# Forecasting Consumer Adoption of Technological Innovation: Choosing the Appropriate Diffusion Models for New Products and Services before Launch

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**ABSTRACT**

There are many good articles on various forecasting models. There is consensus that no single diffusion model is best for every situation. Experts in the field have asked for studies to provide empirical-based guidelines for recommending when various models should be used. This research investigates multiple diffusion models and provides recommendations for which diffusion models are appropriate for radical and really new products and services before the launch of the innovation.

## INTRODUCTION

How does one know when or if consumers will accept a technological innovation before the innovation hits the market? This research evaluates techniques for forecasting consumer adoption of radical technological innovations and develops a methodology for selecting the most appropriate techniques. The focus is on the consumer adoption of a product or service itself, not on the success or failure of a particular firm. The forecasting models discussed here model "if there is a market to acquire this radical product over a period of time", not the switch from another product. Hence we will restrict ourselves to growth curve models of the "whole" market (e.g., not looking at simulated test markets, etc.). For a general overview of forecasting, see Gentry et al (2006).

Our primary goal is to determine which tools are appropriate for forecasting the consumer demand for radical innovation. This suggests three interrelated research questions:

1. Which forecasting methods should be used for forecasting consumer adoption of *radical* technological innovations?
2. Which forecasting methods should be used for forecasting consumer adoption of *really new* technological innovations?
3. Does an innovation's price affect which methods should be used to forecast consumer adoption of technology innovations? In other words, does price affect forecasting accuracy for various methods? If so, what forecasting methods should be used for low and high priced innovations?

This study evaluates the diffusion of the innovations shown in Figure 1. It looks at the diffusion of radical and really new innovations intended for use in the home. Radical innovations cause both macro-marketing and macro-technological disruptions and really new innovations cause either a macro-marketing or a macro-technological disruption (Garcia and Calantone, 2002). The innovations are also classified as either high priced or low priced. The eight data sets were initially selected to include two samples in each cell of consumer electronic innovations; when the research was well underway, we discovered that VCRs were not a radical innovation, but a really new one. Only data sets with a reasonable history were considered. Newer innovations were not feasible as one would have to wait at least 10 years before comparing the results of the various forecasts with actual results. To reduce confounds and to simplify the data-collection process, only consumer electronic innovations in the U.S. market were considered.

**Figure 1: Classification of Eight Consumer Electronic Innovations and Years of Data**

| Price Level | Radical Innovation | Really New Innovation |
|---|---|---|
| High | PCs (1980-2000) | Camcorders (1985-2000) |
| | Satellite Receivers (1986-2000) | Projection TVs (1984-2000) |
| Low | CD Players (1983-2000) | Cordless Phones (1980-2000) |
| | | Telephone Answering Device (1982-2000) |
| | | VCRs (1974-2000) |

## THE RESEARCH QUESTIONS

***RQ1.*** ***Which forecasting methods should be used for forecasting consumer adoption of radical technological innovations?***

***RQ2.*** ***Which forecasting methods should be used for forecasting consumer adoption of really new technological innovations?*** The answer to this question may be the same as RQ1, but this research may show that radical and really new technological innovations should use different forecasting techniques.

***RQ3.*** ***Does an innovation's price affect which methods should be used to forecast consumer adoption of technology innovations?*** In other words, does price affect forecasting accuracy for various methods? If so, what forecasting methods should be used for low and high priced innovations?

## LITERATURE REVIEW

Bright (1978) defined a forecast as "a statement about a condition in the future, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient." Jantsch (1969) first differentiated between two general approaches to forecasting: exploratory and normative. Exploratory forecasting utilizes relevant historical records to project parameters and/or functional capabilities into the future. Normative forecasting starts with future goals and works backwards to identify what barriers must be overcome in order to obtain these goals. Armstrong (2001) considered normative forecasting as synonymous with planning. Lenz (1971) noted that these distinctions are not absolute. All forecasters bring some normative thinking into their forecasts simply by what assumptions they make and what factors they select as important. Conversely, all normative forecasts use exploratory techniques as the starting points for their assumptions. Nevertheless, the distinction between exploratory and normative forecasts is a useful one. All of the forecasts in this study are exploratory forecasts.

Researchers have concluded that little empirical research has been done to investigate the comparative forecasting performance of demand forecasting in various settings (Armstrong, Brodie, and McIntyre, 1987; Meade and Islam, 2001) although many diffusion models have been used in various contexts. Throughout the forecasting literature, one common refrain was repeatedly stressed – no single forecasting method was appropriate for every situation (Cetron and Ralph, 1971; Armstrong, 2001). Among the many well-known forecasting methods, the growth curve based diffusion model is the mostly common used in the area of new product forecasting. Some major growth curve models that seemed most represented in the literature for predicting the adoption of an innovation include the Bass Model and the Extended Logistic Model (Bass, 1969); the Generalized Bass Model (Bass, Krishnan, and Jain, 1994); Bewly and Fiebig's (1988) Flexible-Logistic (FLOG) Models: Inverse Power Transfer (IPT), Exponential (ELOG), and Box and Cox (BnC); four foundational models codified by Gregg, Hassel, and Richards (1964): the Modified Exponential, the Logarithmic Parabola, the Simple Logistic, and the Gompertz Model; the Observation-Based Modified Exponential Model (Meade, 1985) – also known as the Local Logistic Model; and the Log-Logistic Model (Tanner, 1978).

