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Beyond Diffusion: An Affordability Model of the Growth of New Consumer Durables

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ABSTRACT
A firm's ability to compete in new product markets is vital to its profitability and long-term survival. Therefore, it is important to understand the development and growth of these markets. Following a pioneering study by Bass (1969), diffusion models have traditionally provided this understanding in marketing. The great appeal of the Bass model is that it is a simple one that fits the data very well and provides parameters that have an intuitive behavioural interpretation. The model suffers from three well-known limitations: (1) it does not include marketing variables that could influence new product diffusion and sales; (2) the model's parameters are unstable; and (3) the model's forecasts are inaccurate before the sales peak and especially prior to the point of inflection. Subsequent research has made progress especially in extending the Bass model to include marketing variables. However, the extensions have come at the cost of simplicity: the new models are far more complex than the simple Bass model. We propose an alternate simple model of new product growth for consumer durables, based on the concept of affordability rather than on diffusion. We compare this model with the diffusion model in terms of fit, stability and validity of parameters, and forecasting ability. The alternate model is a little inferior to the diffusion model in fit, but superior in terms of the stability and validity of parameters and forecasting ability. We discuss the limitations and implications of our model. © 1998 John Wiley & Sons, Ltd.

KEY WORDS diffusion of innovations; new products; forecasting

INTRODUCTION

Markets for new durables present great opportunities for new firms to become major business enterprises. For a current marketer of durables, the ability to compete in new markets may be vital to its profitability and long-term survival. Thus an understanding of the growth of new consumer durables is critical to management of these products.

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Following an early paper (Bass, 1969), the Bass diffusion model became the standard for analysing the growth of new consumer durables, in the marketing literature. The survival and success of the Bass model is due to three important attributes. First, the model is a simple one, with only three parameters that can be easily estimated. Second, the model fits the trend in sales growth of new products very well. Third, estimates of two key parameters (p and q) of the model have intuitively appealing interpretations as coefficients of innovation and imitation. Innovation and imitation are the main drivers of the theory that underlies the Bass model, the diffusion of innovations.

Despite its strengths, the Bass model suffers from some well-known limitations. First, it does not include any marketing variables. Intuitively, researchers believe that price and advertising are likely to influence the growth of new products. Second, the model's parameters are unstable. These parameters can fluctuate substantially from year to year as new observations are added, especially prior to the first peak in sales (Heeler and Hustad, 1980; Mahajan, Muller and Bass, 1990; Van den Bulte and Lilien, 1996). Third, as a result of this instability, the model's forecasts are not accurate, unless the entire growth history is included (Mahajan, Muller and Bass, 1990). That is, the full growth history, or at least sales beyond the point of inflection, is necessary to overcome parameter instability and make accurate forecasts. But waiting for complete data reduces the model's usefulness. In the words of Mahajan, Muller and Bass (1990, p. 9), 'Parameter estimation for diffusion models is primarily of historical interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes'.

Numerous extensions have been proposed to overcome these problems. However, all these models succeed at a greater or lesser cost to simplicity. We review the Bass model and its limitations, and mention efforts of some researchers to overcome those limitations. We then propose a well-accepted model from economics which maintains the elements of simplicity while addressing the key problems of the Bass model. We also discuss several limitations of our own approach and the situations in which it may be more relevant than traditional diffusion models.

The following sections of the paper present the theoretical background, model, data and empirical results. We conclude with a discussion.

THE DRIVERS OF NEW PRODUCT GROWTH

Following the theoretical work of Rogers (1995), most marketers think of the growth of durables as the result, primarily, of the diffusion of the innovation among buyers. Further, following the interpretation of p and q as coefficients of innovation and imitation (Bass, 1969), marketers have tended to equate diffusion as primarily communication between these two groups of consumers.[1] As a result, the diffusion of innovations is often presented as a social theory of communication (Mahajan, Muller and Bass, 1990). It describes how 'information about an innovation is transmitted to or within the social system' (Mahajan, Muller and Bass, 1990, p. 1).

However, other demand factors may also support diffusion. Examples of these factors are social acceptability, uncertainty reduction and changes in beliefs. Several extensions of the Bass model have tried to capture these multiple dimensions of diffusion (e.g. Jeuland, 1981; Kalish, 1985; Roberts and Urban, 1988). Other extended diffusion models have considered economic factors to explain more fully the spread of durables (e.g. Kalish, 1985; Roberts and Urban, 1988;

[1] Although Jeuland (1981) offers an alternative interpretation of these parameters.

Lattin and Roberts, 1989; Horsky, 1990; Chatterjee and Eliashberg, 1990). Thus the trend in the literature has been to extend the Bass model to include other dimensions of diffusion as well as economic factors that may influence product growth.

While these attempts have been largely successful, they have come at a great cost: simplicity. The extensions of the Bass model tend to be increasingly complex, and have been difficult to estimate. Indeed, no single study has included *all* of the refinements to the Bass model that have been proposed in the literature.

To retain the simplicity of the Bass model while overcoming its limitations, we propose an alternate model of new product growth. Our model uses a Cobb–Douglas type function of economic factors as the primary determinants of new product sales. The model is based on the concept of affordability, rather than that of diffusion that underlies the Bass model. There are three reasons for our choice.

First, we believe that most consumers are informed about new durables long before purchasing them. Sales of new durables often take many years before they reach any meaningful level (Golder and Tellis, 1993). During this period, many consumers learn about new products. The press often trumpets the virtues of a new product as soon as it is introduced to the market, if not before (e.g. HDTV). A major reason consumers hold back from buying a new product is its high price.

Second, a review of the history of new consumer durables indicates that they first appear as very expensive items, often for a small professional or business market. Even though information about these products is available, they become attractive, first only to wealthy consumers, when their prices drop a little. Further, only when prices drop substantially do they appeal to the mass market (Holak, Lehmann and Sultan, 1987). For example, video tape recorders were first sold in 1956 to news and movie producers for about $50,000. They became popular consumer products only in the mid-1970s when prices fell below $1000 (Rosenbloom and Cusumano, 1987). The price history of most consumer durables follows a sharply declining path (Tellis and Golder, 1996). This trend along with log-normally distributed incomes may help to explain the S-shaped sales curve of new products (Russell, 1980). Kalish (1985) provided one of the earlier diffusion models which attempt to capture this phenomenon.

Third, by observing the history of new product introductions over time, consumers can learn that the latest, hottest innovation is invariably expensive. If they wait long enough, they can get today's hot item at a substantial discount tomorrow (Narasimham, 1989). Therefore, many consumers may delay their purchases until prices decline or incomes rise sufficiently. Thus affordability may be an important driver of the growth in sales of a new product.

