average price of mobile handsets is taken as the value of each brand's sales data because of that figure's unavailability. To ensure the estimated data's reliability, we compared the estimated data

[1] See Hamilton (1994, ch.19) for details of this error correction model.

to some actual data that we can observe in part. The South Korean service DART[2] provides domestic profit data and average price data for mobile handsets, and Cetizen (www.cetizen.com), a mobile handset market research firm, provides data related to each brand's number of product models.

Model Estimation

Generally, consumers in the telecommunications market can use products such as mobile handsets and fax connections only after subscribing to a service. This phenomenon means that users of a telecommunication product always have to be subscribed to a telecommunication service. Therefore, we assume that new subscribers to a mobile communication service at time t are first-time purchasers of mobile handsets at time t. On the other hand, replacement purchasers of mobile handsets at time t are defined as consumers who have subscribed to a mobile communication service and tried new mobile handsets by $t-1$. This assumption implies that replacement purchasers include both re-subscribers to a mobile communication service and subscribers switching to competing service providers because they have already used mobile handsets.

We use the original Bass model as the diffusion model in Eq. (4). Thus, cumulative distribution function for Bass model considered in our empirical analysis is as follows:

$$F(t) = \{1 - \exp(-(p+q)t)\} / \{1 + (q/p)\exp(-(p+q)t)\} \tag{8}$$

In Eq. (8), parameters p and q are the innovation and imitation coefficients, respectively. Parameter p reflects the impact of activities such as advertising and promotion on adoption. Similarly, parameter q captures communication internal to the social system such as the word-of-mouth effect.

To estimate the Bass model, we use nonlinear least squares (NLS) estimation reflecting seasonal dummies to eliminate fluctuations in the quarterly data.

The Bass model is applied to the diffusion of new subscribers in South Korea's mobile communication services market from 1984 to 2005. When m is estimated from the data, an unreasonable parameter m is found, in that the parameter's value is smaller than the number of actual cumulative subscribers. Therefore, we exogenously estimate the number of potential subscribers to mobile communication services to be about 44 million based on South Korea's population. Many existing studies of forecasting, such as

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2 A financial supervisory service in South Korea operates the data analysis, retrieval, and transfer system, or DART (http://dart.fss.or.kr).

Hahn et al. (1994), estimate the forecasting model using fixed values of m. Given the number of potential subscribers, the estimated parameters p and q in the Bass model are 0.0216 (σ = 0.0123) and 0.0972 (σ = 0.0491), respectively.

Next, our replacement forecasting model, Eq. (7), is estimated using subscriber data estimated by the Bass model and any other quarterly data. To simplify the model, we assume each brand's market share for first-time purchasers, $\beta_i(t)$, is constant throughout the time period: $\beta_i(t) = \beta_i$.

We choose price and product diversification as marketing-mix variables. As a proxy variable we use the number of product models of each brand to reflect the product diversification. Advertising or any other elements of the marketing mix besides price and product diversification can be used in our model if the data are available.

On the other hand, to determine its Eq. (7)'s lag order, the Akaike information criterion and the Schwarz information criterion, which choose the lag order to minimize some criterion function of lag, are used (Hatanaka, 1996). We determine the lag order, however, based on survey results reported by the market research firm Cetizen (2005) indicating that the replacement cycle of South Korea's mobile handsets is between one and two years. Therefore, the parameters γ_{τ_1}, γ_{τ_2}, and $\gamma_{\tau_{3+}}$ in Eq. (5) can be simply expressed as γ_1, γ_2, and γ_3. The estimated parameters $\hat{\gamma}_1$, $\hat{\gamma}_2$, and $\hat{\gamma}_3$ provide information for the ratio of replacement purchasers with each replacement cycle, and those parameters are used to forecast the demand for the mobile handset.