The review of the literature shows that no single forecasting method can obtain both accurate and valid forecasts over various conditions. Various forecasting methods have unique strengths and weaknesses in the context of different conditions. But little research has been done to investigate the comparative forecasting performance of forecasting models in various settings (Armstrong, Brodie, and McIntyre, 1987; Meade and Islam, 2001). Growth curve models depict the diffusion of new products with different mathematical curves. These curves represent the empirical results of diffusion, but do not explicitly incorporate the explanatory variables affecting the diffusion process. These factors affect the shape of the diffusion curve and the value of the parameters of a certain growth curve, and therefore have important implications for diffusion model selection. Incorporating the theoretical perspective of new product diffusion will help understanding the models and provide important guidelines in model selection under different context.

This research intends to demonstrate (empirically) some guidelines for the selection of forecasting approaches under different conditions (various innovation and price level contexts) for pre-launch forecasts (i.e., forecasts made without the benefit of market data obtained from actually seeing the innovation in the market). We choose two factors, innovation level and price level, to define the context of model selection and investigate the performance of selected growth curve models under different contexts.

## METHOD

This research focuses on consumer electronic innovations and evaluates five well-established models of innovation diffusion and two model variants. The two conditional factors considered are innovation level and price level. It is useful to visualize a quadrant consisting of two continuums – the level of innovation (radical vs. really new) and the price level (high vs. low). The terms same, horizontal, vertical, and opposite were used to describe how similar or different one innovation was from another. If an innovation was from the same quadrant, it meant that the innovations shared both the same level of innovation and the same price level. If an innovation was said to be from a horizontal quadrant, then it belonged to a different innovation classification, but stayed within the same price level. Likewise, if an innovation was said to belong to a vertical quadrant, it had the same innovation classification, but had a different price level. Finally, if an innovation was in an opposite quadrant, then both the innovation and price levels were different. Figure 2 shows how these terms are used in reference to the Personal Computer (radical, high-price) innovation. These descriptive terms are used to separate innovations into four analogous groups.  An analogous group is a collection of innovations that share both the same price level and innovation level.  For example, VCRs, Cordless Phones, and Telephone Answering Devices belong to the same analogous group.

**Figure 2:  How Descriptive Terms (*Same*, *Horizontal*, *Vertical*, & *Opposite*) are Used**

| Example:  Forecasting PCs | | |
|---|---|---|
| **Price Level** | **Radical Innovation** | **Really New Innovation** |
| High | PCs (point of reference) | Camcorders (*horizontal* quadrant) |
| | Satellite Receivers (*same* quadrant) | Projection TVs (*horizontal* quadrant) |
| Low | CD Players (*vertical* quadrant) | Cordless Phones (*opposite* quadrant) |
| | | Telephone Answering Device (*opposite* quadrant) |
| | | VCRs (*opposite* quadrant) |

## HYPOTHESES

Based on the three general research questions, some specific hypotheses were developed.  These hypotheses were created to either provide confirmatory support or falsify assumptions behind the research questions.

**Hypothesis 1.** Forecasts using parameters from the same quadrant for a dataset will be more accurate than forecasts using parameters from other quadrants.

a. Forecasts using parameters from the same quadrant will be significantly more accurate (have less error) than forecasts using parameters from the opposite quadrant.
b. Forecasts using parameters from the same quadrant will be significantly more accurate than forecasts using parameters from horizontal quadrants.
c. Forecasts using parameters from the same quadrant will be significantly more accurate than forecasts using parameters from vertical quadrants.
d. This will be most apparent in comparison to forecasts using parameters from opposite quadrants.
    i. $Z_{H1a} > Z_{H1b}$
    ii. $Z_{H1a} > Z_{H1c}$

**Hypothesis 2.** Forecasts using parameters from adjacent (horizontal and vertical) quadrants for a dataset will be more accurate than forecasts using parameters from opposite quadrants.

a. Forecasts using parameters from a vertical quadrant will be significantly more accurate than forecasts using parameters from the opposite quadrant.
b. Forecasts using parameters from a horizontal quadrant will be significantly more accurate than forecasts using parameters from the opposite quadrant.

**Hypothesis 3.** The level of innovation will have a greater impact on the accuracy of a forecast than the price level.  (i.e., forecasts using parameters from a vertical quadrant will be significantly more accurate than forecasts using parameters from horizontal quadrants.)