Diffusion models certainly have many merits. In particular, they may be most appropriate for certain products with low prices (movies, books, music) or for products with very high benefits (agricultural and medical innovations). In the latter cases, affordability is less of an issue, and product adoptions depend primarily on diffusion of knowledge, social acceptability, or uncertainty reduction for the new product, or on popularity. However, for new big ticket consumer durables, affordability may be a more important factor. Studies which seek a full explanation of the growth of new products should model both affordability and diffusion (e.g. Horsky, 1990). Such modelling may be achieved through a two-stage process in which consumers first become aware of the innovation through diffusion and then purchase it as it becomes affordable.

However, our interest is in parsimoniously modelling the sales growth of new consumer durables which we believe is primarily driven by affordability. Our emphasis on only affordability is to keep the model simple. In the final analysis, whether affordability or diffusion offers more leverage is an empirical issue which depends on the comparative performance of the alternate models. In the empirical analysis, we compare the performance of our model to the Bass model and one major extension of the Bass model. We also discuss several limitations of our own approach and the situations in which it may be more relevant than traditional diffusion models.

PROPOSED MODEL

This section develops the model specification in terms of dependent variable, independent variables, and functional form of their relationship.

Specification

Dependent variable

To analyse the growth of a new durable, we choose total product sales (including replacements) as the dependent variable for three reasons. First, managers are primarily interested in forecasting total sales. In contrast, the Bass model can only logically examine first purchases. Second, by using sales, the proposed model may be applicable to the complete sales history rather than only a short period after takeoff which is the limitation when data are not split between first purchases and replacements. Third, since we believe sales of consumer durables are primarily the outcome of affordability and not communication, there seems to be no compelling need to split them up into adoptions and replacement purchases.[2] This position assumes that the impact of key variables such as price is the same on both groups.

Independent variables

Based on our earlier discussion, we argue that four explanatory variables—price, income, consumer sentiment, and market presence—are the major determinants of sales growth for consumer durables.

Price

Of all marketing variables, price has repeatedly been shown to have the strongest effect on sales. When compared to advertising elasticity, price elasticity is found to be eight to twenty times higher (Assmus, Farley and Lehmann, 1984; Sethuraman and Tellis, 1991; Tellis, 1988). The relatively weak effect of advertising raises some doubts about the central importance of communication in diffusion models. Even during introduction, price elasticity is greater than advertising elasticity. Further, the effect of price may be increasingly important as products mature and the price sensitivity of consumers increases (Simon, 1979; Tellis, 1988).

A causal relationship between price and purchase is central to economic theory. As the prices of products decline, sales increase. In cases where firms strive for the lowest possible price, sales often increase dramatically. For example, the introduction of Henry Ford's Model T led to a dramatic increase in the number of automobiles sold. During the 1970s, Texas Instruments' low-price strategy in calculators led to exponential sales growth.

[2] Many diffusion models use total sales (initial plus replacement) as a surrogate for initial sales.

Income

The role of income is well explicated in standard economic theory. Higher incomes raise the budget constraint of consumers, just as lower prices bring products within consumers' reach. Income variation within the population has been recognized for many decades as having an important impact on consumption. Higher incomes have been related to higher expenditures on discretionary goods (Bonus, 1973; Horsky, 1990). Although this relationship is almost universally accepted, the effect of changes in income *over time* is rarely considered in marketing models. The omission may be because most marketing models cover short periods of time during which incomes do not change much. However, the growth of new products spans many years and even decades. Over these long periods incomes change substantially. As average income increases for the population, sales of durables should increase, just as income differences across segments affect differences in consumption at any single time period.

Increases in income lead to three types of increases in sales: (1) greater first-time purchases (higher product penetration), (2) earlier replacement among prior adopters (higher repurchases), and (3) greater purchases of multiple units. A utility-maximizing model can handle all three of these phenomena.

Consumer sentiment

The sales of durable goods consistently show dramatic increases and decreases over short periods. Since income generally increases steadily over time, it is probably not responsible for these short-term variations in sales. The short-term sales fluctuations may be due to changes in consumer sentiment. As the aggregate economy changes, so do consumers' confidence in their current or future economic security. This confidence affects consumers' tendency to spend, especially for large discretionary items, such as durables.

The role of consumer sentiment can also be explained by prospect theory (Kahneman and Tversky, 1979; Thaler, 1985). An individual's income can be regarded as a reference point, to which the consumer compares short-term fluctuations in the economy. The difference between the income and any short-term changes in income would then be coded as gains or losses. Prospect theory suggests that these gains and losses may be bigger determinants of choice than income itself. It also suggests that changes in certain relevant economic variables may form a basis to capture consumer sentiment.

Because the role of consumer sentiment has been analysed for decades, it has many standard measures, e.g. consumer sentiment (Katona, 1975) or the Conference Board's measure of consumer confidence.

Market presence

While the previous three variables capture the major economic factors affecting the sale of durables, one other factor seems important to include. No matter how inexpensive the product is, or how high consumers' incomes are or how strong consumer sentiment is, the likelihood of purchase still increases as products become more visible and available to consumers. Widespread distribution will lead to higher market presence and will tend to increase the likelihood of new product success (Montgomery, 1975).

Market presence reflects the opportunities that potential consumers have to observe a product. These opportunities occur in several ways. First, as sales increase, interest and excitement among consumers about a product increases. This was certainly the case with pocket calculators and

VCRs as they caught the imagination and excitement of consumers. Conversely, consumer interest in some products may wane as it has with record players and black and white televisions.

Second, as sales of a product increase, retail promotions will increase leading to enhanced visibility. Since store displays are designed to attract consumers' attention and lead to sales, retailers promote products they know consumers have some interest in buying. Therefore, products capable of accomplishing this objective are those that already have a demonstrated sales record.

Third, as sales increase, the number of stores carrying a product will increase leading to enhanced visibility. Once consumers begin to buy a new product, additional stores carry that product. Also, more floor space is devoted to displaying these products. Therefore, the availability and visibility of a new product will depend on how well it has sold in the stores or markets where it was introduced. Strong initial performance will increase product visibility which will lead to higher sales.

Thus, market presence reflecting product visibility, product promotions or availability, may be a fourth major determinant of the sales of new durables.