In estimating our full model in Eq. (7), the least squares estimators are inconsistent because all the endogenous variables are correlated with the disturbances ($\varepsilon_i(t)$). In this case, because an instrumental variable estimator can be used instead, we estimate our model's parameters using three-stage least squares,[3] as proposed by Zellner and Theil (1962). The joint estimates of the nonlinear simultaneous equations' parameters were produced using TSP software.

Table 1 shows our model's estimated coefficients. The estimates of parameters β_1 and β_2 are significant at 1 percent, and they are positive as expected. We see that about 40.1 percent of new mobile communication service subscribers adopt Brand 1's handset, and about 28 percent of new subscribers adopt Brand 2's handset. As for Brand 3's market share of new subscribers, 31.9 percent is automatically derived by Eq. (7)'s constraint condition. We compared each brand's estimated market share to the actual market share in terms of actual aggregate sales to make several inferences about the difference between overall sales and estimated sales to first purchasers. The average

[3] For discussion of the structure and estimation procedure of three-stage least squares, see Greene (2003, ch. 15).

market shares from 2000 to the first quarter of 2005 are reported as 44.6 percent for Brand 1, 19.9 percent for Brand 2, and 35.5 percent for Brand 3. Brands 1 and 3 occupy higher market shares in terms of actual overall sales than their market shares in terms of estimated sales to first-time purchasers, and vice versa for Brand 2. This phenomenon indicates that the diffusion speed for replacement purchases of Brand 2 is slow compared with that of other brands. This result, thus, implies that Brand 2's market condition may include threat factors for its product's diffusion, in that replacement purchasers have stimulated the demand for mobile handsets since the saturation of South Korea's mobile communication service market around 1999.

The parameters γ_1, γ_2 and γ_3 that describe the ratio of replacement purchasers with various replacement cycles are not significant at a significance level of 5 percent, except γ_2. From that, we can observe that about 17.6 percent of previous users who had adopted mobile handsets at time $t-2$ are going to again purchase new handsets at time t.

With two exceptions, all of the estimated parameters of variables related to replacement purchases are significant. First, the estimated values of ζ_{1band} and ζ_{2band} show that the bandwagon effect has a significant impact on the replacement-purchase behavior of previous users with regard to Brand 1. Therefore, we can infer that more users of Brand 1 may increase that brand's market share. Second, both parameters of the price variables, ζ_{1price} and ζ_{2price}, are significant at a significance level of 5 percent. The signs of those parameters are positive, contrary to the general case showing a preference for lower-priced products. The phenomenon reveals that consumers prefer up-to-date products even though the price of mobile handsets increases as advanced technologies—such as MP3 and digital photography capability—are included in the handsets. In the mobile handset market, therefore, advanced functionality realized by new technology may affect handset diffusion more significantly than does price. The introduction of new telecommunication service content, in addition to advances in mobile terminal technology, can also contribute to strategies that seek more functionality. Consumers may exercise their discrimination by observing whether the product is compatible with new telecommunication services. This phenomenon indicates that the development of new functionality and the introduction of new mobile communication services need to operate in parallel. Finally, the results of the estimated parameters ζ_{1diver} and ζ_{2diver} show that demand for mobile handsets is negatively affected by product diversification in the case of Brand 1. These results are consistent with what has been reported by the market research firm iSuppli, that is, that South Korea's mobile handset firms need to reduce the number of their product models and adopt a strategy such as target marketing to keep the mobile handset market's dominant position in the world (Seoul Digital Forum, 2005).

<Table 1> Parameter Estimates of the Proposed Replacement Forecasting Model†

Parameter	Coefficient	Standard Error	t-Statistic
β_1***	0.4010	0.1271	3.1564
β_2***	0.2801	0.0779	3.5938
γ_1	0.0238	0.0655	0.3636
γ_2**	0.1761	0.0731	2.4096
γ_3	0.0075	0.0101	0.7449
ζ_{1band}***	0.5994	0.2283	2.6256
ζ_{1price}**	1.11E-06	5.03E-07	2.2136
ζ_{1diver}*	-5.84E-03	3.08E-03	-1.8991
ζ_{2band}	0.3665	0.2795	1.3111
ζ_{2price}**	4.78E-07	2.15E-07	2.2204
ζ_{2diver}	-1.05E-03	7.78E-04	-1.3522

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

† ζ_{iprice} and ζ_{idiver} represent the parameters of variables related to price and product diversification, respectively.