## DATA SOURCES

In many cases, the specific time point when an innovation was first made available is largely a matter of interpretation.  For the purposes of this diffusion research, an innovation was considered to be first available when it met the following conditions.

1) The innovation had to be available to consumers nationwide.
2) The innovation should be available as a complete product – not merely plans or parts to be assembled by a skilled hobbyist.
3) The innovation had to free of burdensome regulations that would inhibit adoption of the innovation.

The overwhelming majority of the data was obtained from the Consumer Electronics Association (CEA), formerly the Consumer Electronic Manufacturers Association.  With the exception of the CD Player dataset, the

CEA data started several years after the introduction of the product. Other sources were obtained to fill in the missing data wherever possible. In some cases, the missing data had to be partially extrapolated.

**MODELS**

Starting with the established diffusion models listed in Table 1, a manageable number of models were selected for this research according to expert recommendation (e.g. Meade and Islam 2001) and exploratory research which indicated the FLOG Box & Cox was more robust within the consumer electronic context than the other models. Two variant models, a Bass variant and a Generalized Bass (Price) variant, were also included. As a check on this selection of models, an additional forecasting expert was consulted. After review, the additional expert concurred with the authors' decision. Thus, the following seven models were tested in this research: the Bass model (B), the Generalized Bass model – Price (GB), a Bass model variant (Bv), a Generalized Bass model variant (GBv), the Simple Logistic model (SL), the Gompertz model (G), and the FLOG Box & Cox model (BnC).

**BASS MODEL (B)**

The Bass 1969 model has been stated in many forms. This research used the Lilien, Rangaswamy, and Van Den Bulte's (2000) transfiguration of Bass $x(t) = \left[ p + q(\frac{X(t-1)}{m}) \right] \left[ m - X(t-1) \right]$ as it is common in the literature and since Lilien et al. (2000) also provided a large list of Bass parameters.

**BASS MODEL VARIANTS (BV, GB, AND GBV)**

The Generalized Bass model (Bass, Krishnan, and Jain, 1994) was developed to consider the impact of price and advertising in forecasts. Since the datasets provided by the CEA were industry data, information on average pricing was available, but individual firms did not share their related advertising expenditures. Thus a Price-only variant of the Generalized Bass model was used. This equation $x(t) = \left[ p + q(\frac{X(t-1)}{m}) \right] \left[ m - X(t-1) \right] [1 + B(\frac{\Pr(t) - \Pr(t-1)}{\Pr(t-1)})]$ is a subset of the complete Generalized Bass model (GB).

In the process of setting up all the models, the authors became intrigued by the Bass constraint that *m* should remain constant for both the Bass and Generalized Bass models. In the market of interest, the number of US households is continually expanding. Therefore two variant Bass models were also developed that allowed *m* to change over the period to be forecast. Therefore a changing *m* variant was created by the authors for both the Bass model and Generalized (Price) Bass model. The equation for the Bass model variant (Bv) used is $x(t) = \left[ p + q(\frac{X(t-1)}{m(t)}) \right] \left[ m(t) - X(t-1) \right]$ and the equation for the Generalized Bass (Price) model variant (GBv) is $x(t) = \left[ p + q(\frac{X(t-1)}{m(t)}) \right] \left[ m(t) - X(t-1) \right] [1 + B(\frac{\Pr(t) - \Pr(t-1)}{\Pr(t-1)})]$.

The authors investigated changing *m* variants for the other models, but given how the other three models were structured, allowing *m* to change with *t* had zero impact on the results.

**SIMPLE LOGISTIC (SL) & GOMPERTZ (G)**

The Simple Logistic and Gompertz models (Gregg, Hossel & Richardson, 1964) are some of the earliest and simplest diffusion models. Meade & Islam's (2001) transfigurations were used. The equation for the Simple Logistic is $X(t) = \frac{m}{1 + c\exp(-bt)}$ and the equation for the Gompertz is $X(t) = m\exp(-c(\exp(-bt)))$.

#### Flexible logistic (FLOG) – Box and Cox (BnC)

Bewley and Fiebig (1988) developed several flexible logistic models that used the base equation $X_t = \dfrac{m}{1 + c\exp-(B(t))}$. Multiple variants use different formulas for $B(t)$. The Box and Cox model uses $B(t) = (b\dfrac{(1+t)^k - 1}{k})$.

The Box and Cox model has a tendency for one of its variables ($c$) to tend to infinity in some cases. Since using such extreme values would cause the parameters to give poor results for other cases, a cap of 100,000 was placed on the $c$ variable in this research. This value allowed the BnC model to be viable with all the datasets.