Summary

On the basis of the preceding discussion, product sales are expressed mathematically as

$$S_t = f(P_t, I_t, CS_t, MP_t) \tag{1}$$

where

S = sales
P = price
I = income
CS = consumer sentiment
MP = market presence
t = subscript for time

Functional form

The difficulty of correctly modelling marketing phenomena is well known (Cooper and Nakanishi, 1988). Even where strong economic theory specifies relationships among variables, it does not specify the appropriate functional form (Judge *et al*., 1985). Therefore, flexible models are more desirable so results are not constrained (Judge *et al*., 1985). Moreover, we need to develop affordability-based models in an evolutionary manner (Urban, 1974), where complexity and detail are added only as needed. In our case, we need to consider three factors about sales growth. First, sales response to the variables in the model should be non-linear. Second, there should be interactions among the explanatory variables. Third, competition is not a factor, since we are modelling new category sales for which substitutes are not immediate (Cooper and Nakanishi, 1988).

Based on these factors and our goal of developing a simple model, we use a multiplicative form or the well-known Cobb–Douglas model. This model is flexible enough that results will not be constrained. Further, the multiplicative form yields many benefits such as non-linear response, parameters that are elasticities, well-known estimation techniques, interactions among explanatory variables and a straightforward approach to sales forecasting (Cooper and Nakanishi, 1988). Meta-analyses of econometric models of sales indicate that alternate functional forms do not yield consistently superior or even statistically different results (Assmus, Farley and Lehmann, 1984; Tellis, 1988).

Thus, we propose to test the following model:

$$S = P^{\beta_1} \times I^{\beta_2} \times CS^{\beta_3} \times MP^{\beta_4} \times e^{\varepsilon} \tag{2}$$

One limitation of this model is that of constant elasticity: that is, the functional form implies that the elasticity of each independent variable is constant over the range of values of that variable. We overcome this restriction by estimating parameters of the model iteratively as each year is added to the series for each of the categories. These results are presented as part of the analysis of parameter stability.

DATA

This section explains the sampling, data collection and measures used to estimate the model.

Sampling and data collection

We selected two samples of product categories. First, we chose five categories from those that have been commonly researched in previous studies. To enhance the external validity of the findings, we selected a second sample containing five newer categories. The ten categories and the periods considered are presented in Table I. The large number of categories we analyse compares very favourably with typical diffusion studies that analyse four or five categories on average.

We tapped multiple data sources including *Merchandising*, *Merchandising Week*, *Electrical Merchandising*, *Business Week*, *Advertising Age*, the *Statistical Abstract of the United States* and other Department of Commerce and Electronic Industries Association publications. Additional data from the Conference Board and the Survey Research Center at the University of Michigan were also collected.

We gathered data on the following variables: sales (in units), price (average price per year), ownership penetration, disposable income per capita, price indexes, consumer confidence, consumer expectations, and consumer sentiment. All dollar values are standardized to 1987 dollars.

Table I. Sample of categories

Product categories	Period
Clothes dryer	1947–61
Room air conditioner	1946–61
Colour television	1954–70
Dishwasher	1947–68
Electric blanket	1946–61
CD player	1983–91
Camcorder	1984–91
Home VCR	1976–91
Answering machine	1976–91
Microwave oven	1970–91

Measures

The proposed model describes sales as a function of price, income, consumer sentiment, and market presence. Sales, price and income are easily operationalized while consumer sentiment and market presence require more description.

Sales, price and income

The operational measure of sales is the number of units sold annually in the United States at the product category level. This approach follows those researchers applying diffusion models to sales data. The measure of price is the standardized average price for all units sold in that product category. Again, this approach follows that of researchers applying diffusion models that contain a price term. The measure of income is the standardized per capita disposable income in the United States. This measure represents the portion of national income that is available for individual consumers to spend.

Consumer sentiment

Consumer sentiment captures short-term income effects relative to a reference level of current income. This variable should take on positive and negative values. A straightforward measure would be to use the difference between consumer sentiment in each period and its mean over multiple periods. However, the Survey Research Center and the Conference Board did not report consumer sentiment or consumer confidence until many years after some of the products were introduced. Fortunately, the Survey Research Center has determined that consumer sentiment is strongly related to *changes* in real disposable income (Curtin, 1988). Therefore, in the interests of consistency, we use changes in real disposable income across all categories although consumer sentiment or consumer confidence could be used for more recent categories.

Since real disposable income increases most years, percentage changes do not capture the reference level effect. So our reference level is a moving 10-year average of changes in disposable income. Alternative numbers of years were considered for the reference period, but they had negligible effect on the measure. Therefore, the operational measure of consumer sentiment in each year is the real percentage change in disposable income per capita minus the average real percentage change in disposable income during the preceding 10 years. The correlation between our operational measure of consumer sentiment and actual consumer sentiment for the available data is 0.66. This degree of correlation is similar to that between consumer sentiment and consumer confidence which, over a 20-year period, is 0.69.

Market presence

The market presence variable captures the effect of interest and excitement among consumers and the opportunity to observe the product. The difficulty with incorporating this effect is that it is not possible to directly operationalize this variable. Therefore, it is necessary to adopt a proxy variable that is highly correlated with market presence.

Given our discussion of market presence, an ideal variable would be a measure of distribution intensity. However, this data was not available. An alternative measure reflective of market presence is current sales. Because current sales would make the model redundant, a reasonable alternative is prior period sales. This approach may seem similar to Bass' approach of operationalizing all possible imitation effects (awareness, social influence, word-of-mouth, etc.) as cumulative sales. However, our measure of market presence can increase and decrease. By considering only the immediate prior period, this variable will respond more quickly than cumulative sales to the current marketing environment. This ability to adjust quickly seems more reflective of market presence in actual markets.

MODEL ESTIMATION AND RESULTS

To estimate parameters of the proposed model, we linearize the model by taking logs of both sides. Because some values of consumer sentiment are negative, we increase each of these data by one prior to the transformation. With the log-transformed data we estimate the model using ordinary least squares.

To examine the robustness of the proposed model, we perform four tests. First, we found evidence of multicollinearity among the explanatory variables through analysis of correlation matrices and variance inflation factors. The variance inflation factor (VIF) is measured as follows:

$$\mathrm{VIF} = \frac{1}{1 - R_i^2} \tag{3}$$

where $R_i^2 =$ the coefficient of determination produced by regressing one explanatory variable against the other explanatory variables.

To address the difficulty of multicollinearity, we used ridge regression (Green, 1990). This method decreases the large standard errors of parameter estimates while allowing some bias in the estimates. Parameter estimates from ridge regression are determined as follows:

$$\mathbf{b} = [\mathbf{X}'\mathbf{X} + k\mathbf{I}]^{-1}\mathbf{X}'\mathbf{y} \tag{4}$$

where $k =$ shrinkage parameter. We determined the value of the shrinkage parameter with the ridge trace method (see Myers, 1990, adapted from Hoerl and Kennard, 1970). This method calls for plotting the parameter values versus the shrinkage parameter to find the point at which the parameters stabilize. For our data stabilization tended to occur at about 0.1, so we used this value for estimating parameters in all categories.

