CHAPTER 2

A CRITICAL REVIEW OF MARKETING RESEARCH ON DIFFUSION OF NEW PRODUCTS

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Abstract

We critically examine alternate models of the diffusion of new products and the turning points of the diffusion curve. On each of these topics, we focus on the drivers, specifications, and estimation methods researched in the literature. We discover important generalizations about the shape, parameters, and turning points of the diffusion curve and the characteristics of diffusion across early stages of the product life cycle. We point out directions for future research.

Because new products affect every aspect of the life of individuals, communities, countries, and economies, the study of the diffusion of innovations is of vital importance. Researchers have studied this topic in various disciplines, including marketing, economics, medicine, agriculture, sociology, anthropology, geography, and technology management. We present a critical review of research on the diffusion of new products primarily in the marketing literature, but also in the economics and geography literature. We use the word *product* broadly to cover any good, service, idea, or person. We distinguish the term *new product* from the broader term *innovation*, which refers to both new product and new method, practice, institution, or social entity. Even though we restrict our review to the marketing literature, which focuses on the diffusion of new products, the implications of our review may hold as well as for the study of the diffusion of innovations in other disciplines. The marketing literature on this topic is vast, dating back at least as early as the publication by Fourt and Woodlock (1960).

The term diffusion has been used differently in two groups of literatures. Within economics and most nonmarketing disciplines, diffusion is defined as the spread of an innovation across social groups over time (Brown, 1981; Stoneman, 2002). As such, the phenomenon is separate from the drivers, which can be consumer income, the product's price, word-of-mouth communication, and so on. In marketing and communication, diffusion typically has come to mean *the communication of an innovation through the population* (Golder and Tellis, 1998; Mahajan, Muller, and Wind, 2000a; Mahajan, Muller, and Bass, 1990; Rogers 1995). In this sense, the phenomenon (spread of a product) is synonymous with its underlying driver (communication). The Webster (2004) definition of the noun "diffusion" is "the spread of a cultural or technological practice or innovation from one region or people to another, as by trade or conquest" and the verb "diffusing" is "pour, spread out or disperse in every direction; spread or scatter widely." This latter interpretation is synonymous with the term's use in economics and most other disciplines. In addition, some researchers in marketing have subscribed to the definition used in economics (Bemmaor, 1994; Dekimpe, Parker, and Sarvary, 2000a; Van den Bulte and

Stremersch, 2004). Hence, in this review, we define *diffusion* as the spread of an innovation across markets over time.

Researchers commonly measure diffusion using the sales and especially the market penetration of a new product during the early stages of its life cycle. To characterize this phenomenon carefully, we adopt the definitions of the stages and turning points of the product's life cycle by Golder and Tellis (2004):

1. *Commercialization* is the date a new product is first sold.
2. *Takeoff* is the first dramatic and sustained increase in a new product's sales.
3. *Introduction* is the period from a new product's commercialization until its takeoff.
4. *Slowdown* is the beginning of a period of level, slowly increasing, or temporarily decreasing product sales after takeoff.
5. *Growth* is the period from a new product's takeoff until its slowdown.
6. *Maturity* is the period from a product's slowdown until sales begin a steady decline.

Hence, there are two key turning points in the diffusion curve: takeoff and slowdown.

Prior reviews address various aspects of the marketing literature on the diffusion of new products. For example, Mahajan, Muller, and Bass (1990) provide an excellent overview of the Bass model, its extensions, and some directions for further research. Parker (1994) provides an overview of the Bass model and evaluates the various estimation techniques, forecasting abilities, and specification improvements of the model. Mahajan, Muller, and Bass (1995) summarize the generalizations from applications of the Bass model. An edited volume by Mahajan, Muller, and Wind (2000b) covers in depth various topics in diffusion models, such as specification, estimation, and applications. Sultan, Farley, and Lehmann (1990) and Van den Bulte and Stremersch (2004) meta-analyze the diffusion parameters of the Bass model.

The current review differs from prior reviews in two important aspects. First, the prior reviews focus on the S-curve of cumulative sales of a new product, mostly covering growth. This review focuses on phenomena besides the S-curve, such as takeoff and slowdown. Second, the above reviews focus mainly on the Bass model. This review considers the Bass model as well as other models of diffusion and drivers of new product diffusion other than communication.

Our key findings and the most useful part of our study is the discovery of potential generalizations from past research. For the benefit of readers who are familiar with this topic, we present these generalizations before details of the measures, models, and methods used in past research. (Readers who are unfamiliar with the topic may want to read the Potential Generalizations section last). Therefore, we organize the rest of the chapter as follows. In the next section, we summarize potential generalizations from prior research. In the third section, we point out limitations of past research and directions for future research. In the fourth section, we evaluate key models and drivers of the diffusion curve. In the fifth section, we evaluate models of the key turning points in diffusion: takeoff and slowdown.

Potential Generalizations

We use the term potential generalizations or regularities to describe empirical findings with substantial support. By substantial, we mean that support comes from reviews or meta-analyses of the literature or individual studies with a large sample of over ten categories or ten countries. Table 2.1 lists the studies on which the potential generalizations are based. This section covers important findings about the shape of the diffusion curve, parameters of the Bass models, the turning points of diffusion, and findings across stages of the diffusion curve.

Table 2.1

Studies Included for Assessing Potential Generalizations

Authors	Categories	Countries
Gatignon, Eliashberg, and Robertson (1989)	6 consumer durables	14 European countries
Mahajan, Muller, and Bass (1990)	Numerous studies	
Sultan, Farley, and Lehmann (1990)	213 applications	United States, European countries
Helsen, Jedidi, and DeSarbo (1993)	3 consumer durables	11 European countries and United States
Ganesh and Kumar (1996)	1 industrial product	10 European countries, United States, and Japan
Ganesh, Kumar, Subramaniam (1997)	4 consumer durables	16 European countries
Golder and Tellis (1997)	31 consumer durables	United States
Putsis et al., (1997)	4 consumer durables	10 European countries
Dekimpe, Parker, and Sarvary (1998)	1 service	74 countries
Kumar, Ganesh, and Echambadi (1998)	5 consumer durables	14 European countries
Golder and Tellis (1998)	10 consumer durables	United States
Kohli, Lehmann, and Pae (1999)	32 appliances, house wares and electronics	United States
Dekimpe, Parker, and Sarvary (2000)	1 innovation	More than 160 countries
Mahajan, Muller, and Wind (2000)	Numerous studies	
Van den Bulte (2000)	31 consumer durables	United States
Talukdar, Sudhir, and Ainslie (2002)	6 consumer durables	31 countries
Agarwal and Bayus (2002)	30 innovations	United States
Goldenberg, Libai, and Muller (2002)	32 innovations	United States
Tellis, Stremersch, and Yin (2003)	10 consumer durables	16 European countries
Golder and Tellis (2004)	30 consumer durables	United States
Stremersch and Tellis (2004)	10 consumer durables	16 European countries
Van den Bulte and Stremersch (2004)	293 applications	28 countries

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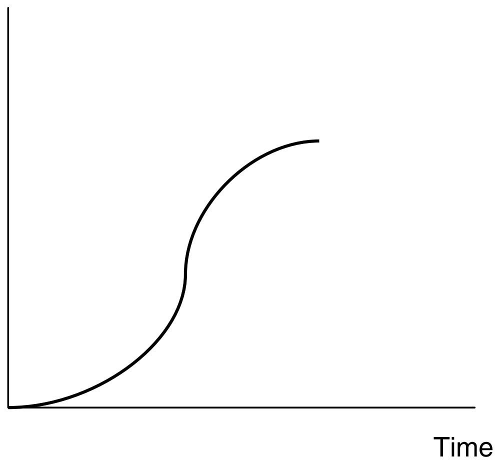
Shape of the Diffusion Curve

The most important and most widely reported finding about new product diffusion relates to the shape of the diffusion curve (see Figure 2.1). Numerous studies in a variety of disciplines suggest that (with the exception of entertainment products) the plot of cumulative sales of new products against time is an S-shaped curve (e.g., Mahajan, Muller, and Bass 1990; Mahajan, Muller, and Wind, 2000a).

Parameters of the Bass Model

Most of the marketing studies use the Bass diffusion model to capture the S-shaped curve of new products sales (see later section for explanation). This model has three key parameters: the coefficient of innovation or external influence (p), the coefficient of imitation or internal influence (q), and the market potential (α or m).

Figure 2.1 **Cumulative Adoptions over Time**



Coefficient of Innovation

- The mean value of the coefficient of innovation for a new product lies between 0.0007 and .03 (Sultan, Farley, and Lehmann, 1990; Talukdar, Sudhir, and Ainslie, 2002; Van den Bulte and Stremersch, 2004).
- The mean value of the coefficient of innovation for a new product is 0.001 for developed countries and 0.0003 for developing countries (Talukdar, Sudhir, and Ainslie, 2002).
- The coefficient of innovation is higher for European countries than for the United States (Sultan, Farley, and Lehmann, 1990).

Coefficient of Imitation

- The mean value of the coefficient of imitation for a new product lies between 0.38 and 0.53 (Sultan, Farley, and Lehmann, 1990; Talukdar, Sudhir, and Ainslie, 2002; Van den Bulte and Stremersch, 2004).
- Industrial/medical innovations have a higher coefficient of imitation than consumer durables and other innovations (Sultan, Farley, and Lehmann, 1990).
- The mean value of the coefficient of imitation for a new product is 0.51 for developed countries and 0.56 for developing countries (Talukdar, Sudhir, and Ainslie, 2002).

Market Potential

The average market penetration potential ceiling of a new product is 0.52 for developed countries and 0.17 for developing countries (Talukdar, Sudhir and Ainslie 2002).

Time to Peak Sales

It takes about nineteen years on average for a new product to reach peak sales in developing countries, which is 18 percent longer than the average of sixteen years for developed countries (Talukdar, Sudhir, and Ainslie, 2002).

Biases in Parameter Estimation

The nonlinear estimation of static models such as the Bass model leads to downward biases in parameter values of market potential and the coefficient of innovation and an upward bias in the coefficient of imitation (Van den Bulte and Lilien, 1997). The market potential can be underestimated by 20 percent, the coefficient of innovation can be underestimated by 20 percent, and the coefficient of imitation can be overestimated by 30 percent (Van den Bulte and Lilien, 1997). Using longer time series and using data with higher frequency is associated with lower estimated q / p values (Van den Bulte and Stremersch, 2004).

Drivers

- There is mostly indirect and some direct support for drivers of diffusion. Key drivers in order of support are word-of-mouth communication, economics, marketing mix variables such as prices, consumer heterogeneity, and consumer learning (Dekimpe, Parker and Sarvary 1998, 2000a; Ganesh, Kumar, Subramaniam, 1997; Kumar, Ganesh and Echambadi 1998; Gatignon, Eliashberg, and Robertson, 1989; Mahajan, Muller, and Bass, 1990; Mahajan, Muller, and Wind, 2000; Putsis et al., 1997; Stremersch and Tellis, 2004; Talukdar, Sudhir, and Ainslie, 2002; Van den Bulte and Stremersch, 2004).
- A 1 percent change in purchasing power parity adjusted per capita income is likely to change the market penetration potential by about 0.3 percent (Talukdar, Sudhir, and Ainslie, 2002).
- A 1 percent change in international trade or urbanization is likely to change the market penetration potential by about 0.5 percent and 0.2 percent respectively (Talukdar, Sudhir, and Ainslie, 2002).

Turning Points of the Diffusion Curve

This section describes findings about the regularities in takeoff, and slowdown—the two turning points of the diffusion curve.

Regularities in Takeoff

Patterns of Takeoff

Estimates of the average time to takeoff range are from six to ten years (Agarwal and Bayus, 2002; Golder and Tellis, 1997; Kohli, Lehmann, and Pae, 1999). However, the average time to takeoff varies across products, countries, and time (Tellis, Stremersch, and Yin, 2003).

- Brown goods (entertainment and information products) take off faster, with an average of two years, than white goods (kitchen and laundry appliances), with an average of eight years (Tellis, Stremersch, and Yin, 2003).
- The average time to takeoff of new products in Scandinavian countries is four years, in mid-European countries the average is six years, and in Mediterranean countries, it is eight years (Tellis, Stremersch, and Yin, 2003).
- The average time to takeoff is eighteen years for categories introduced before World War II (Golder and Tellis, 1997), but only six to ten years for categories introduced after World War II in the United States, as mentioned above.

Drivers of Takeoff

- Every 1 percent decrease in price leads to a 4.2 percent increase in the probability of takeoff (Golder and Tellis 1997).
- Takeoff in the number of firms in the market precedes product takeoff by at least three years (Agarwal and Bayus, 2002).
- The average penetration at takeoff is 1.7 percent (Golder and Tellis, 1997). This finding is consistent with Rogers's (1995) estimate that innovators make up 2.5 percent of the population and Mahajan, Muller, and Srivastava's (1990) upper bound of 2.8 percent for innovators.

Regularities in Slowdown

Patterns of Slowdown

- Sales drop at slowdown in 50–96 percent of categories (Goldenberg, Libai, and Muller, 2002; Golder and Tellis, 2004).
- Sales decline by an average 15–32 percent during these drops after slowdown (Goldenberg, Libai, and Muller, 2002; Golder and Tellis, 2004)

Drivers of Slowdown

Price declines, market penetration, wealth, and information cascades seem to influence the probability of slowdown (Golder and Tellis, 2004). In particular,

- Every 1 percent increase in price is associated with a 5 percent increase in the probability of slowdown.
- Slowdown occurs on average at 34 percent penetration.
- Every 1 percent increase in penetration is associated with a 3.6 percent increase in the probability of slowdown.
- Every 1 percent decrease in total gross national product (GNP) is associated with a 17 percent increase in the probability of slowdown.
- There is indirect evidence for information cascades driving sales increases and declines in the early stage of the life cycle. Products that tend to have large increases during takeoff seem to have large declines at slowdown.

Findings Across Stages

This section compares the key findings on the duration, growth rates, and price declines in the various stages and transition points of the product life cycle.