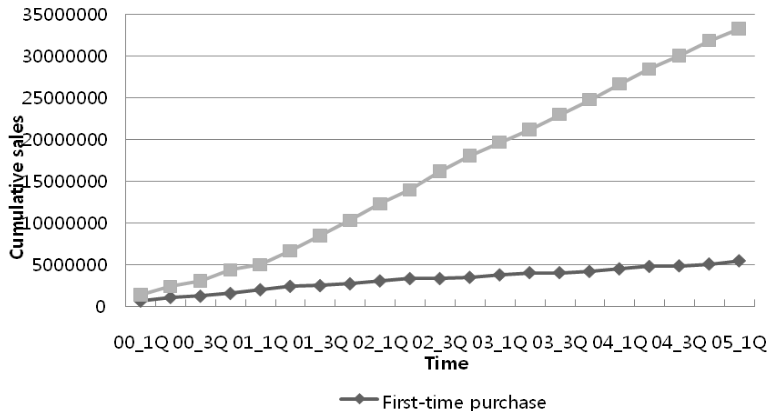
The parameters $\beta_3, \zeta_{3band}, \zeta_{3price}$, and ζ_{3diver} explaining Brand 3's diffusion are not recorded due to the constraint conditions, $\sum_i^n \beta_i = 1$ and $\sum_i^n \lambda_i(t) = 1$.

Sales to First-Time Purchasers and Replacement Purchasers in the Mobile Handset Market

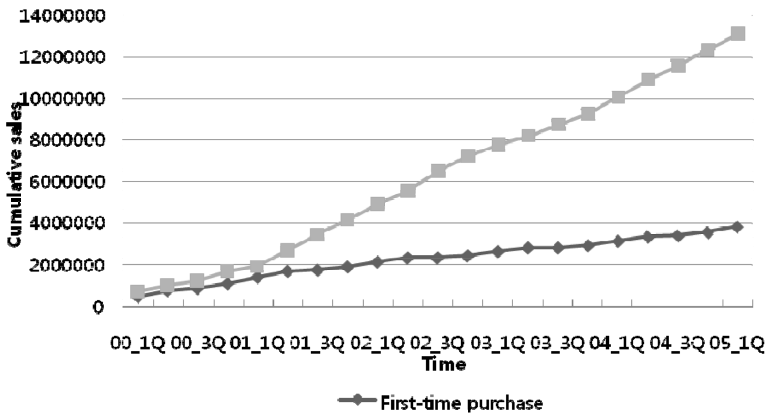
Most forecasting models do not separately identify first-time purchases and replacement purchases because most data sources report only aggregate sales volume, that is, the summation of sales to both first-time purchasers and replacement purchasers. To overcome that shortcoming, the results of the present forecasting model take into account first-time purchases and replacement purchases separately.

Figure 1 shows the estimated cumulative sales of mobile handsets at the brand level (a–c) and the category level (d) since 2000. The gap between sales to first-time purchasers and replacement sales has grown over time, although the two sales figures begin at a similar level. In cumulative sales from 2000 to the first quarter of 2005, total sales of Brand 1 consist of replacement sales of 85.9 percent and sales to first-time purchasers of 14.1 percent. In the case of Brands 2 and 3, replacement sales cover 77.4 percent and 86.1 percent of each brand's total sales, respectively. Overall, 84.3 percent of total sales in the mobile handset market are demand by replacement purchasers. From those results, we can infer that growth of the mobile handset market is being driven mostly by replacement purchases, and a phenomenon we expect will become even more severe given that the market for mobile communication service is becoming saturated. As of the first quarter of 2006, the penetration of mobile telecommunication service in South Korea had already reached 80 percent. We can guess that the diffusion pattern of first-time purchases and replacement purchases in world's mobile handset market is similar to that in South Korea's market, because the number of the world's mobile subscribers showed negative growth in 2001.