The second test we conducted to examine robustness of the proposed model was the Lagrange multiplier test developed by Durbin (1970) to test for autocorrelation. We did not use the standard Durbin–Watson statistic because it is biased in the presence of a lagged dependent variable. Results of this analysis indicate autocorrelation is not statistically significant. Third, we examined the possibility of spurious regressions due to a unit root (Engle and Granger, 1991). Results indicate that this problem is not evident. Fourth, we re-estimated the parameters of the proposed model on first differences of the data. If the model is valid, then these parameters should be similar to the parameters estimated from the non-differenced data. Results of this analysis indicate that the parameters are similar. These four analyses strongly support the robustness of results from the proposed model.

COMPARATIVE PERFORMANCE OF MODELS

Since diffusion models are now the accepted paradigm for modelling the growth of new durables, we compare the performance of the proposed model against two prototypical diffusion models. One is the standard Bass (1969) model estimated with non-linear least squares (Srinivasan and

Mason, 1986). The second model is one proposed by Jain and Rao (1990) to include the effect of price, a key explanatory variable in our model.

We use three criteria to evaluate the performance of the proposed model against the two diffusion models: (1) model fit, (2) parameter stability and validity, and (3) forecasting ability. Use of the latter two criteria require estimation of each of the models over multiple periods *on each category*. That is, we begin by estimating each model on a short data series—four years for the three-parameter Bass model and five years for the two four-parameter models. Then we repeatedly estimate each model in each category after adding one more year to the series. Our analysis requires estimating over *120 parameters for each category* on average. This approach is tedious but necessary for a rigorous comparison. It also has much managerial relevance, because that is how a new product's manager obtains and analyses data. Final results are based on over *1200* parameter estimates, for 10 categories.

Criterion 1: Model fit

We first present estimation results for our model in Table II. Since we estimate the model over multiple periods in all categories, we present the average parameter estimates across these multiple periods as well as the estimates for the full period. In almost all cases, the parameters have the correct sign and in the majority of cases they are statistically significant. These results support the inclusion of these variables as determinants of sales growth.

Table III presents the fit statistics for each category and the average and median across categories. The Bass model provides a very good fit, but the Jain–Rao model has the best fit. This evidence supports the inclusion of price. The average fit of the proposed model is not as good as the Bass and Jain–Rao models. However, in terms of *R*-square, the average fit of the proposed model is still very high at 94%.

Based on this measure, diffusion models perform somewhat better. Although given the high *R*-square of the proposed model, the percentage increase in fit from diffusion models is quite low. The strong performance of diffusion models on this criterion confirms the fact that diffusion models fit widely varying sales patterns quite well. However, the flexible form of the model may be what allows it to fit the data so well. Whether or not this flexibility provides good performance within the estimation period at the expense of robustness outside this period will be more accurately assessed by the next two criteria.

Criterion 2: Parameter stability and validity

By parameter stability we mean that estimated parameters of a model do not vary as each additional year is added to the sales series, unless the change is expected by theory. By parameter validity, we mean that estimated parameters are consistent with values expected from theory. Parameter stability and validity are important measures for assessing whether a model captures the underlying phenomenon in addition to fitting data.

To evaluate parameter stability, we estimate the model repeatedly, starting with a short data series and adding one additional year each time we re-estimate. We then use two measures of parameter stability, one that captures fluctuations from the overall mean and the other that captures year-to-year fluctuations. Additionally, certain parameters such as that of price are expected to change systematically over time (Tellis, 1988). So we test the validity of the price parameter by the ability of the model to capture dynamic price elasticity over time.

Table II. Parameter estimates for proposed model (standard errors in parentheses)

Product category	Periods	Price	Income	Consumer sentiment	Market presence
Answering machine	Multiple[a]	−0.353	0.386	0.065	0.768
		(0.150)	(0.134)	(0.063)	(0.086)
	Full	−0.413	0.421	0.131	0.776
		(0.203)	(0.180)	(0.097)	(0.097)
Home VCR	Multiple	−0.655	0.879	0.071	0.507
		(0.129)	(0.126)	(0.058)	(0.052)
	Full	−0.322	0.536	0.199	0.660
		(0.262)	(0.264)	(0.140)	(0.110)
CD player	Multiple	−0.263	0.521	−0.076	0.575
		(0.104)	(0.080)	(0.019)	(0.033)
	Full	−0.133	0.435	−0.074	0.585
		(0.188)	(0.145)	(0.034)	(0.060)
Microwave oven	Multiple	−0.100	0.309	0.085	0.727
		(0.193)	(0.167)	(0.120)	(0.066)
	Full	−0.043	0.236	0.213	0.783
		(0.120)	(0.117)	(0.136)	(0.050)
Camcorder	Multiple	0.043	0.358	0.007	0.530
		(0.039)	(0.032)	(0.008)	(0.014)
	Full	−0.020	0.403	0.008	0.534
		(0.072)	(0.061)	(0.015)	(0.024)
Electric blanket	Multiple	−0.496	0.955	0.118	0.132
		(0.199)	(0.168)	(0.153)	(0.130)
	Full	−1.117	1.257	−0.013	0.232
		(0.174)	(0.167)	(0.156)	(0.098)
Dishwasher	Multiple	−0.420	0.792	0.160	0.282
		(0.177)	(0.171)	(0.124)	(0.153)
	Full	−0.924	1.061	0.232	0.524
		(0.153)	(0.164)	(0.112)	(0.078)
Colour TV	Multiple	−0.573	0.749	0.385	0.612
		(0.378)	(0.357)	(0.171)	(0.121)
	Full	−0.535	0.652	0.721	0.778
		(0.388)	(0.371)	(0.199)	(0.071)
Clothes dryer	Multiple	−0.136	0.262	0.385	0.829
		(0.151)	(0.129)	(0.116)	(0.068)
	Full	0.104	0.085	0.478	0.803
		(0.191)	(0.166)	(0.115)	(0.046)
Room air conditioner	Multiple	−0.365	0.447	0.384	0.849
		(0.194)	(0.187)	(0.180)	(0.075)
	Full	−0.110	0.237	0.562	0.832
		(0.267)	(0.261)	(0.228)	(0.071)

[a] These values are the average of the parameter estimates obtained by estimating with the minimum number of years required and then re-estimating each time an additional year of data is considered.