Duration

- On average, the duration of the introduction stage is six to ten years, of the growth stage is eight to ten years, and of the early maturity stage is five years (Agarwal and Bayus, 2002; Goldenberg, Libai, and Muller, 2002; Golder and Tellis, 2004; Golder and Tellis, 1997; Stremersch and Tellis, 2004; Tellis, Stremersch, and Yin, 2003).

- Timesaving products are associated with longer growth stages than non-timesaving products (Golder and Tellis, 2004).
- Leisure-enhancing products are associated with shorter growth stages than non-leisure-enhancing products (Golder and Tellis, 2004).
- The duration of the introduction and early maturity stages is getting shorter over time, but not the duration of the growth stage (Golder and Tellis, 2004).
- Overall, a new product reaching 5 percent household penetration in 1946 in the United States took about fourteen years to go from 10 percent to 90 percent of its estimated maximum adoption ceiling. In 1980, that time has dropped to about half, at seven years (Van den Bulte, 2000).

Price

Price reductions are larger in recent periods for both the introduction and the growth stages. The price at takeoff is 80 percent of the price at commercialization for pre–World War II products and 63 percent for post–World War II products. The price at slowdown is 56 percent of the price at commercialization for pre–World War II products and 30 percent for post–World War II products (Golder and Tellis, 2004).

Growth Rates

- The mean growth rate is 31 percent during introduction, 428 percent during takeoff, 45 percent during growth, –15 percent during slowdown, –25 percent during early maturity, and 3.7 percent during late maturity (Golder and Tellis, 2004).
- The mean economic growth rate is 1 percent during introduction, 4.3 percent during takeoff, 3.1 percent during growth, 0.86 percent during slowdown, 2.4 percent during early maturity, and 3.1 percent during late maturity of new products (Golder and Tellis, 2004).
- Timesaving products tend to have lower growth rates in the growth stage than non-time-saving products (Golder and Tellis, 2004).
- Leisure-enhancing products tend to have higher growth rates in the growth stage than non-leisure-enhancing products (Golder and Tellis, 2004).
- The average growth rate during the growth stage is 45 percent per year in the United States, 46 percent for the Nordic countries, 41 percent for Mid-European countries, and 36 percent for Mediterranean countries (Golder and Tellis, 2004; Stremersch and Tellis, 2004).

Future Research

Despite decades of research and a large body of potential generalizations in diffusion, many problems remain unaddressed. This situation provides exciting opportunities for future research. We divide these opportunities into four sections: measurement, theories, models, and findings.

Measurement

The literature in this area has mostly ignored the problem of measurement. Yet, measurement plays a critical role in documenting the phenomena under study. Measurement is also an important prerequisite for modeling. For example, no clear rules are available for the measurement of the start of the product life cycle or the year of introduction of a new product. Most researchers consider the date from which data become available as the date for the introduction of the new product. However, syndicated data sources that track sales of new products tend to do so only when a product has become popular and shows promise of becoming a mass-market product. Using the date of availability of sales as a surrogate for the start date may grossly underestimate the duration of the introductory period and the time for takeoff. In addition, models such as the Bass model, which are highly sensitive to the number of observations, can yield biased estimates and predictions due to erroneous start dates. Researchers can correct for this by using model specifications that give statistically valid estimates of the launch date.

In addition, most researchers use sales as the dependent variable. As such, sales should consist only of first adoptions of the new product. However, in effect, most databases do not discriminate between first purchase and repurchases when describing sales. In addition, the data measured as sales often represent "shipments," which captures supply of products rather than demand.

Further, researchers do not define a clear stopping rule for the period of the study. The period modeled should end when the entire market has made first purchases or at least when adoptions have peaked. Often researchers use the data available until the first peak in sales.

The literature contains several competing measures for takeoff. Measures for slowdown and the saddle or trough in sales are still tentative and have little validation. Although underresearched, measures for some of the key phenomena are very important and play a critical role in the validity and interpretation of the parameters of models. Perhaps this is the most important area for future research.

Theories

Researchers have identified various drivers for the diffusion of innovations. However, no researcher has developed an integrated theory that either incorporates or differentiates among all these drivers. This issue is important because theory constitutes the key explanation for a phenomenon and informs good models and managerial practice.

Models

In the area of modeling, there are five pressing issues. First, most models have focused on modeling diffusion from slightly before the takeoff to approximately the slowdown, while a few models have focused on only takeoff and slowdown. Research needs to develop an integrated model of sales from commercialization to takeoff, during growth, and after slowdown. Second, the marketing literature has focused extensively on consumer durables and a little on movies. Research needs to consider other categories such as services, software, agricultural products, and medical products. Third, research needs to include diffusion of products using new media such as the Internet, where the process can be quite different from the traditional brick and mortar medium. Fourth, researchers are realizing that network effects can play a key moderating role in the takeoff or success of a new product. Thus, research needs to incorporate the role of network effects and technological choices of the suppliers on product diffusion. Fifth, the Bass model has long been the platform of diffusion research in marketing because of its simplicity and good predictive ability. Researchers can explore other platforms for research on diffusion.

Findings

While research in this area has led to some potential generalizations, further research can help to ascertain the extent to which these generalizations either are universal or vary by context. In particular, research could address the following three issues.

First, the bulk of research has focused extensively on identifying patterns of growth *across* countries and *over* time. There is also a need to identify subgroups or regions *within* such populations where we are likely to see varying rates of diffusion.

Second, all research has focused on successful products. Future research needs to study failed products to understand what aspects of their diffusion led to failure.

Third, studies of diffusion speed have been largely limited to the United States. Future research should consider the facets of cross-national speed of diffusion together with how technology and entry strategy affect the speed of diffusion

Bass Model of Diffusion

Much of the literature follows an early model by Bass (1969). The Bass model is similar to epidemiological or contagion models, which describe the spread of a disease through the population due to contact with infected persons (see Bailey, 1957, 1975).

This section discusses the specification of the Bass model, evaluates the model's strengths and weaknesses, and discusses improvements in specification and estimation.

Specification

The basic assumption in the Bass model is that the adoption of a new product spreads though a population primarily due to contact with prior adopters. Hence, the probability that an individual purchases at time T, given that the individual has not purchased before, is a linear function of the number of previous buyers, thus

$$P(t) = f(t) / (1 - F(t)) = p + q / m\, Y(t) \tag{1}$$

where $P(t)$ is a hazard rate, which depicts the conditional probability of a purchase in a (very small) time interval $(t, t + \Delta)$, if the purchase has not occurred before t. $Y(t)$ refers to the cumulative number of adopters up to time t; m is the total number of initial purchases for the time interval for which replacement purchases are excluded. $F(t)$ denotes the cumulative fraction of adopters at time t and $f(t)$ is the likelihood of purchase at time t. By rearranging equation (1),

$$f(t) = (p + qF(t))[1 - F(t)] \tag{2}$$

Since $Y(0) = 0$, p represents the probability of an initial purchase at time 0 and its magnitude reflects the importance of innovators, the product $q / mY(t)$ reflects the pressure of prior adopters on imitators.

The number of adoptions at time t, $S(t)$, is derived by multiplying $f(t)$ in equation (2) with m, the market size, thus:

$$S(t) = mf(t) = pm + (q - p)\, Y(t) - q / m\, Y^2(t) \tag{3}$$

$$\textit{Since } f(t) = dF(t) / dt = (p + qF(t))[1 - F(t)] \tag{4}$$

By rewriting this equation, Bass solves the following differential equation:

$$dt = dF / (p + (q - p)F - qF^2) \tag{5}$$

to obtain

$$F(t) = (1 - e^{-(p+q)t}) / (1 + (q/p)e^{-(p+q)t}) \tag{6}$$

Hence, the cumulative adoptions are

$$Y(t) = m[(1 - e^{-(p+q)t}) / (1 + (q/p)e^{-(p+q)t})] \tag{7}$$

Bass rewrites equation (3) in a discrete form to obtain an equation for sales in only three unknown parameters, which he estimates by simple regression, thus:

$$S_t = a + bY_{t-1} + cY^2_{t-1},\ t = 2, 3 \ldots \tag{8}$$

where S_t refers to sales at time t, Y_{t-1} refers to cumulative sales through period $t - 1$ and

$$a = p \times m, \tag{9}$$
$$b = q - p, \tag{10}$$
$$c = -q / m \tag{11}$$

Hence, he derives the values of p, q, and m from the estimated a, b, and c as follows:

$$p = a / m \tag{12}$$
$$q = -cm \tag{13}$$
$$m = (-b \pm (b^2 - 4ac)^{1/2}) / 2c \tag{14}$$

Evaluation

This section describes the strengths and limitations of the Bass model and relates it to other models in the literature.

Strengths

The derived and testable function of the Bass Model (1969), equation (8), has several excellent properties. First, because sales is a quadratic function of prior cumulative sales, the model provides a good fit to the S-shaped curve that is typical of the sales of most new products. Indeed, decades of subsequent research have shown that the simple Bass model fits sales almost as well as much more complex models that sought to correct its limitations (Bass, Krishnan, and Jain, 1994).

Second, the model has two very appealing behavioral interpretations. Bass interprets the coefficient p as the coefficient of innovation because it reflects the spontaneous rate of adoption in the population. He interprets q as the coefficient of imitation because it reflects the effect of prior cumulative adopters on adoption. Other researchers conservatively interpret p as the external influence referring to the influence of mass-media communications and q as internal influence referring to the influence of interpersonal communication from prior adopters (Mahajan, Muller, and Srivastava, 1990).

Third, the model enables the researcher to resolve an important concern of managers of new products, that is, to determine the time to, and magnitude of, peak sales (t^* and $S(t)^*$), respectively. Bass shows that the time to peak sales and the magnitude are, respectively:

$$t^* = (1 / (p + q))^* \ln (q / p) \tag{15}$$
$$S(t)^* = m^*(p + q)^2 / 4q \tag{16}$$

Fourth, the model encompasses two well-known earlier models in the literature. If p = zero, the Bass model reduces to a logistic diffusion function, assumed to be driven by only imitative processes (Fisher and Pry, 1971; Mansfield, 1961; Van den Bulte, 2000). If q = zero, the Bass model reduces to an exponential function assumed to be driven only by innovative processes (Bernhardt and Mackenzie, 1972; Fourt and Woodlock, 1960).[1] Hence, the Bass model makes fewer assumptions and is more general than these two models.

These four strengths of the Bass model account for its great appeal, popularity, and longevity in the marketing discipline. Indeed, it has spawned a paradigm of research in marketing, which remains unrivalled by any other model or theory.

Limitations

Despite its strengths and strong appeal, the Bass model (1969) suffers from several limitations. Subsequent research has sought to address these problems with varying degrees of success. We describe these efforts in the section that follows this one.

First, any individual fit of the Bass model has poor predictive ability. The model needs data at both turning points (takeoff prior to growth and slowdown prior to maturity) to provide stable estimates and meaningful sensible forecasts. However, by the time those events occur, the predictive value of the Bass model is limited. In other words, the Bass model requires as inputs two of the most important events that managers would like to predict: takeoff and slowdown.

Second, the model's parameters are unstable and fluctuate with the addition of new observations (Bemmaor and Lee, 2002; Golder and Tellis, 1998; Heeler and Hustad, 1980; Mahajan, Muller, and Bass, 1990; Van den Bulte and Lilien, 1997). This variation in estimates for small changes in observations leads one to question whether the parameters really capture the underlying behavior (internal and external influences). Indeed, researchers question the basic assumption that product growth is driven only by communication (Golder and Tellis, 1998; Van den Bulte and Lilien, 2001; Van den Bulte and Stremersch, 2004). One of the strengths of the model may account for the instability in parameters. The quadratic function fits the sales curve so well that it sacrifices estimating the true underlying behaviors (Golder and Tellis, 1998).

Third, the Bass model does not include the direct influence of any marketing variable such as price or advertising. This is a serious problem because most managers want to influence sales with these two variables. The model assumes, however, that the coefficients m or p capture the effect of such external influences.

Fourth, the product definition in the Bass model is static, that is, it assumes that the product itself does not change over time. However, there may be several technological changes within a product category itself, before a dominant design emerges (Srinivasan, Lilien, and Rangaswamy, forthcoming), and this variation is not allowed for in the Bass model.

Fifth, Bass used OLS regression in the model to estimate the values of p, q, and m. However, this method suffers from three shortcomings (Mahajan, Muller, and Bass, 1990). (1) There is likely to be multicollinearity between Y_{t-1} and Y^2_{t-1} making the parameter estimates unstable. (2) The procedure does not provide standard errors for the estimated parameters p, q, and m, and hence it is not possible to assess the statistical significance of these estimates. (3) There is a time interval bias because the model uses discrete time series data to estimate a continuous model.

Sixth, this tradition of research entails several problems in measuring the dependent variable (sales) and determining the starting and ending points of the time interval sampled. (1) Most researchers use sales as the dependent variable. As such, sales should consist of only first adoptions of the new product. However, in effect, most databases do not discriminate between first purchase and repurchases when describing sales. (2) Sales should be from the very first year of commercialization of the new product. However, in effect, the models only use published sales figures, which often report sales when a product has already been selling well, if not after takeoff of the product. (3) Researchers do not define a clear stopping rule for the time interval. The period modeled should end when the entire market has made first purchases or at least when adoptions have peaked.

The next sections describe how researchers correct for some of these weaknesses by improving the estimation techniques, predictive ability, and model specification.

Improvements in Specification

The specification of the Bass model is very simple, as it contains no deterministic explanatory variables. Over the past thirty-five years, a vast body of literature has sought to enrich the model by including marketing variables, supply restrictions, and multiproduct interactions (such as the presence of competitive products, complementary products, and newer technological generations), incorporating time-varying parameters, replacement purchases, multiple purchases, and trial and repeat purchases, and by analyzing cross-country diffusion patterns. The subsections evaluate the literature concerning each of these improvements concluding with an overall evaluation of this stream of literature.

Allowing Marketing Variables

Many authors consider the impact of marketing variables on new product diffusion (Bhargava, Bhargava, and Jain, 1991; Bass, 1980; Bass, Krishnan and Jain 1994; Danaher, Hardie, and Putsis, 2001; Jain and Rao, 1990; Jones and Ritz 1991; Kalish, 1985; Kamakura and Balasubramanian, 1988; Krishnan, Bass, and Jain, 1999; Horsky, 1990; Horsky and Simon, 1983; Robinson and Lakhani, 1975).