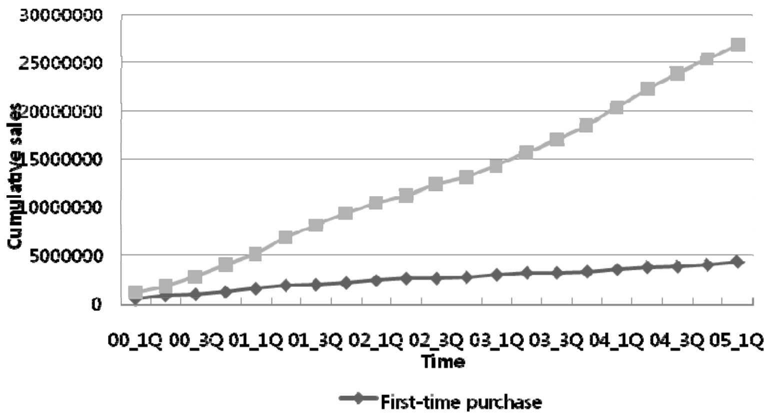
Therefore, to stimulate the mobile handset market, marketing to replacement purchasers should be given a higher priority than marketing to first-time purchasers. Specifically, the bandwagon effect, the incorporation of more sophisticated functions, and a smaller variety of product models may become more critical factors over time for market success in the mobile handset industry.



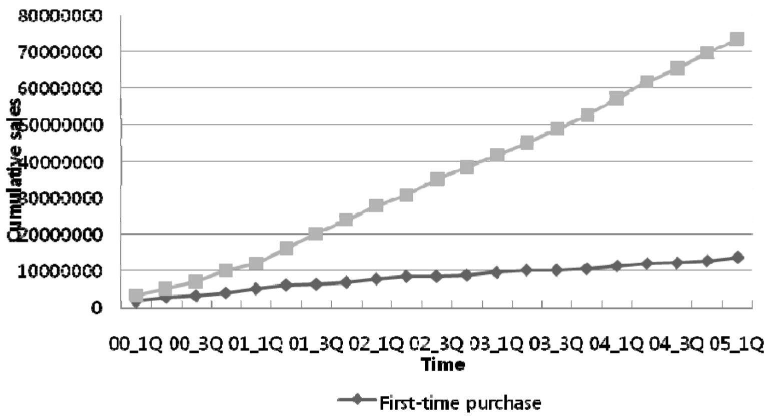
(a) Brand 1



(b) Brand 2



(c) Brand 3



(d) Total of All Brands

Fig. 1. Sales to First-time Purchasers and Replacement Purchasers (Cumulative Sales Since 2000)

Comparisons with Other Forecasting Models Incorporating Replacement and Repeat Purchases

Here we compare the fit and forecasting performance of the Lilien-Rao-Kalish (LRK) model (1981), the Mahajan-Wind-Sharma (MWS) model (1983), and the Hahn-Park-Krichnamurthi-Zoltners (HPKZ) model (1994) to our study's proposed model through applications of South Korea's mobile handset market. To ensure the comparison is fair, however, we use our proposed model excluding the variable describing product diversification in the full model, forcing the kinds of variables to be equal as is the case in the other forecasting models incorporating replacement and repeat purchases.

The original LRK model is expressed in terms of adopters, not sales. After transforming the original LRK model into a sales model, modified by Hahn et al. (1994), the LRK model is expressed as follows:

$$\begin{aligned} n_i(t) = {} & (\beta_0 x_i(t-1) + \beta_1 x_i(t-1)^2)(m_i - N_i(t-1)) \\ & - \beta_2 x_{j \neq i}(t-1) N_i(t-1) + \beta_3 n_i(t-1)(m_i - N_i(t-1)) \end{aligned} , \tag{9}$$

where $x_i(t-1)$ and $x_{j \neq i}(t-1)$ are marketing-mix variables of brand i and competing brands at time $t-1$, respectively. In our study, brand i's product price and the competing brands' average product price are used as marketing-mix data. In Eq. (9), m_i is potential sales in the mobile handset market. Parameters β_0 and β_1 capture the effect of marketing on converting nontriers to triers, and β_2 captures the effect of competition on converting previous triers to nonrepeaters. Finally, β_3 captures word-of-mouth's effect on the trial.