Stability of estimates

The first measure of parameter stability captures fluctuations from the overall mean. It is the mean of the estimates of the parameter divided by the standard deviation of estimates, where the multiple estimates are obtained by adding an additional year to the data, just as it would become available to the product's manager. This approach is similar to estimating parameter stability by

Table III. Model fit statistics (mean squared error—$E + 03$)

Product category	Bass	Jain–Rao	Proposed
Clothes dryer	14.7	8.0	9.3
Room air conditioner	26.1	8.5	53.8
Colour TV	82.2	29.8	274.3
Dishwasher	2.7	2.7	7.5
CD player	40.6	16.5	75.7
Electric blanket	27.5	19.9	155.7
Home VCR	1821.8	256.1	2057.9
Camcorder	22.3	8.2	11.2
Answering machine	59.9	57.3	604.8
Microwave oven	385.3	350.1	880.8
Average	248.3	75.7	413.1
Median	34.1	18.2	115.7

Table IV. Stability of parameter estimates (figures are mean/standard deviation of estimates as each data point is added to the series so that *higher values indicate greater parameter stability*)

	Bass			Jain–Rao				Proposed			
Category	p	q	m	p	q	m	P	P	DI	CS	MP
Clothes dryer	0.48	2.94	0.28	1.14	2.47	0.3	0.43	1.14	3.13	5.29	21.7
Room air conditioner	0.44	1.18	0.29	0.98	1.96	0.29	1.04	2.31	3.07	3.2	13.1
Colour TV	0.24	1.82	0.23	0.28	0.87	0.28	0.76	1.35	2.2	1.27	3.98
Dishwasher	0.48	0.68	0.57	0.38	0.98	0.27	0.59	0.82	3.06	2.41	1.02
CD player	0.69	1.99	0.24	0.84	1.38	0.53	1.15	3.04	8.7	8.58	34.4
Electric blanket	0.79	0.81	0.44	0.52	0.91	0.36	0.27	0.83	3.26	1.14	1.26
Home VCR	0.28	1.61	0.29	0.88	2.02	0.36	0.32	2.03	3.38	0.82	8.09
Camcorder	11.3	1.97	1.56	2.66	2.1	0.5	1.18	0.48	5.58	2.17	92.2
Answering machine	0.48	5.06	0.38	0.23	0.13	0.29	0.58	2.49	6.66	1.5	10.4
Microwave oven	0.75	1.46	0.36	0.14	1.15	0.4	0.4	0.47	1.88	1.01	17
Average	1.59	1.95	0.46	0.81	1.40	0.36	0.67	1.50	4.09	2.74	20.3
Median	0.48	1.71	0.33	0.68	1.27	0.33	0.59	1.25	3.20	1.84	11.8

jack-knifing. If the underlying process of sales growth is fairly stable, a good model will have large values. Table IV presents this measure for each parameter in the ten categories. Note that the parameters of the proposed model are *several times more stable* than those of diffusion models. In particular, the stability values for price and market presence which have analogues in the diffusion models are much more stable in the proposed model.

Our second measure of stability captures year-to-year changes or reverses in the estimates of a parameter. This measure is the average period to period change standardized by the mean of the parameter, as follows:

$$\Sigma \left| \frac{P_t - P_{t-1}}{P_\mu} \right| \frac{1}{N} \tag{5}$$

where P represents the parameter estimate and N the number of estimation periods. In contrast to the previous measure, this measure captures *instability*, so that low values are preferable.

Table V. Instability of parameter estimates (relative change in parameter value from year to year, *so that lower values are better*)

Category	Bass			Jain–Rao				Proposed			
	p	q	m	p	q	m	P	P	DI	CS	MP
Clothes dryer	0.77	0.13	2.16	0.57	0.21	1.10	1.08	0.40	0.15	0.05	0.02
Room air conditioner	1.71	0.58	2.10	0.55	0.21	1.09	0.60	0.21	0.17	0.11	0.06
Colour TV	2.14	0.51	2.56	2.17	0.31	2.17	0.92	0.22	0.15	0.16	0.05
Dishwasher	0.55	0.45	0.42	1.31	0.43	1.93	0.94	0.20	0.06	0.15	0.16
CD player	0.18	0.25	0.33	1.03	0.60	1.08	0.53	0.28	0.11	0.12	0.03
Electric blanket	0.40	0.34	1.00	1.16	0.35	1.04	1.05	0.27	0.07	0.30	0.23
Home VCR	2.20	0.29	2.33	0.57	0.17	1.54	1.28	0.23	0.14	0.46	0.05
Camcorder	0.05	0.27	0.31	0.29	0.52	1.33	0.98	1.60	0.14	0.63	0.01
Answering machine	1.13	0.21	2.12	3.21	4.90	2.18	1.13	0.13	0.08	0.35	0.06
Microwave oven	0.66	0.23	2.14	4.19	0.45	1.21	2.19	0.75	0.21	0.24	0.02
Average	0.98	0.33	1.55	1.50	0.82	1.47	1.07	0.43	0.13	0.26	0.07
Median	0.71	0.28	2.11	1.09	0.39	1.27	1.02	0.25	0.14	0.20	0.05

Table V presents this measure for each parameter in the ten categories. Note, especially, how the measures of instability of all four variables of the proposed model are much lower, with the exception of the coefficient of imitation from the Bass model. Interestingly, this parameter is the only one tied to a measured construct in the Bass model. On the other hand, the estimates of innovation in the diffusion models are much more unstable.

Validity of estimate of price elasticity

A widely accepted hypothesis is that price elasticity is dynamic, increasing steadily over the adoption life cycle (Parker, 1992; Simon, 1979; Tellis, 1988). This change is expected for three reasons. First, consumers' knowledge about the product and prices will be higher later in the life cycle (Tellis, 1988). Second, early adopters 'have relatively high incomes and are therefore less sensitive to price changes than later adopters' (Parker, 1992, p. 358; Robertson, 1967; Rogers, 1995). Third, greater competition later in the life cycle may lead to higher price sensitivity. In an extensive meta-analysis, Tellis (1988) found support for higher price elasticity in later stages of the product life cycle.[3] Therefore, based on theory and some empirical evidence, the most reasonable hypothesis about price elasticity is that it will increase as sales shift from early adopters to later adopters.

Figure 1 shows that the expected pattern of increasing price elasticities is much more clearly evident from the proposed model than from the diffusion model. In addition, the diffusion model yields estimates of price elasticities which more often take on positive values and change sharply from year to year. On the other hand, the pattern of estimates of price elasticity from the proposed model seems to form a fairly smooth curve, which is similar over almost all of the product categories studied. These analyses provide strong evidence to support the idea that the proposed model's estimate of price elasticity is stable and valid.