A decline in price adds households whose reservation price structure accommodates the new prices. Thus, price declines could affect the ultimate market potential. Price declines could also stimulate the flow of households from being potential adopters to adopters by increasing the probability of adoption. Kamakura and Balasubramanian (1988) find that price seems to influence only the probability of adoption and only for relatively high-price goods. Hence, the role of price seems to be heterogeneous across products.

Other models incorporate the effects of advertising on diffusion (Horsky and Simon, 1983; Simon and Sebastian, 1987). For instance, Horsky and Simon (1983) include the level of the producer's expenditures on advertising at time t directly into the Bass model.

Researchers also consider the influence of the distribution process in influencing diffusion. Jones and Ritz (1991) assume that there are two adoption processes occurring for any new product—one for the retailers and one for the consumers. Moreover, the number of retailers who have adopted the product determines the size of the consumer's potential market. The authors show that even if the *consumer* adoption curve is exponential, when the initial level of distribution is limited, the pattern of consumer adoptions takes an S-shaped curve similar to that obtained from a Bass model.

Research on channels of distribution has focused typically on traditional brick-and-mortar channels. Rangaswamy and Gupta (2000) discuss the application of the Bass model to digital environments. They posit that the market potential for an innovation, the coefficient of imitation, and the coefficient of innovation will be larger, leading to increased sales and speed of adoption through online channels. They also expect that in the digital environment, good products, with positive word-of-mouth will succeed faster, whereas bad products, with negative word-of-mouth, will fail faster.

Bass, Krishnan, and Jain (1994) include both price and advertising to give what they call, the Generalized Bass model, wherein:

$$f(t) / [1 - F(t)] = [p + qF(t)]x(t) \tag{17}$$

where $x(t)$ is the current marketing effort that reflects the impact of price and advertising on the conditional probability of product adoption at time t, such that

$$x(t) = 1 + \beta_1 \Delta Pr(t) / Pr(t-1) + \beta_2 \Delta A(t) / A(t-1) \tag{18}$$

where $\Delta Pr(t)$ refers to $Pr(t) - Pr(t-1)$ and $\Delta A(t)$ refers to $A(t) - A(t-1)$. Both these variables refer to the rates of changes in prices and advertising. The model reduces to the Bass model when price and advertising remain the same from one period to the next. Hence, the authors find that when percentage changes in the decision variables are constant the Generalized Bass model provides no better fit than the Bass model. Because the Bass model is quadratic in prior period's cumulative sales, it fits the S-shaped curve very well even when researchers omit marketing variables. However, when the coefficients for the decision variables are statistically significant, the Generalized Bass model provides a better fit than the Bass model.

No study has empirically tested for the effect of all the marketing variables simultaneously. The limitation of the empirical application by Bass, Krishnan, and Jain (1994) is that they consider the effects of changes in only price and advertising and not other marketing variables. However, the Generalized Bass model can potentially include all relevant marketing variables and hence is managerially relevant. The limitation of the model is that it considers only the effect of changes and not the absolute levels of these variables. It also does not allow for the influence of other important nonmarketing factors that influence product growth such as income changes.

Allowing Supply Restrictions

Jain, Mahajan, and Muller (1991) model the impact of restrictions on the production capacity or the distribution system on the diffusion process. They model the customer flow from being potential adopters to waiting applicants and from waiting applicants to adopters, as follows:

$$dA(t) / dt = (p + (q_1 / m)A(t) + (q_2 / m)N(t))\,(m - A(t) - N(t)) - c(t)A(t) \tag{19}$$

$$\text{and } dN(t) / dt = c(t)A(t) \tag{20}$$

In equation (19), $d(A) / dt$ reflects the rate of changes of waiting applicants. This is increased by the new applicants (first term on the right-hand side) generated by the influence of both waiting population $A(t)$ and adopters $N(t)$ on the potential applicants, but is decreased by the conversion rate of waiting applicants to adopters (second term on the right-hand side) where $c(t)$ is the supply coefficient. Equation (20) captures the impact of supply restrictions on adoption rate at time t. The growth process of the total number of new applicants is given by

$$dZ(t) / dt = dA(t) / dt + dN(t) / dt = (p + (q_1 / m)A(t) + (q_2 / m)N(t))\,(m - A(t) - N(t)) \tag{21}$$

Though this model demonstrates a way to incorporate the effect of supply restrictions, the authors assume that the level of capacity grows with the number of back orders. However, in practice, this assumption may not hold. In addition, dissatisfied consumers might cancel orders or negative word-of-mouth might discourage others from ordering. Ho, Savin, and Terwiesch (2002) allow some waiting applicants to abandon their adoption decisions after a point in time in their theoretical model incorporating both demand and supply dynamics. Their results suggest that when faced with the choice between selling an available unit immediately versus delaying the sale to reduce the degree of future shortages, the firm should always favor an immediate sale. The authors thus show that the time benefit of immediate cash flows outweighs the limitation of demand acceleration.

Both these studies show sensitivity to distribution issues and offer an opportunity to blend operations planning and marketing research. Such a confluence helps managers to deal with the dilemma of keeping inventory low while making products available to consumers (Cohen, Ho, and Matsuo, 2000). Nevertheless, a still greater challenge is the tackling of competitive effects.

Allowing Competitive Effects

While most models typically aggregate across individual diffusion processes by studying the product class, asymmetries may exist in diffusion across brands within a category.

Researchers consider the impact of competitive entry on the diffusion of other brands. A new brand may have two effects: (1) it could increase the entire market potential for the category due to increased promotion or product variety; and (2) it could compete for the same market potential and hence slow down the diffusion of the existing brands.

For instance, in an empirical application of the model to the instant-camera market, Mahajan, Sharma, and Buzzell (1993) find that Kodak drew more than 30 percent of its sales from potential buyers of the pioneer brand, Polaroid. However, at the same time, its entry also led to an expansion of the market. Krishnan, Bass, and Kumar (2000) study the impact of a late entrant on the diffusion of a new product. Using brand level sales data from the cellular telephone industry, they find that the impact of entry of a new brand varies from market to market, increasing the market potential of the category in some, hastening or slowing the diffusion process of other brands in others. Parker and Gatignon (1994) find that in the category of hair-styling mousses, for the pioneer, there seem to be strong brand identification effects and the diffusion is independent of competitive effects. For the second brand and other generic followers, prior adopters of the product class as a whole negatively influence their trials. The sensitivity of the diffusion of these brands to marketing variables also varies with the entry of competing brands.

Hence, research on competitive effects indicates that the diffusion process may differ depending on the order of a new brand's entry and the competition it faces. However, while the models help determine the direction of the impact, they do not clearly identify what causes these differential impacts across brands and markets.

Allowing Complementary Effects

Researchers have sought to account for the fact that the adoption of an innovation is dependent on the presence of related innovations (e.g., Rogers, 1995). Bayus (1987) incorporates this notion in forecasting the sales of new contingent products, that is, where the purchase of a product is contingent on the purchase of a primary product. In an empirical application to the CD-player market, the author demonstrates that the hardware sales can be modeled using a standard diffusion framework and the software sales can be forecasted by calculating the sum of current and future software purchase streams of first time hardware owners.

In markets with such indirect network externalities, the sales of software could affect hardware sales as well. Subsequent papers have accounted for two-way interactions in diffusion processes. Bucklin and Sengupta (1993) develop a model to examine the co-diffusion (both one-way and two-way interactions) of two complementary products—universal product codes (UPCs) and scanners. From their analysis of the two categories, the authors find that co-diffusion does exist and may be asymmetric in that one product has a stronger influence on the other product's diffusion than vice versa.

Gupta, Jain, and Sawhney (1999) incorporate the effect of indirect network externalities from suppliers of digital programming in modeling the evolution of digital TV sets. The authors use a combination of a latent class probit model of consumer demand and complementor response models. Consumer demand for digital TV is dependent on the hardware attributes and the software attributes of the set of competing products. Complementor (suppliers of digital programming) response is modeled as a function of the consumer demand for digital TV and exogeneous variables such as regulatory scenarios.

Lehmann and Weinberg (2000) focus on sequentially released products: new products that are released sequentially across channels (for instance, movie releases via movie theaters and then video rentals). A crucial question in the distribution of these products is the optimal timing of release across the channels in the face of cannibalization. Waiting too long to release the videos may reduce the marketing impact from the theater release. The authors determine that the sales of the initial product (theater attendance) can help forecast the sales of the sequential product (videotape rentals), and also that the optimal time to release the video is sooner than what is being done in practice.

These models reflect growing efforts to understand strategic interdependencies among complementary and competing products. It would be useful to model the effects of supplier actions/reactions, apart from consumer response, on complementor response. It would also be useful to trace these effects when a new market of an initially complementary product grows to the extent that it becomes a competitive product. For example, mobile phones have become competitive with landlines (Shocker, Bayus, and Kim, 2004). A related issue is modeling the evolution of successive generations of products.

Allowing Technological Generations

Norton and Bass (1987) assess the market penetration for successive generations of a high-technology product. The diffusion equation for the first-generation product when r_2 is the time of introduction of the second-generation product is

$$S_1(t) = m_1 F_1(t) - m_1 F_1(t)\, F_2(t - r_2) \tag{22}$$

The diffusion equation for the second-generation product is

$$S_2(t) = F_2(t - r_2)[m_2 + F_1(t)\, m_1] \tag{23}$$

where $S_i(t)$ refers to the sales of generation i in time period t, $F_i(t)$ refers to the fraction of adoption for each generation, where i =1,2; m_1 refers to the potential for the first generation, and m_2 refers to the potential for the second generation. Hence, this simultaneous model captures both adoption and substitution effects. The authors empirically test the model in the semiconductor industry. Norton and Bass (1992) extend this model to cover the electronics, pharmaceutical, consumer, and industrial goods sectors.

Mahajan and Muller (1996) account for the fact that users may skip a generation and buy a later generation (leapfrogging behavior) in a model that also captures both adoption and substitution patterns for each successive generation of a durable technological good. They propose a "now or at maturity" rule for new product introduction, that is, they determine that the optimal rule for a firm to use in the decision to introduce a new generation of a technological durable good is either to introduce it as soon as possible or to delay its introduction until the maturity stage in the life cycle of the first generation.

Kim, Chang, and Shocker (2000) try to capture not only the substitution effects between successive generations within a product category, but also complementary and competitive effects among product categories in a single model. Hence, the market potential of a generation of a product category is affected not only by technological substitution from another generation within the category but also by the sales of other categories. The authors illustrate the model by capturing the growth dynamics among pagers, analog and digital cellular phones, and the cordless telephone 2 in the wireless telecommunications market in Hong Kong. Their results indicate that the category of pagers that was introduced earliest seems to have a positive impact on the cellular phone's market potential while the cellular phone appears to have a negative impact on the pager's market potential. The cordless telephone 2, however, has a positive impact on both pager and digital cellular phone, possibly because it serves as a complement.

Danaher, Hardie, and Putsis (2001) capture the role of interdependencies in marketing-mix variables in the diffusion of successive generations of technology and show that there are substantial price response interactions across two generations of technology in the cellular telephone industry in Europe.

Allowing Time-Varying Parameters

The parameters of the Bass model can change over time due to several factors such as the changing characteristics of the population, products, or economy. Researchers have looked for ways to incorporate this dynamic specification into the Bass model (Bass, Krishnan, and Jain, 1994; Bretschneider and Mahajan, 1980; Bretschneider and Bozeman, 1986; Horsky, 1990; Lavaraj and Gore, 1990; Mahajan and Peterson, 1978; Sharma and Bhargava, 1994; Xie et al., 1997).

Mahajan and Peterson (1978) model the market potential as a function of time-varying exogenous and endogenous factors such as socioeconomic conditions, population changes, and government or marketing actions. Easingwood, Mahajan, and Muller (1983) develop a nonuniform influence model that allows the coefficient of imitation to be time varying. They use the specification

$$dF(t)/dt = [p + qF(t)^{\delta}][1 - F(t)] \tag{24}$$

where δ is called the nonuniform influence factor. If the value of δ equals 1, it indicates that diffusion takes place with uniform influence, similar to the Bass model. Values of δ between 0 and 1 cause an acceleration of influence leading to an earlier and higher peak. This leads to a high initial coefficient of imitation, which declines with penetration. Values of δ greater than 1 cause delay in influence leading to a lower and later peak. This indicates that the coefficient of imitation increases with penetration. Indeed, Easingwood (1987) demonstrates that nine classes of diffusion shapes can be determined by examining different values of the coefficient of imitation and the nonuniform influence parameter. For instance, a product with low values of both parameters has a brief initial period where influence is relatively high, leading to a steep start to the diffusion process. Subsequently, adoption is constant and low as influence becomes low.

Sharma and Bhargava (1994) question the assumption that all prior adopters are equally influential. They propose an extension of the nonuniform influence model where not only is the influence of previous adopters considered nonuniform, but also adopters who have adopted in the recent past are considered more influential than those who did so much earlier.

Several researchers propose alternate functional forms capable of allowing for dynamic formulation of the parameters. Hjorth (1980) proposes the term "IDB" to denote the distribution that can describe increasing (I), decreasing (D), constant and bathtub (B) shaped failure rates. Lavaraj and Gore (1990) demonstrate the use of this distribution to model an adoption function flexible enough to incorporate increasing, decreasing, constant or bathtub shapes, and nonuniform parameters. Bretschneider and Mahajan (1980), Bretschneider and Bozeman (1986), and Xie et al. (1997) demonstrate the use of feedback estimation approaches to estimate dynamic parameter paths.

The advantage of such dynamic specifications is that they provide a realistic interpretation of the diffusion process. They not only improve the estimation results but also help to examine the causes of accelerating or decelerating influences over time. However, the gain of accuracy and insights from the model comes with a loss of parsimony.

Allowing Replacement and Multi-Unit Purchases

Though the Bass model covers only first purchases of a durable good, typically the sales comprise both replacement and multiple purchases. Several papers in the diffusion literature cover these phenomena (Bayus, Hong, and Labe, 1989; Kamakura and Balasubramanian, 1987; Olson and Choi, 1985; Steffens, 2002).