#### Verification of Models

The Lilien, Rangaswamy, and Van Den Bulte's (2000) Bass model was verified by comparing its results to other Bass formulas (Meade and Islam 2001 and Bass 1969), and comparing the Bass parameters obtained from this research with those listed by Lilien et al (2000). The innovations listed by Lilien et al overlapped with four of the datasets used in this study. The other models were reviewed to ensure they were working as expected and giving similar results similar to the Bass model.

#### Curve Fitting

In order to calculate which seven diffusion models had the potential to work best, all seven models were run with the eight innovation datasets provided by the CEA. Only the CEA datasets were used as they contained perfect (non-extrapolated) information for these fifty-six models. The curve fitting exercise was then duplicated with the extended datasets. The extended datasets cover the time period of interest for the forecasting.

#### Forecasting

The model parameters obtained through extended curve-fitting procedures were used to create the forecasts. The parameters from each of the 8 innovations were used to forecast the diffusion of the other 7 innovations. This was done for each of the seven models. Thus, a total of 392 forecasts were created. As part of the forecasting analysis, it was clear that the Generalized Bass models were not as well suited for diffusion forecasts as the other models, so the GB models were not used for the quadrant analysis.

#### Hypotheses Testing (Quadrant Analysis)

Using the squared sum of errors obtained by the forecasting models, the results for each forecast were used to compare the relative importance of price level and innovation type. This was done in two ways. First, each forecasting method was reviewed as a whole and segmented by the two price levels and two innovation levels. Then the specific hypotheses were tested by seeing how many results predicted by the hypotheses were actually correct. This provided two distinct methods of looking at the price levels, innovation levels, and forecast method.

While analyzing this information, it became clear that forecasts based upon the PC parameters did not work as well as the parameters from other innovations. A posteriori, this may be because PCs may have been purchased for reasons other than home entertainment such as home offices or education. Given the unique characteristics of the personal computer diffusion curve, the quadrant analyses were repeated without using the PC dataset.

## RESULTS

#### Potential Fit of Models

After determining and using the optimal parameters for seven models, the sum of the squared errors (SSE) were obtained by subtracting the curve-fitting results from the actual results in order to show how well each model did in comparison to one another for each innovation. One can make a case for measuring the best and worse models by either the total SSE (Table 3) or by their cumulative placement rankings (Table 4).

**Table 3: Curve Fitting Results**

| Innovation (data starts) | $e^2$ of B | $e^2$ of Bv | $e^2$ of GB | $e^2$ of GBv | $e^2$ of SL | $e^2$ of G | $e^2$ of BnC |
|---|---|---|---|---|---|---|---|
| PCs (1980) | 0.011 | 0.012 | 0.007 | 0.007 | 0.016 | 0.015 | 0.013 |
| Sat. Receivers (1986) | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| VCRs (1974) | 0.074 | 0.063 | 0.036 | 0.029 | 0.055 | 0.017 | 0.027 |
| CD Players (1983) | 0.038 | 0.033 | 0.035 | 0.031 | 0.047 | 0.016 | 0.008 |
| Camcorders (1985) | 0.002 | 0.002 | 0.002 | 0.002 | 0.007 | 0.004 | 0.003 |
| PTVs (1984) | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.001 |
| Cordless Phones (1980) | 0.005 | 0.005 | 0.005 | 0.005 | 0.007 | 0.012 | 0.005 |
| TADs (1982) | 0.021 | 0.018 | 0.011 | 0.011 | 0.042 | 0.012 | 0.006 |
| Total SSE: | 0.153 | 0.135 | 0.097 | 0.087 | 0.177 | 0.077 | 0.064 |

**Table 4: Curve Fitting - Comparative Placement**

| Innovation (data starts) | B | Bv | GB | GBv | SL | G | BnC |
|---|---|---|---|---|---|---|---|
| PCs (1980) | 3 | 4 | 1 | 2 | 7 | 6 | 5 |
| Sat. Receivers (1986) | 4 | 5 | 2 | 3 | 1 | 6 | 7 |
| VCRs (1974) | 7 | 6 | 4 | 3 | 5 | 1 | 2 |
| CD Players (1983) | 6 | 4 | 5 | 3 | 7 | 2 | 1 |
| Camcorders (1985) | 3 | 4 | 1 | 2 | 7 | 6 | 5 |
| PTVs (1984) | 5 | 4 | 3 | 2 | 7 | 1 | 6 |
| Cordless Phones (1980) | 4 | 2 | 3 | 1 | 6 | 7 | 5 |
| TADs (1982) | 6 | 5 | 2 | 3 | 7 | 4 | 1 |
| Total: | 38 | 34 | 21 | 19 | 47 | 33 | 32 |

Judging by total SSE, the Box and Cox model is the best potential model (.064) given perfect information. However, if one uses the comparative placement method, the Generalized Bass variant is the best potential model. In either case, the Simple Logistic model is clearly the worse potential model. However, it is important to note that even the Simple Logistic model only had a total SSE of 0.177 for all eight innovations. Since this was a curve-fitting exercise, not a forecast, the accuracy of the various diffusion models is not surprising. At the .05 level of testing, there were no significant differences between any of the seven models.