[3] However, Parker (1992) concluded that 'there is no consistent pattern of price elasticity dynamics over the adoption life cycle for the durable goods studied' (p. 365). The problem Parker had with confirming the dynamic price elasticity hypothesis may have been due to the fact that he used diffusion models, which are prone to unstable and fluctuating parameter estimates.

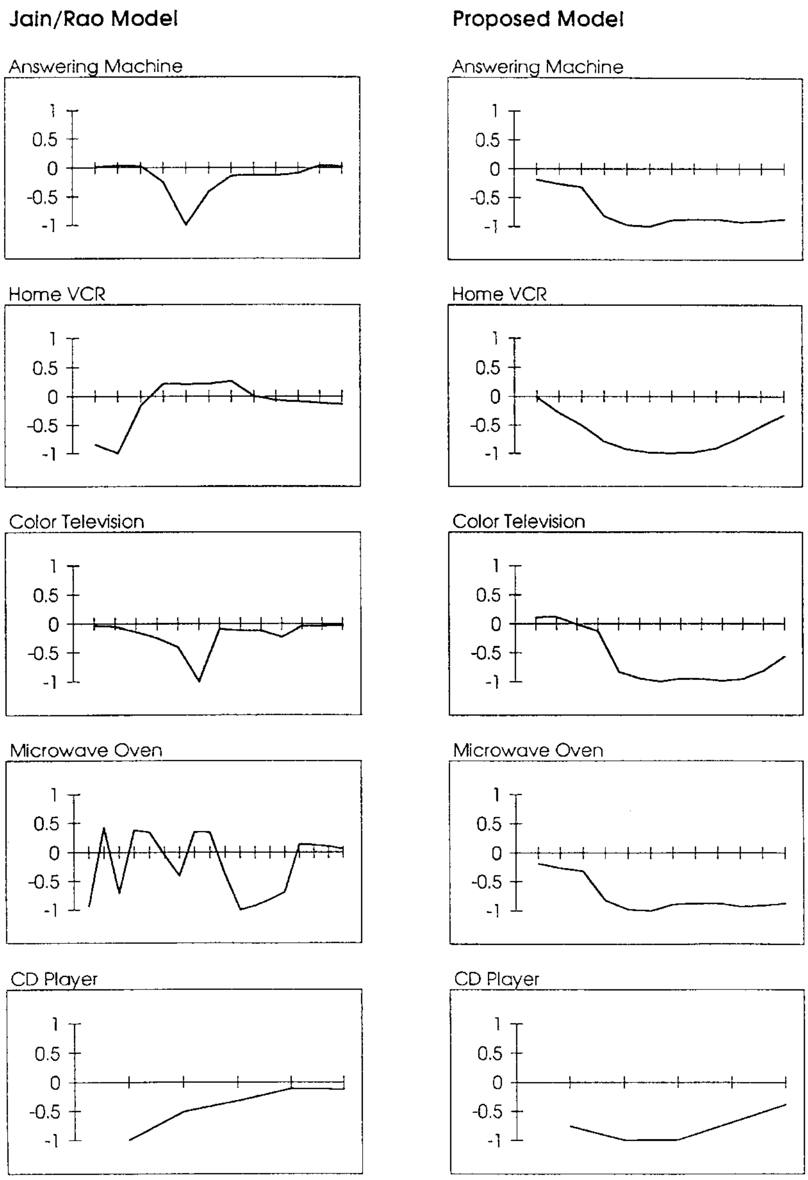

Figure 1(a). Standardized price coefficients

Criterion 3: Forecasting ability

Because models can be designed to fit current sales, a potentially better test of a model's performance is its ability to forecast future sales. It will be interesting to see whether the better fit of diffusion models or the superior parameter stability of the proposed model offers more leverage in forecasting ability.

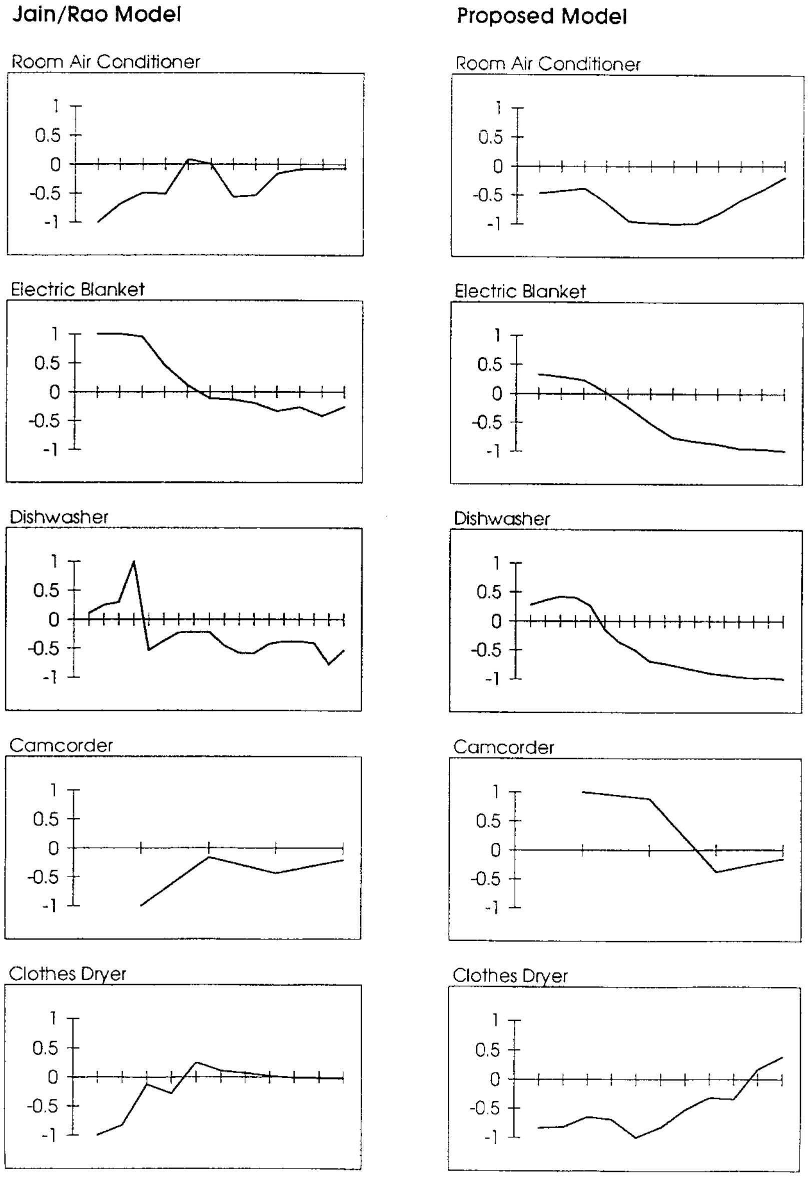

Figure 1(b). Standardized price coefficients

To develop valid forecasts of sales for the proposed model, we must forecast the explanatory variables themselves. We forecast price based on extrapolations of the price trend using the experience curve function. For disposable incomes, we use a surrogate measure of GNP, because the two variables are highly correlated (99%) and forecasts of GNP are easily available. We use consensus GNP forecasts published annually by *Business Week*, and supplement them with forecasts from *The Wall Street Journal* and *Journal of Business* as necessary.