Kamakura and Balasubramanian (1987) incorporate the role of replacement purchases in the following model:

$$y(t) = [a + bX(t)]\,[\alpha Pop(t)\, Pr^{\beta}(t) - X(t)] + r(t) + e(t) \tag{25}$$

where $y(t)$ is the sales of a product at year t, $Pr(t)$ is the price index, $Pop(t)$ is the population of electrified homes, $X(t)$ is the total number of units in use at the beginning of year t assuming that all dead units are replaced immediately, and $r(t)$ is the number of units that have died or need replacement at year t. The parameters a and b denote the coefficients of innovation and imitation, β denotes the impact of price changes on ultimate penetration, and α refers to the ultimate penetration, if price was kept at its original level. The researchers demonstrate the incorporation of replacement purchases into a diffusion setting even when replacement data are not specifically available.

A related problem is the purchase of multiple units by one household. Steffens (2002) develops and tests a model for multiple unit adoptions of durable goods. He models first-unit ownership using a Bass diffusion model with a dynamic population potential. External influences and earlier adopters of multiple units drive a proportion $\prod_1$ of first unit adopters to making multiple purchases giving the model for multiple unit adopters $M(t)$ as

$$dM(t) / dt = (\textstyle\prod_1 N(t) - M(t))\,(a_1 + b_1 M(t)) \tag{26}$$

where $N(t)$ refers to the number of cumulative adopters at time t, a_1 and b_1 are parameters representing external and word of mouth influences on the first multiple unit adoption. There are people who adopt more than two units. The upper potential of subsequent multiple unit adoptions is modeled as a fixed proportion $\prod_2$ of multiple unit adopters $M(t)$. The model for subsequent multiple unit adoptions $Q(t)$ is

$$dQ(t) / dt = (\prod_2 M(t) - Q(t)) (a_2 + b_2 M(t)) \quad (27)$$

where a_2 and b_2 are parameters representing external influences and word of mouth influences on subsequent multiple unit adoptions.

While these models throw light on how to capture replacement demand and multiple purchases, they do not give insights on what drives these processes. For instance, Olson and Choi (1985) assume that the life of a product ends due to wear-out failure only and hence product age and wear-out drive replacement demand. Other factors such as ability to pay could also determine replacement demand (Bayus and Gupta, 1992).

Allowing Trial-Repeat Purchases

Markets grow not only through acquiring new trials (first purchases) but also through repeat purchases by the original buyers. While some researchers look at trial-repeat purchase behavior in the context of packaged goods industries (Blattberg and Golanty, 1978; Fourt and Woodlock, 1960), other researchers examine trial-repeat purchase in the context of the pharmaceutical goods industries (Hahn et al. 1994; Lilien, Rao, and Kalish, 1981).

Hahn et al. (1994) develop a four-segment trial-repeat purchase model in which the four segments comprise nontriers, triers, post-trial nonrepeaters, and post-trial repeaters. They find that while word-of-mouth from prior adopters and marketing efforts influence trial, product quality, marketing activity, and market familiarity influence the repeat rate.

Allowing Variations Across Countries

The initial application of the Bass model was limited to the study of diffusion of new products within the United States. Researchers have since examined the role of wealth, social system heterogeneity, cosmopolitanism, activity of women, mobility, mass media availability, culture, and learning, in inducing variations in diffusion parameters across countries (Dekimpe, Parker and Sarvary, 1998, 2000a, 2000b; Ganesh and Kumar, 1996; Ganesh, Kumar, and Subramaniam, 1997; Gatignon, Eliashberg, and Robertson, 1989; Helsen, Jedidi, and DeSarbo, 1993; Kumar and Krishnan, 2002; Kumar, Ganesh, and Echambadi, 1998; Putsis et al., 1997; Talukdar, Sudhir, and Ainslie, 2002; Takada and Jain, 1991; Van den Bulte and Stremersch, 2004).

Evaluation

These improvements have individually addressed various limitations of the Bass diffusion model. While a single model, which incorporates all these improvements would enable a rich and comprehensive analysis, this benefit would likely come at the loss of parsimony. As a result, the contributions remain separate. In the meantime, managers and analysts can use any one of these models that addresses the most salient limitation for the product and category they are modeling. In addition, many of these models assume that the underlying behavior driving the process is knowledge dispersion through communication across consumers. This is, however, only *one* of the many processes driving growth. We describe models capturing alternate processes in a later section (alternate models of diffusion).

Improvements in Estimation

Since the Bass (1969) model, many articles have attempted to better estimate the parameters of these models (Lenk and Rao, 1990; Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986; Venkatesan, Krishnan, and Kumar, 2004; Xie et al., 1997). Schmittlein and Mahajan (1982) propose a maximum likelihood estimation (MLE) to estimate the parameters of the Bass model from the expression of the cumulative fraction of adopters $F(t)$ derived in the Bass model. Though the maximum likelihood approach eliminates the time-interval bias, Srinivasan and Mason (1986) suggest that the approach underestimates the standard errors of the parameter estimates as it focuses only on sampling errors and ignores other forms of errors. They propose an alternative estimation technique termed the nonlinear least squares approach. We classify subsequent improvements as belonging to one of four approaches: nonlinear least squares, hierarchical Bayesian methods, adaptive techniques, and genetic algorithms.

Nonlinear Least Squares

Srinivasan and Mason (1986) propose the following nonlinear least squares approach:

$$S(i) = m[F(t_i) - F(t_{i-1})] + u_i \tag{28}$$

where m is the number of eventual adopters, and $S(i)$ is the sales in the interval (t_{i-1}, t_i)

$$S(i) = m[(1 - e^{-(p+q)ti}) / (1 + (q/p)\, e^{-(p+q)ti}) - (1 - e^{-(p+q)t\,i-1}) / (1 + (q/p)\, e^{-(p+q)t\,i-1})] + u_i \tag{29}$$

where i =1, 2,…T

Jain and Rao (1990) also propose a similar nonlinear approach. These models can be easily estimated using standard software packages such as SAS. The nonlinear approach provides the following advantages over the OLS approach. First, the model is not constrained to be linear in the parameters. Second, the model overcomes the time-interval bias of the OLS estimation. Third, the model provides valid estimated standard errors and T-ratios.

However, researchers have determined that the nonlinear technique suffers from a few limitations. The estimates can be poor and noisy when obtained from data sets with too few observations. Van den Bulte and Lilien (1997) point at a downward bias in the estimates of m and p and an upward bias in the estimates of q. Using longer time series and using data with higher frequency is associated with lower estimated q / p values (Van den Bulte and Stremersch, 2004). These biases may cause managers to underinvest in advertising and external media and overestimate the impact of the social contagion.

One reason for the biases could be the omission of time-varying parameters. For instance, as price falls, lower income households may be better able to afford the new products, increasing the market potential, while the nonlinear least squares estimation would provide a downward-biased estimate of m. However, Van den Bulte and Lilien (1997) show and Bemmaor and Lee (2002) corroborate that a bias exists even if the model is correctly specified, which is perhaps more surprising.

In addition, the model proposed by Srinivasan and Mason (1986) does not allow for parameter updating and hence does not have good predictive ability for forecasting sales of very new products. Parameter updating is necessary to improve the stability of new product market forecasts. The next section examines attempts by researchers to incorporate Bayesian updating procedures with the nonlinear least squares estimation method.

Hierarchical Bayesian Methods

To estimate the Bass model reliably and make accurate predictions, researchers need data beyond the two inflexion points: takeoff and slowdown. Some researchers propose using expert judgments coupled with industry surveys or purchase intention questionnaires (Infosino, 1986) or information acceleration techniques (Urban, Weinberg, and Hauser, 1996) to develop prelaunch estimates.[2] Other researchers suggest using data for similar products, termed as analogies, for this purpose (Easingwood 1989). However, to do so, we need to answer two questions: (1) How can products be classified as similar/dissimilar? (2) What happens when products are dissimilar? Bayus (1993) proposes a solution to the first question by developing a product segmentation scheme using demand parameters, marketing and manufacturing related variables. He demonstrates its application to generate pre-launch forecasts for the high-definition TV.

As a solution to the second question, that is, when data of only dissimilar products are available, researchers propose the use of hierarchical Bayesian methods to model new product sales more accurately (Lee, Boatwright, and Kamakura, 2003; Lenk and Rao, 1990; Neelamegham and Chintagunta, 1999; Talukdar, Sudhir, and Ainslie, 2002). Here, the forecaster can obtain information from different products that share some common structures, even when no sales data for the focal product is available. Researchers then develop prelaunch forecasts for the focal product, updating them when sales information about the focal product does become available (Putsis and Srinivasan, 2000). The approach helps to produce more stable forecasts (Lenk and Rao, 1990; Neelamegham and Chintagunta, 1999; Talukdar, Sudhir, and Ainslie 2002).

Talukdar, Sudhir, and Ainslie (2002) demonstrate an application of the hierarchical Bayesian technique to the international diffusion context, pooling information across multiple products and countries. They use the nonlinear Bass diffusion model proposed by Srinivasan and Mason (1986), while incorporating two changes: (1) they model the error term in a multiplicative fashion to reduce the effects of heteroscedasticity, and (2) they model autocorrelated errors to allow for the possibility of serial correlation. They model the evolution of a cumulative fraction of adopters over time as

$$F_{pr,c}(t)= \{1-exp[-(p_{pr,c} + q_{pr,c})\, t]\}/ \{1 + (q_{pr,c} /p_{pr,c})exp[-(p_{pr,c} + q_{pr,c})\, t]\} \qquad (30)$$

where the subscripts *pr* and *c* refer to the product and country, respectively, and *t* refers to the time. The subscripts denote the fact that the authors allow for heterogeneity in the values across both countries and products. They find that their procedure yields lower mean-squared errors when compared either to models that estimate the parameters of the Bass model for one product across many countries (Gatignon, Eliashberg, and Robertson, 1989) or to models that estimate the parameters across multiple products for one country (Lenk and Rao, 1990). However, the limitation of this model is that the parameters are not allowed to vary over time.

Adaptive Techniques

Other researchers use stochastic techniques that allow parameters to vary over time to model new product growth. These techniques use feedback filters and Bayesian techniques to update the parameters over time (Bretschneider and Bozeman, 1986; Bretschneider and Mahajan, 1980; Xie et al, 1997).

Xie et al. (1997) propose the use of the *augmented Kalman filter* (AKF) to update parameter estimates as new data become available. The estimation technique uses continuous and discrete observations (AKF (C – D)) thus:

$$dn / dt = f_n [n(t), u(t), \beta, t] + w_n \tag{31}$$

$$d\beta / dt = f_\beta [\beta, n(t), t] + w_\beta \tag{32}$$

$$z_k = n_k + v_k \tag{33}$$

where n is the cumulative number of adopters, u is the marketing mix variable vector, β is the unknown parameter vector, w_n and w_β are the process noise, n_k and z_k are the actual and observed cumulative number of adopters at time t_k, and v_k is the observation noise.

Equation (31) is the *systems* equation that characterizes the diffusion rate at time t (the evolution of the cumulative adopters) as a function of the current adopters (n), the marketing mix variables (u), the diffusion parameters β, time t, and random noise w_n. Equation (32) specifies the time varying behavior of the parameters while equation (33) is the *measurement* equation that specifies the errors in measuring the number of adopters. At time 0, based on prior information, the best prior estimates of the parameter distributions are developed. At a specific time, the diffusion model predicts the sales and parameter values for the next period, using a *time updating process* given the current observations. There is also a *measurement update* as new information arrives, using the forecast error between the predicted and observed number of adopters.

The authors show that the augmented Kalman filter estimates the parameters directly, avoids time interval bias, forecasts more accurately than other techniques such as the nonlinear least squares and the OLS, and can estimate time-varying parameters. This technique is however not as easy to use as the nonlinear regression.

Genetic Algorithms

Venkatesan, Krishnan, and Kumar (2004) propose the use of genetic algorithms to estimate the Bass model. They find that since this technique combines the advantages of both systematic search and random search, it has a better chance of reaching the global optimum as compared with sequential-search-based nonlinear least squares. In simulations, the authors find that unlike the nonlinear least squares method, this technique does not suffer from bias and systematic change in parameter values as more observations are added. The authors also find that the mean of the absolute deviations in forecasting for the genetic algorithms is significantly lower than the augmented Kaman filter estimation technique. However, the technique does not allow for the fact that the parameters can vary over time.

Evaluation

This body of research indicates that improved estimation techniques, combined with product classification schemes such as that developed by Bayus (1993) can lead to increased accuracy in the forecasts of peak sales and the sales evolution from takeoff to peak during the growth stage. However, the models, which focus on the general diffusion curve, have paid scant attention to the turning points in sales, such as slowdown and especially takeoff. For these critical events, researchers have proposed entirely new models, which will be described below in the section on modeling the turning points in diffusion..

Alternate Models of Diffusion

Due to the many limitations of the Bass model, especially its reliance on only a process of communication, several researchers have departed from the framework and proposed entirely new models. Three of these relate to alternate drivers: affordability, heterogeneity, and strategy; and two relate to alternate phenomena, spatial diffusion, and diffusion of entertainment products

Affordability

The assumption that underpins the Bass model is that the market consists of a homogenous population of adopters, all of whom can afford the product equally well. Their different times of adoption occur because they hear of the product, either from the firm or from other adopters, at different times. We review models that question this assumption.

Golder and Tellis (1998) propose an alternate model based on the idea of *affordability.* They argue that most consumers know about new products long before purchasing them. They hold back from purchasing these products due to high prices. New products are expensive when they first appear on the market, and become attractive to the mass market only when their price drops sufficiently. Consumers delay their purchases until prices decline or incomes rise sufficiently for them to afford the new product. Hence, *affordability* is a key driver of new product growth. The authors wish to model product sales as a function of price, income, consumer sentiment, and market presence, in a parsimonious manner. Hence, they use the Cobb-Douglas model, which is:

$$S = P^{\beta 1} \times I^{\beta 2} \times CS^{\beta 3} \times MP^{\beta 4} \times e^{\epsilon} \tag{34}$$

where S denotes sales, P denotes price, I denotes income, CS denotes consumer sentiment, and MP denotes market presence. While this model does not fit the data as well as the Bass model, the estimates of the coefficients and price response seem more stable with the addition of observations to the data series and the model seems to yield better year-ahead forecasts.