### OPTIMAL PARAMETERS

The curve fitting exercise was duplicated with the extended datasets to determine the optimal parameters for each model. For the Box and Cox model, an upper limit of 100,000 was used for variable c.

**Table 5: Curve Fitting - Optimized Parameters for B, Bv, GB, and GBv Models**

| | B | | Bv | | GB | | | GBv | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | p | q | p | q | p | q | B | p | q | B |
| **PCs** | 0.0076 | 0.1267 | 0.0076 | 0.1453 | 0.0075 | 0.1401 | -1.5073 | 0.0074 | 0.1604 | -1.536 |
| **Sat. Receivers** | 0.0003 | 0.2604 | 0.0003 | 0.2771 | 0.0005 | 0.2586 | 1.0531 | 0.0005 | 0.2747 | 1.0545 |
| **VCRs** | 0.0014 | 0.3554 | 0.0013 | 0.3871 | 0.0017 | 0.2243 | -8.5919 | 0.0017 | 0.253 | -7.7575 |
| **CD Players** | 0.017 | 0.223 | 0.0164 | 0.2494 | 0.016 | 0.2603 | 1.5604 | 0.0154 | 0.2889 | 1.5009 |
| **PTVs** | 0.0088 | 0.1329 | 0.0087 | 0.1499 | 0.0023 | 0.1195 | -8.9563 | 0.0022 | 0.1319 | -9.1342 |
| **Camcorders** | 0.0054 | 0.0515 | 0.0054 | 0.0651 | 0.006 | 0.0547 | 4.2393 | 0.0059 | 0.0691 | 3.567 |
| **Cordless Phones** | 0.0039 | 0.2313 | 0.0038 | 0.2552 | 0.0041 | 0.236 | 0.7047 | 0.0039 | 0.2607 | 0.7328 |
| **TADs** | 0.0049 | 0.2175 | 0.0048 | 0.2418 | 0.0053 | 0.2188 | 0.4371 | 0.0036 | 0.2352 | -1.6927 |

**Table 5: Curve Fitting - Optimized Parameters for SL, G, and BnC Models**

| | SL | | G | | BnC | | |
|---|---|---|---|---|---|---|---|
| | b | c | b | c | p | q | B |
| **PCs** | 0.1599 | 35.2554 | 0.0865 | 4.9556 | 0.8919 | 224.4 | 0.3748 |
| **Sat. Receivers** | 0.2403 | 1016.76 | 0.0856 | 12.1903 | 1.2582 | 26500 | 0.4417 |
| **VCRs** | 0.3705 | 632.638 | 0.2566 | 55.7292 | 2.2013 | 100000 | 0.3718 |
| **CD Players** | 0.2839 | 30.4163 | 0.1877 | 6.2126 | 6.3438 | 100000 | -0.2766 |
| **PTVs** | 0.1828 | 38.4293 | 0.0898 | 4.6937 | 2.7401 | 2118.1 | -0.0818 |
| **Camcorders** | 0.1236 | 54.1284 | 0.0458 | 4.4081 | 2.4619 | 1560.3 | -0.1931 |
| **Cordless Phones** | 0.2431 | 95.7757 | 0.153 | 11.5618 | 0.7533 | 534.4 | 0.6042 |
| **TADs** | 0.2377 | 78.5701 | 0.1543 | 11.0536 | 3.8056 | 100000 | 0.0193 |

**ACTUAL FIT OF MODELS (FORECASTING)**

For the purposes of forecasting the consumer adoption of innovations, the Generalized Bass models were not as reliable as the other five diffusion models. Therefore, only the results of the other five models were presented here. For each of the eight innovations, forecasts were created by using the optimal parameters of the other seven innovations. The results for the five diffusion models still of interest were tabulated by both sum of the squared errors and by the comparative placement method.

**Table 6: Forecasting Results for Five Models**

| | Total SSEs | | | | | Total Placement Scores | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Forecasts of | SSE of B | SSE of Bv | SSE of SL | SSE of G | SSE of BnC | B | Bv | SL | G | BnC |
| PCs | 5.865 | 5.822 | 6.007 | 5.809 | 5.543 | 15 | 23 | 21 | 25 | 21 |
| Sat. Receivers | 13.15 | 13.34 | 13.44 | 13.15 | 12.726 | 16 | 24 | 23 | 26 | 16 |
| VCRs | 13.52 | 13.85 | 12.45 | 14.04 | 14.658 | 20 | 11 | 30 | 25 | 19 |
| CD Players | 11.35 | 11.24 | 11.58 | 11.46 | 11.337 | 16 | 15 | 25 | 28 | 21 |
| PTVs | 5.382 | 5.531 | 5.486 | 5.61 | 5.426 | 18 | 22 | 16 | 29 | 20 |
| Camcorders | 2.229 | 2.249 | 2.329 | 2.409 | 2.294 | 20 | 26 | 14 | 22 | 23 |
| Cordless Phones | 6.773 | 6.751 | 6.546 | 6.787 | 6.868 | 16 | 21 | 16 | 27 | 25 |
| TADs | 7.147 | 7.106 | 6.919 | 7.01 | 7.126 | 20 | 25 | 22 | 18 | 20 |

To comply with space constraints, Table 6 summarizes sixteen original tables, but may be more difficult to follow. Lower numbers indicate more accuracy.