Mahajan et al. (1983) proposed a repeat-purchase forecasting model that uses only aggregate sales data. They base their model on the assumption that the word-of-mouth variable is nonuniform over time. The MWS model's basic framework is simple in that it ignores brands' marketing-mix variables and consists only of purchasers and nonpurchasers. The MWS model expressed by our notation is as follows:

$$n_i(t) = [\beta_o + \beta_1 (n_i(t-1)/m_i)^{\phi}][m_i - n_i(t-1)] + \beta_2 n_i(t-1) , \tag{10}$$

where the parameters β_0 and β_1 reflect product diffusion's innovative and imitative effects, respectively; the parameter ϕ captures the dynamic word-of-mouth effect; and

β_2 indicates the fraction of adopters in time $t-1$ who continue to adopt in period *t*.

The HPKZ model has two forms, which emphasize the marketing effort's competitive aspect and its informative nature, respectively. In this study we compare the competitive-aspect HPKZ model with our model, because that one is consistent with our formulation that reflects brands' competitive structure. The HPKZ model can be written as follows:

$$n_i(t) = [(\beta_0 + \beta_1 \ln(x_i(t) / \sum_i x_i(t)) + \beta_2 (n_i(t-1)/m_i)][m_i - q_i(t-1)] + \beta_3 q_i(t-1) \text{ ,(11)}$$

where $x_i(t-1)$ is brand i's marketing-mix variable in time $t-1$, and $q_i(t-1)$ is the cumulative adopters by time $t-1$,which has the relation $q_i(t) - q_i(t-1) = n_i(t) - \beta_3 q_i(t-1)$. Hahn et al. (1994) estimate the model's parameters using an iterative procedure and ordinary least squares estimation because $q_i(t-1)$ is not directly observed from the data.[4] However, we estimated the HPKZ model's parameters using nonlinear least squares (NLS) with mobile communication service subscriber data, which equals $q_i(t-1)$.

In each case, the estimates of the equation systems' parameters were produced utilizing nonlinear least squares (NLS) on TSP software. To compare the models' fit and forecasting performance, each model's Bayesian information criterion (BIC)[5] and mean absolute percentage error (MAPE) is computed. Each model's BIC and MAPE are given in Table 3. The data set's estimation period was 21 quarters. The result of the fitted BIC (Table 2a), which is measured as logs of fit over the estimation period, reveals that our model produces the lowest BIC (average fitted BIC = 11.34) for the most part, except for Brand 3. Specifically, as shown in Figure 2, which compares each brand's actual sales and their diffusion patterns estimated with various forecasting models incorporating replacement and repeat purchases, our model exhibited the best fit performance. The HPKZ model that allows for marketing efforts' competitive effect and that includes a repeat-purchase component also indicates good model fit (average fitted BIC = 11.37). On the other hand, the MWS model reports the worst model fit overall (average fitted BIC =11.57). From those results, we can infer that consideration of marketing-mix variables such as price tends to have a significant impact on the model's fit in that only the MWS model does not include marketing-mix variables.