Horsky (1990) develops a model that incorporates the role of price and income (affordability) in addition to the word-of-mouth effect in aiding sales growth. He assumes distributions for both wages and prices, and considers that only a proportion of the population will purchase the product. He models sales as:

$$S(t) = [\theta M(t) / (1 + e^{-(K + \acute{w}(t) - k\,p(t)) / \delta(t)}) - Q(t)]\,[\alpha + \beta Q(t)] \tag{35}$$

where $M(t)$ refers to the number of households in the population, with an average wage $\acute{w}(t)$, its dispersion being $\delta(t)$; $p(t)$ refers to the average price of the durable; θ refers to the fraction of the population who will buy the product; and $Q(t)$ is the number of eligible individuals who have purchased before time t. The term $[\alpha + \beta Q(t)]$ depicts how an eligible individual may become aware of a product due to word-of-mouth information from those who have already purchased the product. If the size of the population, the income distribution, and price remain constant, the equation reduces to the more familiar

$$S(t) = [N - Q(t)]\,([a + \beta Q(t)] \tag{36}$$

where N equals the number of people eligible to purchase. In an empirical application of the performance of the model, the author determines that in categories where the word-of-mouth effects are weak, the model fits the data better than the Bass model. The author also derives the policy implication that a price skimming strategy is appropriate for a monopolist when weak word-of-mouth effects exist and a price penetration strategy is appropriate when word-of-mouth effects are strong.

Evaluation

These models have the advantages of specifically accounting for the role of price, income and product benefits in the adoption process, hence providing a richer interpretation. However, this richness comes at the cost of either parsimony, ease of interpretation, or predictive ability, which are the key benefits of the Bass model.

Heterogeneity

Some researchers have looked at the adoption problem as a decision problem under conditions of belief updating and heterogeneity among consumers (Roberts and Lattin 2000). The models that fall under this classification have typically been termed "disaggregate level" diffusion models as they do not assume an aggregate homogenous population. Individual level models first originated in the economics literature (Feder and O'Mara, 1982; Hiebert, 1974; Stoneman, 1981). Here we review eleven models, the first seven predominantly from marketing and the next four from economics.

Roberts and Urban (1988) assume that individual consumers choose the brands that provide them with the highest expected risk-adjusted utility and update their prior beliefs about the brand in a Bayesian fashion with the arrival of new information. This updating occurs in two ways. (1) Word-of-mouth communications (positive or negative reviews) may change the estimated mean attribute levels of the brand. (2) Uncertainty may decline due to the availability of new information. The authors derive the individual hazard of purchase as a multinomial logit model. The authors apply the model to the prelaunch planning of a new automobile where they collect measures of mean values, perceived attribute levels, uncertainty, and purchase probabilities from respondents, and aggregate the probabilities of purchase over consumers to get the expected market share.

Oren and Schwartz (1988) study the choice between an innovative new product with uncertain performance and a currently available product with certain performance. Uncertainty leads risk-averse consumers to delay adoption until they get more evidence on the performance. Early adopters are those who are less averse to risk while later adopters are imitators who delay purchase until they get enough information from the market to overcome their initial uncertainty. The authors derive an aggregate-level logistic market growth model for market share.

Chatterjee and Eliashberg (1990) develop a model where consumers are risk averse and adopt a product only if their expectations of its performance exceed a "risk hurdle" and a "price hurdle." The consumers update their expectations of performance based on the information (positive or negative) they receive. Consumers are hence heterogeneous in the cumulative information they need for adoption. The authors derive a diffusion curve by aggregating the predicted individual adoption behavior over the population. The authors show conditions in which their model can reproduce the Bass (1969) and Fourt and Woodlock (1960) models. The authors obtain individual level parameters for price, risk, and uncertainty by means of a survey of respondents.

Bemmaor (1994) demonstrates that an aggregate level diffusion model can be derived from individual level heterogeneity assumptions in the gamma/shifted Gompertz model (G/SG). Bemmaor and Lee (2002) demonstrate the superiority of this model to the Bass model in terms of forecasting ability. In this model, individual level adoption timing is randomly distributed according to a two-parameter shifted Gompertz distribution whose cumulative distribution function is as follows:

$$F(t / \eta, b) = (1 - e^{-bt}) \exp(-\eta\, e^{-bt}),\ t > 0 \tag{37}$$

where b is a scale parameter constant across all consumers, and η captures an individual's propensity to buy, which varies across consumers according to a gamma distribution, with a shape parameter α, and a scale parameter β. Here, small values of α indicate greater heterogeneity. The authors derive an aggregate level distribution of adoption times given by

$$F(t) = (1 - e^{-bt}) / (1 + \beta\, e^{-bt})^{\alpha} \tag{38}$$

Here, if $\alpha = 1$, $b = p + q$ and $\beta = q / p$, equation (38) reduces to the Bass model, and if $\alpha = 0$, equation (38) reduces to the exponential model. The authors test the model by forecasting the sales of twelve new products and find that the G/SG model provides better forecasts than the Bass model. However, they show that with the addition of more observations, there are systematic changes in the market potential and imitation coefficients. Hence, the more complex G/SG model shows greater parameter instability than the Bass model.

Song and Chintagunta (2003) develop a model in which they account for both heterogeneity and forward-looking behavior by consumers in the adoption of new high-tech durables products. They use aggregate sales data, rather than intent measures obtained from surveys, to estimate the model. In the model, consumers have expectations of the future states of prices and quality levels, both of which change over time, leading to a probability distribution on the transition of future states of these variables conditional on current states. A consumer can choose either to buy or not to buy a product in each period, selecting the alternative that maximizes the discounted sum of expected utility. The authors aggregate these individual level adoption decisions to obtain an aggregate diffusion curve, and use the more easily available aggregate level data to estimate the individual level decision parameters.

Sinha and Chandrasekaran (1992) demonstrate the application of a split hazard model to analyze the probability of adoption and adoption timing of an individual firm. By splitting the population into eventual adopters and nonadopters, and modeling both the probability and the timing of adoption as a function of individual level variables, they capture heterogeneity at the individual level. They test their model in the context of the adoption of automated teller machines in a sample of individual banking firms.

Chandrashekaran and Sinha (1995) account for variation in the volume of adoption as well as the timing of adoption by applying a split-population Tobit duration model in examining the adoption of personal computers by a sample of firms.

Karshenas and Stoneman (1993) and Stoneman (2002) describe what they term "rank," "stock" or "order" effects. In models considering "rank" effects, actors adopt as soon as the utility of the innovation exceeds some critical level or threshold. If the utility increases systematically over time and the thresholds follow some bell-shaped distribution, then the cumulative number of adopters, that is, the diffusion curve, will be S-shaped. In the consumer marketing literature, income distribution within a population can determine reservation prices, and hence pose one such threshold (Van den Bulte and Stremersch, 2004). In models considering "stock" effects, the assumption is that the marginal benefit from adoption decreases with the number of prior adopters (Karshenas and Stoneman, 1993; Stoneman, 2002). Over time, cost of acquisition falls, increasing the number of adopters. As more firms adopt the new technology, costs of production fall, increasing output.

As a result, the industry price falls and adoption is unprofitable beyond a certain point. In the economics literature, such models typically follow a game-theoretic approach (Reinganum, 1981). In models incorporating the "order" effects, the assumption is that there are first-mover advantages in using a new technology. The returns to the firm from the new technology depend on its position, with higher-order firms getting more returns than lower-order firms do. Each firm, considering how moving down the order affects its return, generates the diffusion path. For any given costs of acquisition, only some firms will find it profitable to adopt at a given point in the order, and only these numbers adopt. As costs of acquisition fall, more firms adopt. Fudenberg and Tirole (1985) develop a game theoretic model where they argue that earlier adopters get the highest return and hence there will be a race to be an early adopter, and the decisions of higher-order firms can then influence the decision of lower-order firms.

Karshenas and Stoneman (1993) determine the effect of rank, stock, order, and epidemic effects on the diffusion of CNC machine tools in the U.K. engineering industry. They estimate a hazard model of the form

$$h(t / X, \beta) = h_0(t) \times \exp(X'\beta) \tag{39}$$

where X incorporates acquisition costs, cumulative number of adopters at time t (stock), firm characteristics (rank), expected change in the number of cumulative adopters in the time interval $(t, t+1)$ (order), price, and expected change in price, and the baseline hazard denotes the epidemic effects. They find that rank and endogenous learning effects play an important role in the diffusion process, but find little support for the stock and order effects prescribed by game theoretic models, *lending support for the interest paid by the marketing literature to the communication process in adoption.*

Evaluation

Following the Bass model, the vast tradition of diffusion research in marketing has focused on communication among potential adopters and prior adopters as the main driver of diffusion. In contrast, the models discussed in this section indicate alternate reasons as to why individual consumers adopt new products and change their judgments over time.

However, these models, which focus extensively on individual level adoption decisions, have some limitations. First, most individual models lack the parsimony and ease of understanding that are the strengths of aggregate level models. Second, when individual level models use aggregate level data, it is difficult to identify the precise drivers of the adoption process.

Strategy

By strategy, we mean the explicit modeling of a firm or a central decision maker's choices such as market entry, marketing mix efforts and location.. In this section, we consider three such models. While some extensions of the Bass model do consider the marketing mix, as seen in a previous section (Bass, Krishnan, and Jain, 1994), such extensions are subservient to the model structure and lead to potentially understated effects for marketing variables.

DeKimpe, Parker, and Sarvary (2000a) consider two stages in the technological adoption of digital communication switches: (1) the time between the first availability of an innovation in the world and its introduction in a country (the implementation stage), and (2) the time between the introduction of an innovation into a country and its full adoption (the confirmation stage). They examine the impact of economic, sociodemographic factors, installed base, and the international experience of the innovation on the transition times from one stage to another, using the coupled hazard approach. The authors point out that for telecommunications innovations, the local government or a central communications unit often acts as a key decision maker in setting standards and regulations. This may affect the product's diffusion path. For instance, in some small countries, the central decision-making unit may decide to replace the old technology fully with the new technology, and hence these countries may reach full penetration immediately on adoption whereas other countries may exhibit the more gradual S-shaped diffusion path.

Van den Bulte and Lilien (2001) reexamine the medical innovation study (Coleman, Katz, and Menzel, 1966). This study examines the role of social networks in the diffusion of the broad-spectrum antibiotic tetracycline among 125 physicians in the United States in the 1950s. Van den Bulte and Lilien (2001) use a discrete time hazard modeling approach to examine the role of both social influence and marketing efforts by drug companies in influencing the hazard of adoption by a physician. They find that marketing efforts, rather than contagion seem to influence the diffusion process, and indicate that the medical innovation study might have confounded social contagion with marketing effects.

Bronnenberg and Mela (2004) study the spatial and temporal introduction of two brands in the frozen pizza category in the United States. The process begins with manufacturers deciding which markets to enter. Subsequently, in the markets that they enter, manufacturers offer the product along with incentives to retail chains. The retail chain decides whether to approve the brand for distribution on its entire trade area. Individual stores from this chain can carry the brand once it becomes locally available and is approved for adoption. The authors model the manufacturer's timing of local market entry and the retailer's timing of adoption of the brand, conditional on entry, using a discrete time hazard modeling approach. They determine that manufacturers sequentially enter markets based on the spatial proximity to markets already entered, and based on whether the chains in these markets have previously adopted the product elsewhere. The retail chains adopt the product, based on whether competing chains have adopted the product, and the manufacturers push into the trade area of the retailer. The study highlights the importance of taking into account the marketing actions (launch strategy) of manufacturers, without which the effect of local competitive contagion may be overstated. The study also points out the importance of understanding how products diffuse over *space*, which we elaborate upon in the next section.

Evaluation

Researchers who consider strategic factors, such as marketing variables, or entry decisions, find that these factors often dominate the role of communication in driving diffusion (Bronnenberg and Mela, 2004; Sultan, Farley, and Lehmann, 1990; Van den Bulte and Lilien, 2001). This finding highlights the need to consider such variables in order to avoid spurious results.

Modeling Diffusion Across Space

Spatial diffusion models address the way products diffuse over *space* rather than over *time* as the prior models do. Though not considered explicitly in the field of marketing, spatial diffusion has had a long tradition of research in the fields of geography and agricultural history, originating in the seminal work of Hagerstrand (1953).[3] There are various types of spatial diffusion (Morrill, Gaile, and Thrall, 1988). *Contagious* diffusion occurs when the distance or adjacency is the controlling factor, for instance, the spread of infectious diseases. *Expansion* diffusion describes a process similar to that of a wildfire, when there is a source and the diffusion occurs outward from the source. *Hierarchical* diffusion occurs when diffusion progresses through an ordered series of classes, such as a phenomenon first being observed in the largest city, then jumping to the next largest, and so on. *Relocation* diffusion occurs when the number of agents with the diffusion characteristics does not change. The agents merely change spatial location or as the trait passes on to additional agents, it is lost in the original agents. Here we consider some aspects of the seminal work by Hagerstrand (1953) as well as four models in marketing that examine explicitly the notion of diffusion across space (Bronnenberg and Mela, 2004; Garber et al., 2004; Mahajan and Peterson, 1979; Redmond, 1994).

Hagerstrand (1953) conducts a detailed mapping of the geographic spread of agricultural indicators such as state-subsidized pastures and of general indicators such as postal checking services, automobiles, and telephones. He observes that a synoptic growth curve could conceal a large number of individual events that occur simultaneously in different parts of the observed area. Typically, diffusion seems to have the following spatial regularities: at first, there is a local concentration of initial acceptance followed by a radial dissemination outward while the original core of acceptance continues to become denser. Finally, growth ceases, as there is saturation. For agricultural indicators, the initial acceptance groups are clear and radial dissemination proceeds along clear-cut lines. For instance, the acceptance of state-subsidized pastures spreads from the west to the eastern part of the area. In contrast, for general indicators, the initial acceptance is more dispersed and the subsequent dissemination less orderly. Much of Hagerstrand's work is relevant to marketing. For instance, he introduces the notion of a "mean information field" where the frequency of contacts in a social network is assumed to diminish with distance. He also argues that potential adopters may vary in their "resistance" to the innovation, leading to a longer period of incipient growth and a greater degree of spatial concentration that is evident in the diffusion of some products.