**Hypotheses Testing (Quadrant Analysis)**

While the previous set of tables looked at the forecasts for each innovation, the following set of tables looks at of the forecasts as a whole and then as segments. The Bass model performed the best overall for forecasting the diffusion of *all* innovations with a SSE of 65.4 (second best) and placing first in the comparative results. However, the results are not statistically significant. For forecasting the diffusion of *radical* innovations, the Bass model and the Box and Cox model performed the best with respective SSEs of 30.4/29.6 and placements of first/second in the comparative results. For forecasting the diffusion of *really new* innovations, the Bass model and the Simple Logistic model performed the best with respective SSEs of 35.0/33.7 and placements of first/second in the comparative results. The Box and Cox model performed the best overall for forecasting the diffusion of *radical, high-priced* innovations with a SSE of 18.3 and placing second in the comparative results. The Bass model variant performed the best overall for forecasting the diffusion of *radical, low-priced* innovations with a SSE of 11.2 and placing first in the comparative results. The Bass model performed the best overall for forecasting the diffusion of *really new, high-priced* innovations with a SSE of 7.6 and placing first in the comparative results. The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *really new, low-priced* innovations with respective SSEs of 27.4/25.9 and placements of first/second in the comparative results. The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *low-priced* innovations with respective SSEs of 38.8/37.5 and placements of first/second in the comparative results. The Bass model and the Box and Cox model performed the best overall for forecasting the diffusion of *high-priced* innovations with respective SSEs of 26.6/26.0 and placements of first/second in the comparative results.

#### CELL TESTING (HYPOTHESES TESTING)

The specific hypotheses discussed earlier were tested by measuring the differences between the sum of squared errors for forecasts using parameters from various quadrants. Since the hypotheses made specific predictions about the accuracy of various comparisons, the total number of successful predictions was counted to compute the binomial distribution (Berry and Lindgren, 1996).

**Table 28: Results of Cell Comparisons**

| | n | number correct | percent correct | z score |
|---|---|---|---|---|
| H1 | 270 | 206 | 76.3% | 8.6** |
| H1a (opp) | 100 | 85 | 85.0% | 7.0** |
| H1b (hz) | 70 | 40 | 57.1% | 1.2 |
| H1c (vt) | 100 | 81 | 81.0% | 6.2** |
| H2 | 280 | 173 | 61.8% | 3.9** |
| H2a (vt vs. op) | 140 | 73 | 52.1% | 0.5 |
| H2b (hz vs. op) | 140 | 100 | 71.4% | 5.1** |
| H3 | 140 | 33 | 23.6% | -6.3** |

**P < 0.01

Strong support for the first two hypotheses was found, although the results for hypotheses H1b and H2a were not significant. Support for H1d (not shown on Table 28) was also found as $Z_{H1a} > (Z_{H1b}; Z_{H1c})$. Not only was support lacking for the third hypothesis, but it was clearly refuted.

#### QUADRANT ANALYSIS WITHOUT PCS

Because the diffusion of PCs followed a pattern that differed from the other consumer electronic innovations, the quadrant analysis was repeated without using this dataset. The results are generally consistent with previous analysis except for some minor difference. Bass model did not show best performance for diffusion of *radical* innovations and *really new*, *low-priced* innovations. The Simple Logistic model did not show best performance for forecasting the diffusion of *low-priced* innovations.

#### CELL TESTING (HYPOTHESES TESTING) WITHOUT PCS

**Table 29: Results of Cell Comparisons**

| | n | number correct | percent correct | z score |
|---|---|---|---|---|
| H1 | 170 | 146 | 85.9% | 9.4** |
| H1a (opp) | 40 | 40 | 100.0% | 6.3** |
| H1b (hz) | 40 | 35 | 87.5% | 4.7** |
| H1c (vt) | 90 | 71 | 78.9% | 5.5** |
| H2 | 170 | 132 | 77.6% | 7.2** |
| H2a (vt vs. op) | 85 | 57 | 67.1% | 3.1** |
| H2b (hz vs. op) | 85 | 75 | 88.2% | 7.1** |
| H3 | 85 | 31 | 36.5% | -2.5** |

**P < 0.01

Strong support for the first two hypotheses was found, the results for all sub-hypotheses were significant. Support for H1d (not shown on Table 29) was also found as $Z_{H1a} > (Z_{H1b}; Z_{H1c})$. Not only was support still lacking for the third hypothesis, but it was also clearly refuted.