Table VI. Mean absolute percentage error of one-year-ahead sales forecasts

Product category	Bass model (%)	Jain–Rao model (%)	Proposed model (%)
Microwave oven	21.1	24.0	18.8
Camcorder	20.1	11.1	8.1
Answering machine	16.8	29.9	18.6
CD player	20.5	17.0	14.8
Home VCR	30.6	28.4	32.9
Colour TV	49.0	32.1	33.8
Average of categories	26.4	23.8	21.2
Median of categories	20.8	26.2	18.7

Table VII. Mean absolute percentage error of three-years-ahead sales forecasts

Product category	Bass model (%)	Jain–Rao model (%)	Proposed model (%)
Microwave oven	70.4	74.4	57.4
Answering machine	95.7	61.6	53.1
Home VCR	428.0	137.0	94.9
Colour TV	147.5	93.4	76.4
Average of categories	185.4	91.6	70.5
Median of categories	121.6	83.9	66.9

For one-year-ahead forecasts, we carry out the analysis for six of the ten categories, because consensus disposable income forecasts are not available for four older categories. For three-year-ahead forecasts, we carry out the analysis for only four categories because two of the remaining six categories (camcorders and CD players) have series that are too short. The results of the forecasting ability of the three models are in Tables VI and VII.

For one-year-ahead forecasts, the proposed model performs better than the Jain–Rao and Bass models in four of six categories. Moreover, the lower average and median values for forecast errors also support the proposed model. For three-year-ahead forecasts, the proposed model performs better than the Jain–Rao and Bass models in *all* four categories. A model is more likely to capture the underlying phenomenon and be useful, the further ahead it can forecast sales.

To examine whether the improvement in forecast accuracy is statistically significant, we pooled each model's one-year-ahead forecasts across categories. Then we conducted paired t-tests of the forecasts across the two models. As expected, these results suggest that one-year-ahead forecasts from the proposed model may be better than those from the Jain–Rao model ($p = 0.25$) and the Bass model ($p = 0.12$). We repeated the same test for the three-year-ahead forecasts. The proposed model's three-year-ahead forecasts are significantly better than those from the Jain–Rao model ($p = 0.01$) and the Bass model ($p = 0.02$). This analysis provides additional evidence that forecasts from the proposed model are more accurate than those from diffusion models.

A major forecasting problem with diffusion models occurs in the early years when sales are increasing rapidly. Here, diffusion models tend to forecast a sales peak which is much higher than the actual peak. These models require data indicating a downturn in sales *before* the model stops

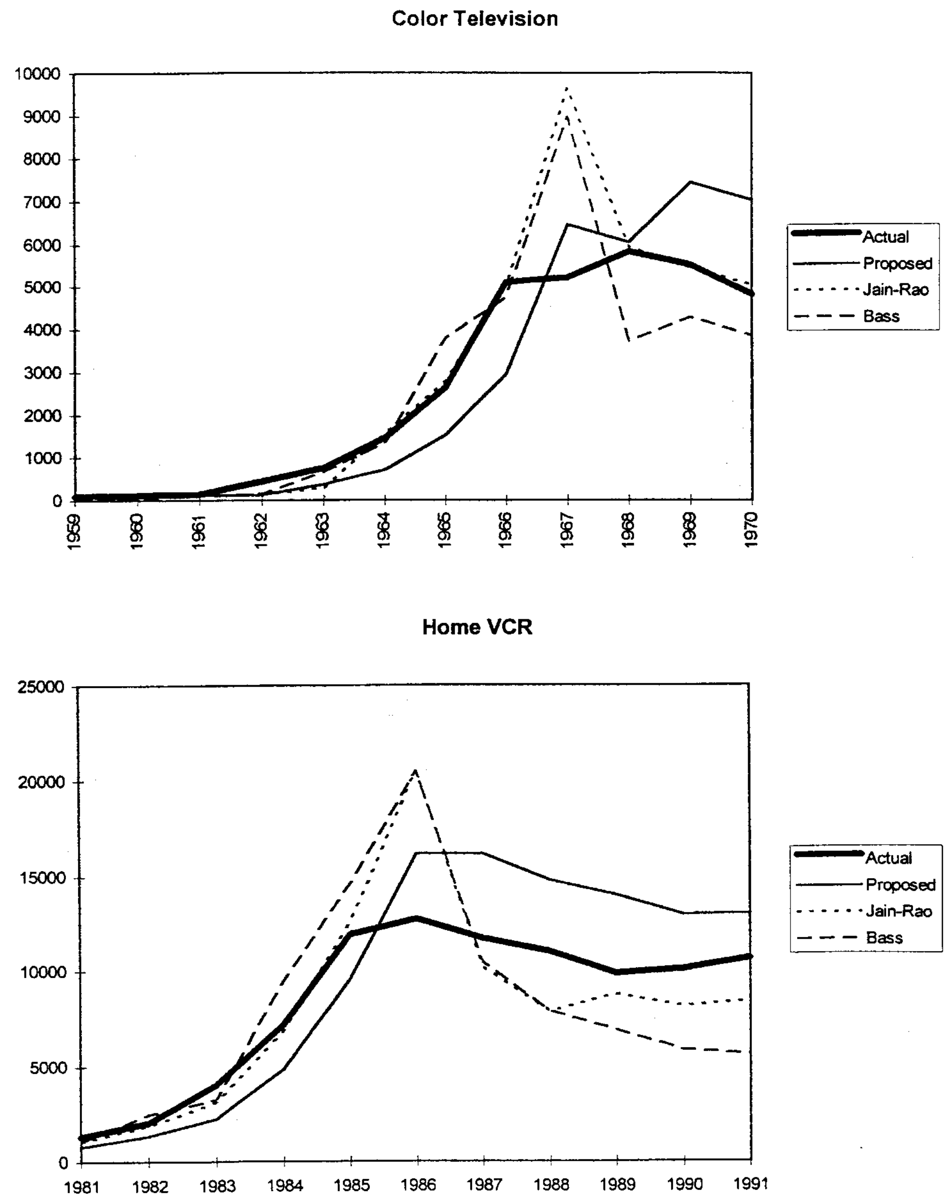

Figure 2. One-year sales forecasts

forecasting sales increases at an increasing rate. This problem is exacerbated when forecasts are made farther into the future. In Figure 2, we present some representative results of one-year-ahead forecasts for two categories, colour television and home VCR.[4] While forecasts from the proposed model lag sales growth, they do not produce the large errors of diffusion models, at and

[4] Some of these forecasts are based on constrained estimates similar to that of Srinivasan and Mason (1986).

after the sales peak. Additionally, if we could have operationalized market presence with a measure of distribution intensity, the lag in forecasted sales may have diminished.