Mahajan and Peterson (1979) introduce the notion of the "neighborhood effect" in technological substitution models in the marketing literature, that is, the further a region is from the "innovative region," the later substitution will occur.

Redmond (1994) argues that diffusion models typically assume spatial homogeneity by examining the process at a national level, and this ignores variations within a country. In an application of the Bass model to the diffusion of two consumer durables across nine regions within the United States, he determines that differing local conditions and demographics across regions lead to differing diffusion rates within a country.

Garber et al. (2004) argue that it is possible to predict the success of new products by looking at spatial patterns of diffusion by means of complex systems analysis. In such an analysis, the market is a matrix in which the discrete cells represent adoption by individuals. Each cell interacts with the other cells, the interactions not being limited to strictly neighboring cells (in what is termed a "small-world" framework). The value "0" represents nonadopters and "1" represents adopters; "p" represents the probability that an individual will be affected by external factors, and "q" the probability that an individual is affected by an interaction with a single other individual who has adopted the product. The probability that an individual adopts at time t given that the individual has not yet adopted is:

$$Prob\ (t) = 1 - (1 - p)\ (1 - q)^{v(t) + r(t)} \tag{40}$$

where $v(t)$ represents the number of neighboring previous adopters with whom the individual maintains contact and $r(t)$ is the number of previous adopters who are weak-tie contacts. The authors argue that a spatial analysis of diffusion data can help in the early prediction of new product success. They state that for a well-received product, word-of-mouth and imitation will feed the flow of internal influence, leading to the formation of clusters. However, if the product is a failure, then internal effects activity will be minimal, diffusion will be mainly due to external effects, and adopters will hence be randomly distributed. Thus, the distribution in the case of a failure would be closer to a uniform distribution. Therefore, the authors argue that it is possible to predict the success of a new product within a few periods of its introduction by comparing the spatial distribution of the product with respect to a uniform distribution using a measure of divergence known as *cross-entropy*. They expect successful products to have a declining cross-entropy measure while failures will have a consistently low cross-entropy measure.

Evaluation

There is a trend in marketing to consider diffusion across both time and space. The use of techniques such as complex systems analysis helps to provide a microview of the patterns of interaction among individuals and an understanding of how this influences the diffusion of new products. However, these models seem to follow the Bass model tradition of viewing new product diffusion entirely through a process of "communication," ignoring alternate explanations such as those described in previous sections.

Modeling Entertainment Products

The sales of entertainment and information products, especially release of movies to theaters, typically follow a pattern of exponential decay rather than the bell-shaped pattern of durable goods sales. A vast stream of marketing research has focused on forecasting sales in the movie industry and sales of other entertainment products. This section reviews some of the important models in this area.

Eliashberg and Sawhney (1994) develop a model to predict individual differences in movie enjoyment. Sawhney and Eliashberg (1996) model the total time to adopt (see) a movie by an individual as the sum of the total time to decide, which is related to information intensity and the total time to act, which is in turn related to distribution intensity. Both these processes are assumed to be exponentially distributed with the stationary parameters and . The authors find that their model can determine three classes of adoption patterns that can represent all box-office patterns. The authors hence develop a simple model, based on just two parameters, which needs less data than the Bass model to forecast effectively. However, when the authors extend their analysis in an attempt to model with little or no revenue data, they find that while their model does well in predicting the ultimate cumulative box-office potential, it does not help capture the shape parameters λ and γ and hence provides little insight regarding how the box-office performance is spread over time.

Subsequent researchers of entertainment products show how to develop better prelaunch forecasts. For instance, Eliashberg et al. (2000) assume that initially all consumers are in an "undecided" state and are exposed to both media advertising and word-of-mouth (positive or negative). Depending on the impact of advertising and word-of-mouth effects, there is a behavioral transition from the "undecided" to the "considerer" (one who eventually sees the movie) or "rejector." The considerer becomes either a positive or a negative spreader. The authors model the state transitions via an interactive Markov chain model. The parameters of the model—word-of-mouth frequency, duration of spread, consideration duration, and distribution delay—are determined via prerelease experiments. This model is intuitive and appealing as it reflects the actual behavioral states and transitions of a movie consumer.

Elberse and Eliashberg (2003) examine movie forecasting in a cross-cultural context and determine how the performance of a movie in a domestic market influences its performance in a subsequent international launch. Researchers have also examined the impact of advertising (Zufryden 1996), movie critics (Eliashberg and Shugan 1997), and movie Web site promotion (Zufryden 2000) in forecasting box-office performance. Shugan (2000) and Shugan and Swait (n.d.) demonstrate how researchers can utilize consumer intent-to-see measures in developing prerelease forecasts.

A number of other models examine various aspects related to the sales evolution of entertainment products. For instance, Moe and Fader (2002) demonstrate the use of the hierarchical Bayesian technique to develop prelaunch forecasts of new product sales of entertainment goods such as music CDs, based on patterns of advance purchase orders. Lee, Boatwright, and Kamakura (2003) elaborate a hierarchical Bayesian model to develop prelaunch forecasts of recorded music.

Evaluation

These models show in general that alternate models help capture the growth of entertainment products better than the Bass model in terms of insights, fit, and prelaunch predictions of sales. The question is whether these different models are generalizable beyond the specific product modeled to all entertainment products. They are unlikely to be suitable to nonentertainment products. In contrast, the strength of the Bass model is that it can be generalized beyond the durable goods setting.

Modeling the Turning Points in Diffusion

This section examines the definition, measurement, drivers, and models of the specific turning points of the general diffusion, that is, takeoff and slowdown.

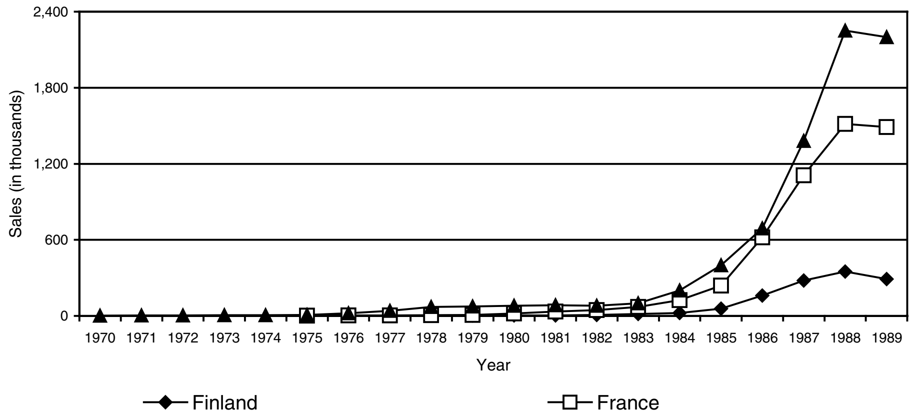
Takeoff

A key characteristic of new products is that not all consumers accept them instantaneously at the time of introduction. The Bass model assumes the presence of a certain number of consumers ($p \times m$) before "takeoff" (Golder and Tellis, 1997; Mahajan, Muller, and Bass, 1990, p. 21). Researchers using the Bass model also frequently use data from the point of takeoff or slightly before (Golder and Tellis, 1997). However, most new products experience a long period when sales are low. At some point, a sudden spurt in sales is followed by a period of rapid growth. When viewed graphically this trend appears as a sharp bend in the curve or a "takeoff." Figure 2.2 compares the takeoff patterns of a white good (microwave oven) across various West European countries. The sharp bend in the curves of the graphs signals takeoff.

Prior to 1997, academic literature and the trade press have often referred to the takeoff of new products, without any formal definition or measure of the phenomenon. However, a few articles discuss the phenomenon from select angles.

For instance, Gort and Klepper (1982) define the diffusion of product innovations as the spread in the number of producers engaged in manufacturing a new product. They define the takeoff as the second stage in this evolution, involving a sharp increase or *takeoff* in the number of *producers*. However, though they are able to demonstrate these distinct stages of market entry, they do

Figure 2.2 **Takeoff of Microwave Oven Sales in Europe**



not relate it to the adoption of the new products by consumers. Thus, we cannot be sure that the takeoff in number of producers coincides with takeoff in sales.

Kohli, Lehmann, and Pae (1999) define a concept termed "incubation time" as the time between the completion of product development and the beginning of substantial sales of the product. They find that the length of the incubation time affects parameters of the Bass diffusion model. The beginning of "substantial sales" of the product can be analogous to takeoff. However, their definition of "substantial" and the measurement of when substantial sales begin, and hence of incubation time, is vague.

Golder and Tellis (1997) define takeoff in sales of a new product as the point of transition from the introduction stage to the growth stage of the product life cycle. They also provide the first formal and precise measure of takeoff. We describe this measure later in the context of other measures for takeoff.

Why is takeoff important? A sudden and sharp increase in sales requires enormous resources in terms of manufacturing, inventory, distribution, and support. Hence, knowing when it occurs and what causes it is critical for managers in handling the sales and success of a new product. Most important, takeoff represents a difficult-to-predict turning point in a new product's life. It might well be a sign to the managers that the product has become desirable to the mass market. It might also be an early sign of the future success of the new product.

Measuring Takeoff

The literature describes many different measures of takeoff.

Golder and Tellis (1997) provide a simple measure for this phenomenon that they find to work quite well in an extensive study of new consumer durables in the United States. The authors find that when the base level of sales is small, a relatively large increase in sales can occur without signaling takeoff. Alternatively, when the base sales are large, a relatively small increase in sales can signal takeoff. Hence, they develop a threshold of takeoff, which is a plot of percentage sales growth relative to a base level of sales, common across all categories. The authors measure takeoff as the first year in which an individual category's growth rate relative to the base sales crosses this threshold. They find that this heuristic measure of takeoff successfully fits a visual inspection for 90 percent of the categories in their sample.

Golder and Tellis (1997) also compare this rule to measure takeoff with two alternatives: a logistic curve rule and a maximum growth rule. The logistic curve rule involves finding the first turning point of a logistic curve fitted to each sales series. This involves determining the maximum of the second derivative of the logistic curve since this captures the largest increase in sales growth. The maximum growth rule uses the largest sales increase within three years of takeoff as determined by the logistic curve rule. However, the authors identify problems with the latter two rules. Researchers can apply the logistic curve rule only in hindsight, as it requires sales beyond takeoff. The logistic curve rule is also a continuous rule to measure what is essentially a discontinuity. The maximum growth rule has three limitations. First, the largest sales growth sometimes occurs after takeoff has already occurred and sales are clearly in the growth stage. Second, large percentage increases can occur even with small base level sales. Third, the researcher can apply this rule only in hindsight.

Agarwal and Bayus (2004, 2002) propose a fourth measure of takeoff. They distinguish between any two consecutive intervals by examining the data on annual percentage change in sales (for the sales takeoff) and annual net entry rates (for firm takeoff) for each product. To determine the takeoff year for a product, first they partition the appropriate series into three categories. Here, the first and third categories contain the years where the percentage change in sales or net entry rate reflect the pre- and post-takeoff periods, respectively. They classify the in-between years based on mean values. This is a method similar to that used by Gort and Klepper (1982) to identify firm takeoff.

Stremersch and Tellis (2004) and Tellis, Stremersch, and Yin (2003) use a fifth measure of takeoff to suit an international sample of countries. It is similar in spirit to the threshold rule proposed by Golder and Tellis (1997). The authors define the threshold as a standard plot of growth in sales for various levels of *market penetration* to provide for a more standard comparison across several countries. Takeoff is the first year in which an individual category's growth rate relative to the base sales crosses this threshold

Garber et al (2004) and Goldenberg, Libai, and Muller (2001a) use a measure that takeoff occurs when 16 percent of the population adopts. This is similar to Rogers' (1995) argument that the S-shaped curve of diffusion "takes off" at around 10–20 percent adoption.

So far, no study has compared these six different measures of takeoff to assess their simplicity, domain of relevance, validity, and predictive accuracy.

Explaining Takeoff

We consider the literature on takeoff itself to be in the introductory and pretakeoff stage of its life cycle. Our search revealed only a few studies on this topic, three of which deal specifically with the determinants of takeoff. These three studies examine three different drivers of takeoff: affordability, infrastructure factors, and heterogeneity, and they reach substantially different conclusions.

Golder and Tellis (1997) propose that price declines are a principal driver of takeoff. At some point in the price decline, the new product crosses a critical point of affordability, leading to a takeoff. They find that economic characteristics such as GNP, consumer sentiment, or number of households do not affect the probability of takeoff, arguing that this may be because when the primary condition for takeoff (consumer affordability) is satisfied, even a weak economy cannot forestall takeoff.

Agarwal and Bayus (2002) argue that an increase in firm entry leads to increased consumer awareness due to an increase in the number and quality of product offerings, marketing infrastructural facilities, and promotions. The authors examine both product takeoff and firm takeoff and find that both firm entry and price declines are related to product takeoff times. Moreover, they find that firm entry dominates price declines in explaining takeoff times.

Tellis, Stremersch, and Yin (2003) examine the relative impact of country, product, and time characteristics on the takeoff of new products across categories and countries. They determine that a "venturesome" culture seems to affect takeoff, and similar to the results in Golder and Tellis (1997), they find that economic wealth and economic progressiveness do not seem to affect takeoff.

Modeling Takeoff

Researchers typically use a hazard function to model takeoff. Both Agarwal and Bayus (2002) and Golder and Tellis (1997) model the rate at which takeoff occurs as a function of a baseline hazard function that captures the effect of time since introduction, and independent variables. Hence, they model time to takeoff using the following proportional hazards specification:

$$h_i(t) = h_0(t)e(z_{it}\beta) \tag{41}$$

where $h_0(t)$ is an unspecified baseline hazard, z_{it} is the vector of independent variables for the ith category and β is the vector of unknown parameters.