## DISCUSSION

This research has provided additional support for the view that no single forecasting method is best for every situation, although the Bass model comes pretty close. The unique contribution of this forecasting research was in providing guidance for selecting forecasting models in various price and innovations contexts.

### Answering the Research Questions

When forecasting the diffusion of a radical high-priced innovation, one should use the Box & Cox model. It is recommended that one also generate a Bass model forecast if a second opinion is desired. When forecasting the diffusion of really new high-priced innovation, one should use the Bass model with the Box & Cox model serving as a backup. The Bass variant model should be used when forecasting the diffusion of low-priced radical innovations, with either the Bass model or the Box & Cox model providing a second opinion. When forecasting the diffusion of low-priced really new innovations, the Simple Logistic model should be used. The robust Bass model may also be used if multiple models are desired.

**Figure 3: Recommended Models by Context**

| Recommendations for Consumer Innovations | | |
|---|---|---|
| **Price Level** | **Radical Innovation** | **Really New Innovation** |
| High | Box & Cox | Bass |
| | Bass | Box & Cox |
| Low | Bass variant | Simple Logistic |
| | Bass / Box & Cox | Bass |

### Lessons From the Hypotheses

Hypotheses 1 and 2 stated that the various combinations of innovation levels (radical and really new) and price levels (high and low) would result in four populations that were significantly different from one another. The research supported these claims. As theorized, parameters from populations that were different in terms of both innovation level and price level did less well than parameters from more similar populations.

Hypothesis 3 presumed that the level of innovation would have a greater impact on the accuracy of a forecast than the price level. This presumption was clearly wrong. Not only did the research falsify it, it did so to such an extent that the opposite statement appears to be true. The price level of an innovation actually has more impact on the accuracy of a forecast than the innovation level.

### Models

The Box and Cox and Generalized Bass models were the best models when it came to curve-fitting while the Simple Logistic model did the poorest. However, the results of the research showed that a curve-fitting advantage did not translate into a forecasting advantage when creating a forecast for an innovation without a market history. The popularity of the Bass model derives from two unique factors. As this research has reinforced, the Bass model is very robust. In addition, the Bass model's two coefficients have a theoretical foundation. The Bass model variants created for this research deliberately violated the assumption of a constant $m$. This resulted in a model (Bv) that outperformed any of the others in the radical low-priced innovation context. Unfortunately, there was just one innovation in this context – additional research is recommended to test the viability of this variation with more datasets in various contexts.

The Simple Logistic model is one of the oldest diffusion models known. It is a very basic model, but it clearly outperformed the other models in the context of really new low-priced innovations. The Gompertz model it is not recommended for forecasting the diffusion of really new or radical innovations before the launch of an innovation. However, the Gompertz model may be very well suited for forecasts generated well after the launch of an innovation. While not the focus of this research, it was observed that the diffusion of the Projection Television innovation follows a perfect Gompertz curve.

The Flexible Logistic Box and Cox model has a problem where the $c$ variable tends to run to infinity in some scenarios. This was addressed by capping the upper limit of $c$ to 100,000. Despite (or because of) this fix, the authors must admit to being skeptical as to how well the Box and Cox model would do in comparison to the other models. As it turned out, the Box and Cox was second only to the Bass model in terms of robustness. The Box and Cox was also the best model in the context of radical high-priced innovations.

## REFERENCES


Armstrong, J. S. (2001). Principles Of Forecasting: A Handbook For Researchers And Practitioners. Boston: Kluwer Academic Publishers.

Armstrong, J. S., Brodie, R., & McIntyre, S. H. (1987). Forecasting Methods For Marketing: Review Of Empirical Research. International Journal of Forecasting, 3, 355-376.

Bass, F. M. (1969). A New Product Growth Model For Consumer Durables. Management Science, 15, 215-227.

Bass, F. M., Krishnan, T. V., & Jain, D. C. (1994). Why The Bass Model Fits Without Decision Variables. Marketing Science, 13, 203-223.

Bass, F. M (1978). An Integration of the New Product Growth Model with the Experience Cost function and Optimal Pricing. Presented at the TIMS/ORSA National Meeting in New York City, May, 1978.

Berry, D. A. & Lingren, B. W. (1996). Statistics: Theory And Methods. (second ed.) New York: Duxbury Press.

Bewley, R. & Fiebig, D. (1988). Flexible Logistic Growth Model With Applications In Telecommunications. International Journal Of Forecasting, 4, 177-192.

Bright, J. R. (1978). Practical Technology Forecasting. Austin: The Industrial Management Center, Inc.