To compare the models' forecasting performance, Table 2b reports the MAPEs of one-ahead forecasts, which measure MAPEs for out-of-sample from the first quarter of

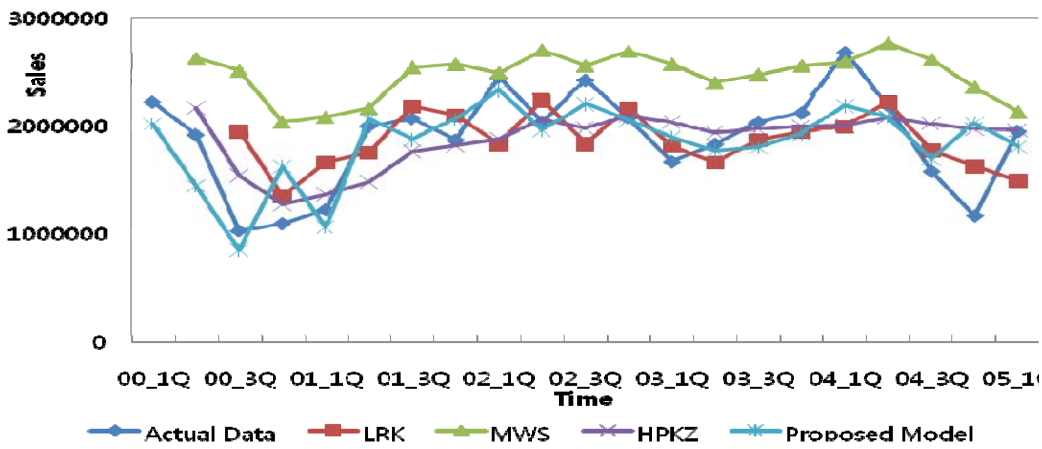
[4] For the specific estimation, see Hahn et al. ([6], p. 229).

[5] As the models have different numbers of parameters, Bayesian information criterion is used for fit criterion.

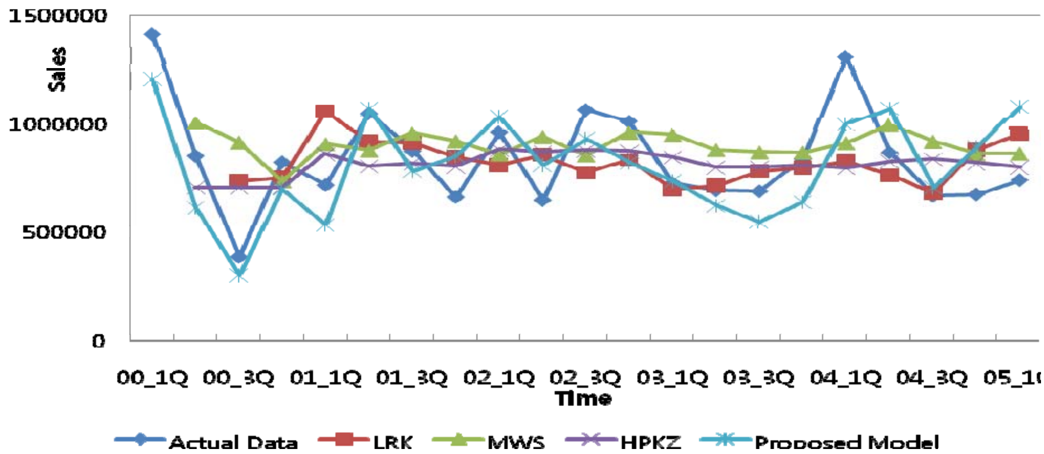
1995 to the fourth quarter of 2004. Our model also produces the lowest MAPE values for Brands 1 and 3. In summary, our study's proposed model shows good performance in terms of its fit and forecasting as it is combined with a diffusion model and a time series model considering various realistic factors such as marketing effort, replacement cycle, and bandwagon effect.