The advantage of using this specific formulation is that it does not constrain the baseline hazard to be of any specific functional form, such as monotonically increasing or decreasing. Cox's partial likelihood estimator provides a method for estimating β without requiring estimation of the baseline hazard. Positive beta coefficients increase the hazard of takeoff, negative beta coefficients decrease the hazard of takeoff, and the effect of an increase by one unit of any independent variable on the hazard of takeoff is captured by the magnitude 100 * (e^{β} – 1). In a similar vein, Tellis, Stremersch, and Yin (2003) use the parametric log-logistic hazard approach to model time to takeoff.

Evaluation

The literature on takeoff is small but critical to managers and researchers for several reasons. First, it identifies an important phenomenon and shows that it can be scientifically modeled. Second, the models are somewhat successful in identifying explanatory variables and predicting the phenomenon. Third, managers have already applied the models in practice and for formulating strategy (e.g., Foster, Golder, and Tellis, 2004).

At the same time, the literature has some important limitations. First, it considers only successful innovations. As such, its implications are good for predicting *when* a takeoff might occur. It cannot tell *whether* a takeoff might occur or predict the success or failure of a new product. Second, the empirical applications of takeoff have involved only a limited geographic domain (only the United States and Western Europe). Third, models of takeoff focus only on the growth of the product until takeoff, which on average occurs at 2 percent penetration of the market. The models give no insights about the sales pattern *after* takeoff. So far, no published study has tried to integrate the modeling of these two phenomena.

Slowdown

The most common conception of a product life cycle portrays the sales history of a product as following a smooth bell-shaped curve, with just four stages—introduction, growth, maturity, and decline. Some researchers have noted, however, that the classic bell shape might not be

Figure 2.3 **Slowdown in Growth of Dishwasher Sales in Europe**

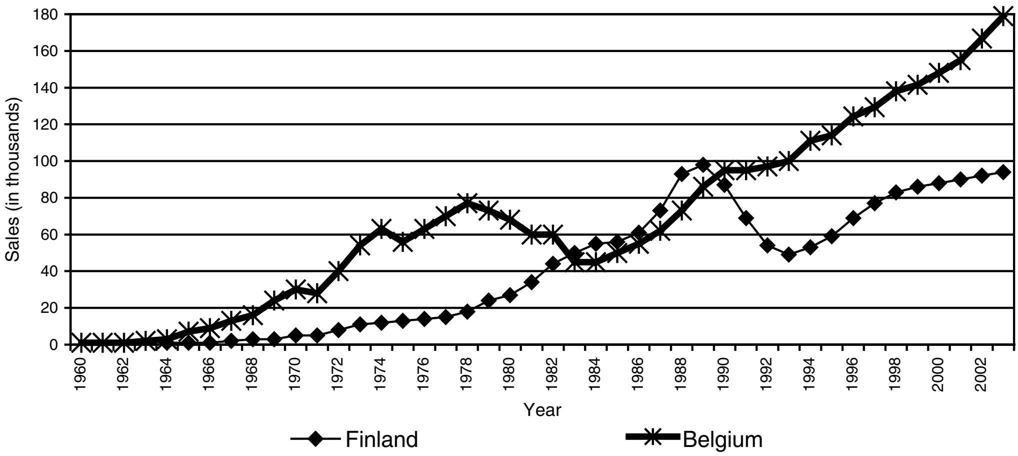
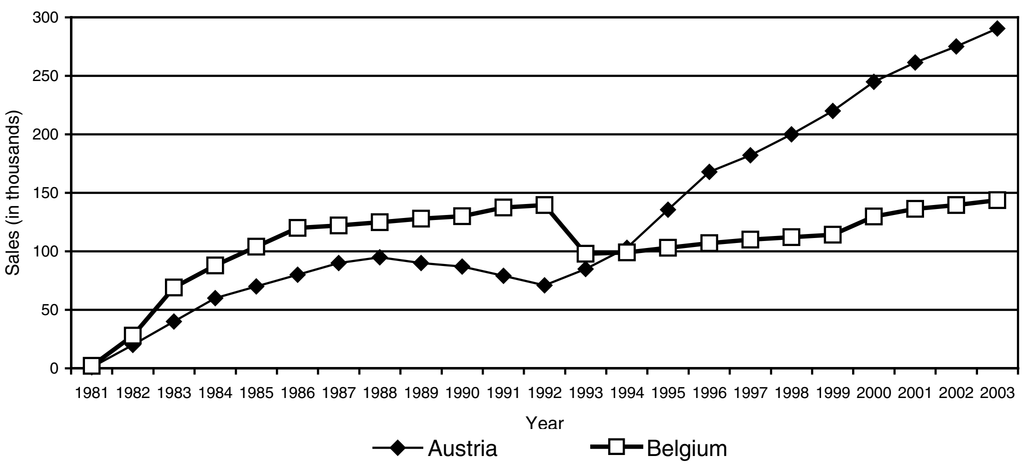


Figure 2.4 **Slowdown of Growth of Computer Sales in Europe**



quite so smooth. Cox (1967) documented evidence for a scalloped product life cycle. Wasson (1978) argued that there is a period of *slowdown* in sales, or "competitive turbulence," which follows the period of rapid growth. In his review of the literature on product life cycles, Day (1981) remarked that while interesting, this pattern had virtually no empirical evidence to support it. Nearly twenty years later, three papers (Stremersch and Tellis, 2004; Golder and Tellis, 2004; Goldenberg, Libai, and Muller, 2002) find empirical evidence of a sudden decline in sales following the growth stage.

As mentioned earlier, Golder and Tellis (2004) define *slowdown* to be the point of transition from the growth stage to the maturity stage of the product life cycle. Hence, *early maturity* begins with the year sales slow down and continues until sales grow to the previous local peak. This is similar in spirit to the concept of the "saddle" proposed by Goldenberg, Libai, and Muller (2002).

Figure 2.3 shows the typical pattern of a slowdown in sales in the case of dishwashers in Europe. After takeoff, the sales of the products reach an initial peak, followed by a sharp and deep decline, and seem to take some time before regaining the initial peak. Figure 2.4 shows similar patterns for the newer electronic goods category of computers.

Measuring Slowdown

Early maturity begins with the year sales slow down and continues until sales grow to the previous local peak (Golder and Tellis 2004).

Late maturity begins with the first year sales being higher than the local peak and continues until a product's sales begin to fall steadily during the decline stage (Golder and Tellis, 2004).

Goldenberg, Libai, and Muller (2002) define and measure the saddle as a trough following an initial peak in sales, reaching a depth of at least 20 percent of the peak, lasting at least two years, followed by sales that ultimately exceed the initial peak. Golder and Tellis (2004), and Stremersch and Tellis (2004) operationalize slowdown, or the end of growth, as the first year, of two consecutive years after takeoff, in which sales are lower than the highest previous sales.

Explaining Slowdown

What are the reasons for the sudden decline in sales following slowdown? Recent literature in marketing proposes three key reasons for what may be the main processes driving slowdown of new products: dual-market phenomenon, informational cascades, and affordability.

Dual Market Phenomenon. Goldenberg, Libai, and Muller (2002) argue that the initial product offered to consumers is different from that offered in a later phase, and the consumers in two stages of the product life cycle differ in a meaningful way. Hence, the early market and the late market adopt in different ways, and the social contagion process is *broken* at the point of transition from the early market to the late market. Both demand-side and supply-side factors seem to be at work here.

This theory builds on work by Moore (1991), who argues that a *chasm* exists between the early adopters and early majority. He posits that in the case of technological products, early adopters are looking to buy a change agent and expect to get a jump on competition. They expect some radical discontinuity between the old and new ways and are prepared to champion the cause. The early majority on the other hand, wants to buy a product improvement for existing operations. They are looking to minimize discontinuity with old ways and want technology that enhances, not overthrows established ways of doing business. This lack of communication between the two segments can create a difference in the adoption rates of both segments, leading to the slowdown in sales.

Informational Cascades. Golder and Tellis (2004) posit an alternative explanation based on the theory of informational cascades (Bikchandani, Hirshleifer, and Welch, 1992). Cascades occur when many consumers base their choice on the behavior of a few other consumers rather than on their own private assessments of the utility of alternatives. Some consumers first decide to buy a new product on its merits. A few other consumers note their behavior and follow suit, causing an increase in sales. The increase triggers still more consumers to buy the new products, leading to much bigger increases. The process cascades into the takeoff and rapid growth of the new product. Due to the cascade, during the growth stage, sales increase far more than they would have based on consumers' private assessment of the utility of the new product to them.

Such cascades are fragile. Some small doubt or turbulence in the market can cause a slowdown in sales and hence trigger a negative cascade. Such behavior can account for the common drop in sales of a new product after slowdown, and the pickup of sales after the turbulence.

Affordability. Golder and Tellis (2004) posit a third explanation for slowdown based on the notion of affordability. A decline in national income or an economic contraction can trigger a corresponding decline in the disposable income of consumers. As a result, consumers cut down on discretionary expenditures, such as purchases of new products, which have typically not yet become essential (Deleersnyder et al., 2004). If the economic decline is substantial, it can lead to the slowdown and even subsequent drop in sales that we observe at the end of the growth stage of a new product life cycle.

Modeling Slowdown

The two studies of slowdown offer conflicting explanations of what determines slowdown and they use different models to test their hypotheses.

Goldenberg, Libai, and Muller (2002) use *cellular automata* to describe the process by which internal communication breaks down between the early adopters and early majority. As mentioned earlier in the review, cellular automata models are simulations that reveal aggregate patterns based on local interactions between cells. This technique has three benefits. First, researchers often find it difficult to obtain data at the individual level. Second, aggregate level models sometimes do not provide insight about individual level phenomena. Third, there is the persistent difficulty of determining how aggregate phenomena evolve from changes in individual actions. The use of cellular automata helps to circumvent this problem. These models can help validate the assumptions made in aggregate level models (Goldenberg, Libai, and Muller 2001a, 2001b). However, the cellular automata models consider adoptions only in a binary state (0 or 1). There do not seem to be ways of obtaining socioeconomic characteristics of these adopters or any such information that aids the modeling of diffusion processes.

Golder and Tellis (2004) use hazard modeling to determine the impact of explanatory variables such as price declines, income declines, and market penetration on the time to slowdown. They find that every 1 percent decrease in total GNP is associated with a 17 percent increase in the probability of slowdown, indicating that economic factors affect slowdown in a substantial manner (though Golder and Tellis [1997] find no effect of economics on takeoff). In addition, they find that categories with large sales increases at takeoff will also have large sales declines at slowdown, giving some support to the notion of informational cascades. They find that every 1 percent higher price is associated with a 4.7 percent increase in the probability of slowdown, indicating that price declines can extend the duration of the growth stage. They also find that every 1 percent increase in penetration is associated with a 3.6 percent increase in the probability of slowdown, indicating that the probability of slowdown increases with a depleting pool of adopters.

Support for economic variables leading to a slowdown in sales is also found to some extent in Deleersnyder et al. (2004). These authors find that consumer durables are highly sensitive to business-cycle fluctuations. In addition, they find that every percentage decrease in the cyclical component of GNP translates to a drop in the cyclical component of durable sales by, on average, more than 2 percent.

Evaluation

Research on the slowdown in new product growth is new. There is still no consensus on whether and to what extent the phenomenon is pervasive, how to define and model it, and what factors drive it. If the pattern proves to be regular, it represents a challenge for research to model it and integrate it within any of the prior models. New research in this area can also make a substantive contribution by developing one integrated model to investigate the impact of the different drivers of slowdown.

Conclusion

This comprehensive review of the marketing literature on the diffusion of new products provides the following benefits to the reader. First, the review delineates key phenomena associated with the diffusion of innovations such as the shape, turning points, and stages of diffusion. Second, the review identifies the variety of drivers of diffusion and explains how they have been either modeled or ignored in various research traditions. Third, the review provides a critical evaluation of the models. This evaluation give readers a simple synopsis of the models with their strengths and weaknesses. Fourth, the review identifies a large number of regularities or potential generalizations in the areas of shape of the diffusion curve, the turning points, and the early stages of the new product's life cycle.

While extensive, the review is still incomplete in one important respect. It does not cover the literature in many related fields such as medicine, agriculture, sociology, anthropology, and technology management. It also covers only very limited aspects of the economics and geography literatures. While we believe that the models, drivers, and potential generalizations identified in marketing can be extended to these other fields, this is a topic for further research.

Notes

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1. New product growth can follow alternate growth patterns. A shape of growth that has not been captured by the logistic or the exponential growth curves is seen when the period of rapidly increasing sales is shorter than the period in which sales converge to a certain saturation level. Frances (1994), in an illustration of the Dutch new car market, and Chow (1967), in the rental of electronic computers in the United States, capture these growth processes using a Gompertz curve. Bemmaor (1994) develops a gamma/shifted Gompertz model, which will be discussed later in this chapter.

2. Urban, Weinberg, and Hauser (1996) suggest a technique known as "information acceleration" to forecast consumer reactions to radically new products such as electric vehicles. Here, researchers utilize a multimedia computer to create a virtual buying environment and accelerate information to a consumer so that he/she can react as if they were in the future. The authors develop market forecasts using combinations of stated intent measures, conjoint analysis, and diffusion models. See Urban et al. (1997) for further applications of this technique.

3. See Morrill, Gaile, and Thrall (1988) for a review of more recent approaches to model spatial diffusion, in the geography literature tradition, examining both spatial diffusion and the incorporation of time and space in diffusion.

References

Agarwal, Rajshree, and Barry L. Bayus. (2002) "Market Evolution and Sales Takeoff of Product Innovations." *Management Science*, 48 (8), 1024–1041.

———. (2004) "Creating and Surviving in New Industries." In *Business Strategy over the Industry Life Cycle: Advances in Strategic Management*, vol. 21, ed. J.A.C. Baum and A.M. McGahan. Oxford: JAI/Elsevier, forthcoming.

Bailey, Norman T.J. (1957) *The Mathematical Theory of Epidemics*, 1st ed. London: Griffin.

———. (1975) *The Mathematical Theory of Infectious Diseases and Its Applications*. London: Charles Griffin and Company.