Cetron, M. J. & Ralph, C. A. (1971). Industrial Applications Of Technological Forecasting: Its Utilization In R&D Management. New York: Wiley-Interscience.

Chow, G. C. (1967). Technological Change and the Demand for Computers. American Economics Review, 57(December), 1117-1130.

Dodson, J. A. and Muller, E. (1978). Models of New Product Diffusion Through Advertising and Word-of-mouth. Management Science, 24 (November), 1568-1578.

Easingwood, C., Mahajan, V., & Muller, E. (1981). A Non-Symmetric Responding Logistic Model For Forecasting Technological Substitution. Technological Forecasting and Social Change, 20, 199-213.

Easingwood, C., Mahajan, V., & Muller, E. (1983). A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance. Marketing Science, 2(summer), 199-213.

Garcia, R. & Calantone, R. (2002). A Critical Look At Technological Innovation Typology And Innovativeness Terminology: A Literature Review. Journal of Product Innovation Management 110-132.

Gentry, L., Calantone, R., & Cui, S. (2006). The Forecasting Classification Grid: A Typology for Method Selection. Journal of Global Business Management, Volume 2, Number 1, pages 48-60.

Gregg, J. V., Hossell, C. H., & Richardson, J. T. (1964). Mathematical Trend Curves: An Aid To Forecasting. Edinburgh: Oliver & Boyd.

Horsky, D. (1990). A Diffusion Model Incorporating Product Benefits, Price, Income and Information. Marketing Science, 9 (4), 342-365.

Horsky, D. and Simon,L. S. (1983). Advertising and the diffusion of New Products. Management Science, 1 (winter), 1-18.

Jain, D. C., Mahajan, V., & Muller, E. (1991). Innovation Diffusion in the Presence of Supply Restrictions. Marketing Science, 10(1), 83-90.

Jain, D. C. and Rao, R. C. (1990). Effect of Price on the Demand for Durables: Modeling, Estimation, and Findings. Journal of Business & Economic Statistics. 8 (2), 163 –170.

Jantsch (1967). Technological Forecasting In Perspective. Paris: Organization For Economic Co-Operation And Development (OECD).

Kalish, S. (1985). A New Product Adoption Model With Pricing, Advertising and Uncertainty. Management Science, 31 (December), 1569-1585.

Kamakura, W. A. and Balasubramanian, S. K. (1988). Long-term View of the Diffusion of Durables. International Journal of Research in Marketing, 5, 1-13.

Lackman, C. L. (1978). Gompertz Curve Forecasting: A New Product Application. Journal of the Market Research Society, 20 (January), 45-47.

Lenz, R. C. J. (1971). Technological Forecasting Methodology. In M.J.Cetron & C. A. Ralph (Eds.), Industrial Applications of Technological Forecasting: Its Utilization in R&D Management (pp. 225-242). New York: Wiley-Interscience.

Lilien, G. L., Rangaswamy, A., & Van Den Bulte, C. (2000). Diffusion Models: Managerial Applications And Software. In V.Mahajan, E. Muller, & Y. Wind (Eds.), New-Product Diffusion Models (pp. 295-311). Boston: Kluwer Academic Publishers.

Mahajan, V. and Peterson, R. A. (1978). Innovation Diffusion in a Dynamic Potential Adopter Population. Management Science, 24 (November), 1589-1597.
Mahajan, V. and Peterson, R. A. (1979). Integrating Time and Space in Technological Substitution Models. Technological forecasting and Social Change, 14 (August), 231-241.
Meade, N. (1985). Forecasting Using Growth Curves--An Adaptive Approach. Journal of the Operational Research Society, 36, 1103-1115.
Meade, N. & Islam, T. (2001). Forecasting The Diffusion Of Innovations: Implications For Time-Series Extrapolation. In J.S.Armstrong (Ed.), Principles of Forecasting: A Handbook for Researchers and Practitioners Boston: Kluwer Academic Publishers.
Nelder, J. A. (1962). An Alternative Form of a Generalized Logistic Equation. Biometrics, 18 (December), 614-616.
Peterson, R. A. and Mahajan, V. (1978). Multi-Product Growth Models. In J. Sheth (Ed.), Research in Marketing, Greenwich, CT: JAI Press, Inc.
Robinson, B. and Lakhani, C. (1975). Dynamic Price Models for New Product Planning. Management science, 10(June), 1113-1122.
Simon, H. and Sebastian, K. (1987), Diffusion and Advertising: The German Telephone Company. Management Science, 33 (April), 451-466.
Tanner, J. C. (1978). Long Term Forecasting Of Vehicle Ownership And Road Traffic. Journal of the Royal Statistical Society, Series A, 141, 14-63.
Von Bertalanffy, L. (1957). Quantitative Laws in Metabolism and Growth. Quarterly Review of Biology, 32, 217-231.