<Table 2> Performance Measures of Forecasting Models Incorporating Replacement and Repeat Purchases

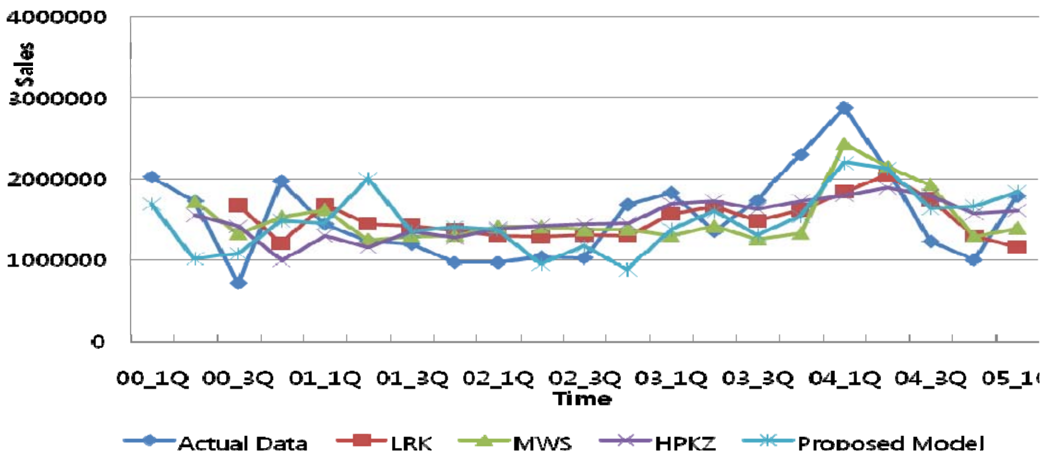
	LRK	MWS	HPKZ	Proposed Model
(a) Fitted BIC				
Brand 1	11.55	12.05	11.50	11.43
Brand 2	10.97	11.05	10.93	10.86
Brand 3	11.73	11.62	11.67	11.74
(b) Forecast MAPE				
Brand 1	9.68	9.15	9.62	8.38
Brand 2	48.52	16.63	16.21	51.89
Brand 3	85.29	24.68	39.05	2.33



(a) Sales of Brand 1 Products



(b) Sales of Brand 2 Products



(c) Sales of Brand 3 Products

Fig. 2. Comparison of Actual Data and Estimated Sales in Forecasting Models Incorporating Replacement and Repeat Purchases

IV. Conclusion

As the marketplace for a product evolves, consumer preferences also evolve. Replacement cycles for a new product become shorter, and competition among brands becomes fiercer. To demonstrate and forecast complicated markets, forecasting models need to address consumers' replacement patterns and the interrelationships among brands. To that end, we have developed a new replacement forecasting model that can explain the diffusion of a product at the brand level and can forecast future demand for the product taking into consideration such factors as bandwagon effect and marketing mix. This model is especially appropriate for separating first-time purchases from replacement purchases.

We compared our model's fit and forecasting performance to that of other forecasting models that account for replacement and repeat purchases, including the LRK (1981), MWS (1983), and HPKZ (1994) models. As shown in the results of fitted BICs and forecast MAPEs, our model outperforms previously developed forecasting models despite its removal of a critical variable that indicates product diversification. The results demonstrate that the combination of a diffusion model and a time series model incorporating realistic factors such as marketing effort, replacement cycle, and bandwagon effect contributes to the model's fit and forecasting performance. The results suggest especially that multiple brands competing in the new product market should not be treated as being totally independent of each other because their mixing behavior drives the diffusion process of each brand's new product.

As with any analysis, there are limitations to this one. Further research should explore diffusion with respect to several different product categories. That should be done to see how well results derived from the model presented here generalize to other data sets. In addition, further research should investigate how the results drawn here change when other forecasting models or growth models, such as a multigeneration model or a logistic model, are used instead of the original Bass model. Moreover, there are alternative specifications available for the lag order of a time series model used in this research. It would be worthwhile to investigate the implications of such alternative specifications.

Despite the limitations, our empirical results are promising. The replacement forecasting model described here should be useful for explaining the diffusion of a new product sales and generating accurate long-term sales forecast. Furthermore, the model has the flexibility to include marketing-mix variables in the regression process, the inclusion of which helps to explain differences across various brands and the mechanisms leading to replacement purchases. We believe practitioners and academics alike have an interest in understanding the mobile communication market and in developing a forecasting model.

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