Heeler and Hustad (1980) found that diffusion models have difficulty forecasting the sales peak. Our results indicate that not only do diffusion models have difficulty forecasting the sales peak, they have limitations forecasting even one and three years into the future. While researchers have acknowledged forecasting limitations of diffusion models (Mahajan, Muller and Bass, 1990), they continue to be used extensively.

DISCUSSION

Publication of the Bass model in 1969 represented a breakthrough in the modelling of new product growth, because it fits the data relatively well and had an appealing behavioural interpretation. The estimated parameters could be interpreted as coefficients of innovation and imitation which were presumed to drive consumer adoptions. However, the model suffers from three well-known limitations: (1) it does not include marketing variables that could influence new product diffusion and sales; (2) the model's parameters are unstable, and (3) the model's forecasts are inaccurate unless the entire history of new product growth is included. The appeal of the model generated numerous replications and extensions as researchers sought to overcome the limitations and build on this promising line of research. However, all these models succeed at a greater or lesser cost to simplicity.

We propose an alternative model based on the concept of affordability. Our model retains the simplicity of the Bass model while addressing some of its limitations. A comparison of the proposed model with two diffusion models indicates the two perform quite differently on the evaluation criteria. Note, especially that while our model fits the data less well (see Table III), it performs better on the sales forecasts (see Tables VI and VII). Further, the estimates of the coefficients from our model are more stable (see Tables IV and V). Most importantly, our model's estimates of price response are more stable, valid and consistent with theory. Thus, at the least, the proposed model suggests that economic variables may be necessary to model sales growth. Since fits with past data are primarily of historical interest, the proposed model does better on two important criteria: sales forecasting and explaining the role of price in new product growth.

One important question that readers may ask is why the Bass model fails to forecast well, even though it fits past data so well. The answer probably lies in the structure of the model. Early sales of new products often follow an S-shaped curve. The flexible form of the Bass model allows it to fit any S-shaped sales curve well. The parameters of the model adjust to ensure that the fit to the S-shaped pattern is accurate. In so doing, the parameters probably fail to accurately capture the underlying behavioural process. It is the underlying process that determines future sales. Thus, fitting with past data may occur at the cost of accurate parameter estimates and sales forecasts.

Ironically, forecasting inaccuracy is most acute when it is most important—at the sales peak. Most managers would like to know when sales of their new product will slow down. But the Bass model must have this turning point in advance to provide even reasonable forecasts. In the absence of this point, the model tends to extrapolate past patterns thereby overpredicting growth at the peak. In contrast, the proposed model, based as it is on affordability, is driven by variables such as price and economic conditions. To the extent that price drops cause sales growth and economic downturns cause the slowdown, the proposed model may better capture the sales pattern of new products.

A related question is whether stable estimates of diffusion can be obtained using appropriate statistical techniques. One approach would be Bayesian updates based on average estimates of the parameters from meta-analysis of past studies (Sultan, Farley and Lehmann, 1990). Another approach would be to impose a constraint on the saturation level for estimation purposes. Even these approaches may be questionable. Estimates of the Bass model may be of a process (diffusion) that largely takes place before the purchase event. Similarly, the use of the parameters as measures of innovation and imitation, are primarily *an interpretation*. Since researchers do not actually go out and obtain data on how and when consumers *learn about an innovation*, they have no means to confirm whether the underlying process is one of diffusion as the model assumes, or one of affordability as we argue. Since new consumer durables are often high priced, receive wide publicity, and experience dramatic decreases in price, the underlying process could well be one of affordability, with knowledge of the innovation having diffused well in advance of the sales increase. Thus more sophisticated estimation of diffusion coefficients does not ensure that the estimates are valid.

We can easily point out many limitations of our approach which suggest areas for future research. First, our model was tested only on consumer durables. It may not work as well on other categories. For example, sales of new agricultural and medical products may be influenced more by diffusion than by affordability. Similarly, sales of novelties (such as books, movies, music, or fashion products) may also follow a diffusion process. For all these products, price is not as much of a concern to consumers as benefits or novelty. Knowledge of benefits and novelty is likely to diffuse through the population of consumers. Thus, diffusion models may fit such products better than our model.

Second, a combined approach that includes both affordability and diffusion may be worth exploring. Individual level diffusion models or models that combine economic and communication elements seem especially promising (Chatterjee and Eliashberg, 1990; Horsky, 1990; Kalish, 1985; Lattin and Roberts, 1989). However, research should assess the forecasting ability and parameter stability of these combined models. Also, research should explore better measures of innovation and imitation, as well as other variables such as acceptability, risk and perceived need, to fully test the role of diffusion. However, parsimony should be an important criterion in model development. A fully specified integrated model may be feasible but is likely to be complex and cumbersome.

Third, our model does not include a built in saturation constraint. If sales decline after a sales peak, this feature is more appropriately captured by diffusion models. However, while a peak is very likely for adoptions, it may not occur for sales. Our own data show that sales in many categories continue to increase for many years past the so called 'peak'. In addition, other researchers have found that 'the decline stage is absent' in some categories (Horsky, 1990, p. 354) or that the 'sales peak often occurs, if ever, decades after the first purchase peak. . . .' (Parker, 1994, p. 368). Moreover, to the extent that sales slow down due to a slowing economy, or a flattening out of the price curve, it would be picked up by our affordability model.

Fourth, our approach does not clearly decompose sales into first purchases and repeat purchases. While we believe that this decomposition may not be a dominant factor in the first few years of a new consumer durable, it is a refinement in data and estimation that should be undertaken.

Fifth, our measures of consumer sentiment and market presence are weak. Better measures may enhance the performance of such models.

Sixth, and most importantly, we suspect that the takeoff and slowdown in sales are the points in the life of a new product that would be of most interest to managers. Research on models that are designed to predict these turning points would be most fruitful. We submit that a hazard model that predicts the probability of an event, such as takeoff or slowdown, given that it has not occurred would be a promising candidate for this line of research (Golder and Tellis, 1997).

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