Bass, Frank M. (1969) “A New Product Growth Model for Consumer Durables.” *Management Science*, 15 (5), 215–227.

———. (1980) “The Relationship Between Diffusion Rates, Experience Curves and Demand Elasticities for Consumer Durable Technological Innovations.” *Journal of Business*, 53 (2), 51–68.

Bass, Frank M., Trichy V. Krishnan, and Dipak C. Jain. (1994) “Why the Bass Model Fits Without Decision Variables.” *Marketing Science*, 13 (3), 203–223.

Bayus, Barry. (1987) “Forecasting Sales of New Contingent Products: An Application to the Compact Disc Market.” *Journal of Product Innovation Management*, 4, 243–255.

———. (1993) “High-Definition Television: Assessing Demand Forecasts for a Next Generation Consumer Durable.” *Management Science*, 39 (11), 1319–1333.

Bayus, Barry, and Sunil Gupta. (1992) “An Empirical Analysis of Consumer Durable Replacement Intentions.” *International Journal of Research in Marketing*, 9, 257–267.

Bayus, Barry, S. Hong, and R.P. Labe Jr. (1989) “Developing and Using Forecasting Models of Consumer Durables.” *Journal of Product Innovation Management*, 6, 5–19.

Bemmaor, A. (1994) “Modeling the Diffusion of New Durable Goods: Word-of-Mouth Effect Versus Consumer Heterogeneity.” *Research Traditions in Marketing*, ed. Gilles Laurent, Gary L. Lilien, and Bernard Pras, pp. 201–229. Boston: Kluwer.

Bemmaor, A., and Yanghyuk Lee. (2002) “The Impact of Heterogeneity and Ill-Conditioning on Diffusion Model Parameter Estimates.” *Marketing Science*, 21, 209–220.

Bernhardt, Irwin, and Kenneth M. Mackenzie. (1972) “Some Problems in Using Diffusion Models for New Products.” *Management Science*, 19, 187–200.

Bhargava, Subhash, Raj K Bhargava, and Ashok Jain. (1991) “Requirement of Dimensional Consistency in Model Equations: Diffusion Models Incorporating Price and Their Applications.” *Technological Forecasting and Social Change*, 41, 177–188.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. (1992) “A Theory of Fads, Fashion, Custom and Cultural Change as Information Cascades.” *Journal of Political Economy*, 100 (5), 992–1026.

Blattberg, Robert, and John Golanty. (1978) “Tracker: An Early Test Market Forecasting and Diagnostic Model for New Product Planning.” *Journal of Marketing Research*, 15 (2), 192–202.

Bretschneider, Stuart I., and Barry Bozeman. (1986) “Adaptive Diffusion Models for the Growth of Robotics in New York State Industry.” *Technological Forecasting and Social Change*, 30, 111–121.

Bretschneider, Stuart I., and Vijay Mahajan. (1980) “Adaptive Technological Substitution Models.” *Technological Forecasting and Social Change*, 18, 129–139.

Bronnenberg, Bart J., and Carl F Mela. (2004) “Market Adoption and Retailer Rollout of New Brands.” *Marketing Science*, 23 (4), 500.

Brown, Lawrence. (1981) *Innovation Diffusion: A New Perspective*. London: Methuen.

Bucklin, Louis P., and Sanjit Sengupta. (1993) “The Co-Diffusion of Complementary Innovations: Supermarket Scanners and UPC Symbols.” *Journal of Product Innovation Management*, 10, 148–160.

Chandrashekaran, Murali, and Rajiv K. Sinha. (1995) “Isolating the Determinants of Innovativeness: A Split-Population Tobit (SPOT) Duration Model of Timing and Volume of First and Repeat Purchase.” *Journal of Marketing Research*, 32 (4), 444.

Chatterjee, Rabikar, and Jehoshua Eliashberg. (1990) “The Innovation Diffusion Process in a Heterogeneous Population: A Micro Modeling Approach.” *Management Science*, 36, 1057–1079.

Chow, Gregory C. (1967) “Technological Change and the Demand for Computers.” *American Economic Review*, 57 (5), 1117–1130.

Cohen, Morris A., Teck H. Ho, and Hirofumi Matsuo. (2000) “Operations Planning in the Presence of Innovation Diffusion Dynamics.” In *New Product Diffusion Models*, ed. V. Mahajan, E. Muller, and Y. Wind, pp. 237–259, Boston: Kluwer Academic.

Coleman, James, Elihu Katz, and Herbert Menzel. (1966) *Medical Innovation*. New York: Bobbs-Merrill.

Cox, W.E. Jr. (1967) “Product Life Cycles as Marketing Models.” *Journal of Business*, 40, 375–384.

Danaher, Peter J., Bruce G.S. Hardie, and William P. Putsis Jr. (2001) “Marketing-Mix Variables and the Diffusion of Successive Generations of a Technological Innovation.” *Journal of Marketing Research*, 38 (November), 501–514.

Day, George. (1981) “The Product Life Cycle: Analysis and Application Issues.” *Journal of Marketing*, 41, 60–67.

Dekimpe, Marnik, Philip Parker, and Miklos Sarvary. (1998) “Staged Estimation of International Diffusion

Models: An Application to Global Cellular Telephone Adoption." *Technological Forecasting and Social Change*, 57, 105–132.

———. (2000a) "Global Diffusion of Technological Innovations: A Coupled-Hazard Approach." *Journal of Marketing Research*, 37 (1), 47–59.

———. (2000b) "Multimarket and Global Diffusion." In *New Product Diffusion Models*, ed. Vijay Mahajan, Eitan Muller, and Yoram Wind, pp. Boston: Kluwer Academic.

Deleersnyder, Barbara, Marnik Dekimpe, Miklos Sarvary, and Philip Parker. (2004) "Weathering Tight Economic Cycles: The Sales Evolution of Consumer Durables over the Business Cycle." *Quantitative Marketing and Economics*, 4, 347–383.

Easingwood, Christopher. (1987) "Early Product Lifecycle Forms for Infrequently Purchased Major Products." *International Journal of Research in Marketing*, 4 (1), 3–9.

———. (1989) "An Analogical Approach to Long Term Forecasting of Consumer Durable Sales." *International Journal of Forecasting*, 5 (1), 69–82.

Easingwood, Christopher, Vijay Mahajan, and Eitan Muller. (1983) "A Non-Uniform Influence Innovation Diffusion Model of New Product Acceptance." *Marketing Science*, 2 (3), 273–295.

Elberse, Anita, and Jehoshua Eliashberg. (2003) "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures." *Marketing Science*, 22 (3), 329–354.

Eliashberg, Jehoshua, and Mohanbir S. Sawhney. (1994) "Modeling Goes to Hollywood: Predicting Individual Differences in Movie Enjoyment." *Management Science*, 40 (9), 1151–1173.

Eliashberg, Jehoshua, and Steven M. Shugan. (1997) "Film Critics: Influencers or Predictors?" *Journal of Marketing*, 61, 68–78.

Eliashberg, Jehoshua, Jedid-Jah Jonker, Mohanbir S. Sawhney, and Berend Wierenga. (2000) "MOVIEMOD: An Implementable Decision Support System for Pre-Release Market Evaluation of Motion Pictures." *Marketing Science*, 19 (3), 226–243.

Feder, Gershon, and Gerald O'Mara. (1982) "On Information and Innovation Diffusion: A Bayesian Approach." *American Journal of Agricultural Economics*, 64, 145–147.

Fisher, J.C., and R.H. Pry. (1971) "A Simple Substitution Model of Technological Change." *Technological Forecasting and Social Change*, 3, 75–88.

Foster, Joseph A., Peter N. Golder, and Gerard J. Tellis. (2004) "Predicting Sales Takeoff for Whirlpool's New Personal Valet." *Marketing Science*, 23 (2), 180–191.

Fourt, L., and Joseph Woodlock. (1960) "Early Prediction of Market Success of New Grocery Products," *Journal of Marketing*, 25(2), 31–38.

Frances, Philip Hans. (1994) "Modeling New Product Sales: An Application of Cointegration Analysis." *International Journal of Research in Marketing*, 11, 491–502.

Fudenberg, Drew, and Jean Tirole. (1985) "Preemption and Rent Equalization in the Adoption of New Technology." *Review of Economic Studies*, 52, 383–402.

Ganesh, Jaishankar, and V. Kumar. (1996) "Capturing the Cross-National Learning Effect: An Analysis of an Industrial Technology Diffusion." *Journal of the Academy of Marketing Science*, 24 (4), 328–337.

Ganesh, Jaishankar, V. Kumar, and V. Subramaniam. (1997) "Learning Effect in Multinational Diffusion of Consumer Durables: An Exploratory Investigation." *Journal of the Academy of Marketing Science*, 25 (3), 214–228.

Garber, Tal, Jacob Goldenberg, Barak Libai, and Eitan Muller. (2004) "From Density to Destiny: Using Spatial Dimension of Sales Data for Early Prediction of New Product Success." *Marketing Science*, 23 (3), 419–428.

Gatignon, Hubert, Jehoshua Eliashberg, and Thomas S. Robertson. (1989) "Modeling Multinational Diffusion Patterns: An Efficient Methodology." *Marketing Science*, 8 (3), 231–247.

———. (2001a) "Using Complex Systems Analysis to Advance Marketing Theory Development: Modeling Heterogeneity Effects on New Product Growth Through Stochastic Cellular Automata." *Academy of Marketing Science Review* (http://www.findarticles.com/p/articles/mi_qa3896/is_200101/ai_n8944761, last accessed April 4 2006).

Goldenberg, Jacob, Barak Libai, and Eitan Muller. (2001b) "Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth." *Marketing Letters*, 12 (3), 209–221.

———. (2002) "Riding the Saddle: How Cross-Market Communications Can Create a Major Slump in Sales." *Journal of Marketing*, 66, 1–16.

Golder, Peter N., Gerard J. Tellis. (1997) "Will It Ever Fly? Modeling the Takeoff of Really New Consumer Durables." *Marketing Science* 16 (3), 256–270.

———. (1998) "Beyond Diffusion: An Affordability Model of the Growth of New Consumer Durables." *Journal of Forecasting*, 17 (3/4), 259–280.

———. (2004) "Going, Going, Gone: Cascades, Diffusion, and Turning Points of the Product Life Cycle." *Marketing Science*, 23 (2), 207–218.

Gort, Michael, and Steven Klepper. (1982) "Time Paths in the Diffusion of Product Innovations." *Economic Journal*, 92 (367), 630–653.

Gupta, Sachin, Dipak C. Jain, and Mohanbir S. Sawhney. (1999) "Modeling the Evolution of Markets with Indirect Network Externalities: An Application to Digital Television." *Marketing Science*, 18, 396–416.

Hagerstrand, Torsten. (1953) *Innovation Diffusion as a Spatial Process*. Chicago: University of Chicago Press.

Hahn, Minhi, Sehoon Park, Lakshman Krishnamurthi, and Andris Zoltners. (1994) "Analysis of New Product Diffusion Using a Four Segment Trial-Repeat Model." *Marketing Science* 13 (3), 224–247.

Heeler, R., and Thomas Hustad. (1980) "Problems in Predicting New Product Growth for Consumer Durables." *Management Science*, 26 (10), 1007–1020.

Helsen, Kristaan, Kamel Jedidi, and Wayne DeSarbo. (1993) "A New Approach to Country Segmentation Utilizing Multinational Diffusion Patterns." *Journal of Marketing*, 57 (4), 60–71.

Hiebert, L Dean. (1974) "Risk, Learning and the Adoption of Fertilizer Responsive Seed Varieties." *American Journal of Agricultural Economics*, 56, 764–768.

Hjorth, Urban. (1980) "A Reliability Distribution with Increasing, Decreasing, Constant and Bathtub-Shaped Failure Rates." *Technometrics*, 21 (2), 99–107.

Ho, Teck-Hua, Sergei Savin, and Christian Terwiesch. (2002) "Managing Demand and Sales Dynamics In New Product Diffusion Under Supply Constraint," *Management Science*, 48 (2), 187–206.

Horsky, Dan. (1990) "A Diffusion Model Incorporating Product Benefits, Price, Income and Information." *Marketing Science*, 9, 342–365.

Horsky, Dan, and Leonard Simon. (1983). "Advertising and the Diffusion of New Products." *Marketing Science*, 2 (1), 1–17.

Infosino, William J. (1986) "Forecasting New Product Sales from Likelihood of Purchase Ratings." *Marketing Science*, 5 (4), 372–390.

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

Jain, Dipak, Vijay Mahajan, and Eitan Muller. (1991) "Innovation Diffusion in the Presence of Supply Restrictions." *Marketing Science*, 10 (1), 83–90.

Jones, Morgan, and Christopher J. Ritz. (1991) "Incorporating Distribution into New Products Diffusion Models." *International Journal of Research in Marketing*, 8, 91–112.

Kalish, Shlomo. (1985) "A New Product Adoption Model with Pricing, Advertising and Uncertainty." *Management Science*, 31, 1569–1585.

Kamakura, Wagner, and Siva K. Balasubramanian. (1987) "Long-Term Forecasting with Innovation Diffusion Models: The Impact of Replacement Purchases." *Journal of Forecasting*, 6, 1–19.

———. (1988) "Long-Term View of the Diffusion of Durables: A Study of the Role of Price and Adoption Influence Processes Via Tests of Nested Models." *International Journal of Research in Marketing*, 5, 1–13.

Karshenas, M., and P. Stoneman. (1993) "Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model." *Rand Journal of Economics*, 24, 503–528.

Kim, Namwoon, Dae Ryun Chang, and Allan D. Shocker. (2000) "Modeling Inter-Category And Generational Dynamics for a Growing Information Technology Industry." *Management Science*, 46 (4), 496–512.

Kohli, Rajeev, Donald Lehmann, and Jae Pae. (1999) "Extent and Impact of Incubation Time in New Product Diffusion." *Journal of Product Innovation Management*, 16, 134–144.

Krishnan, Trichy V., Frank Bass, and Dipak Jain. (1999) "Optimal Pricing Strategy for New Products." *Management Science*, 45 (12), 1650–1663.

Krishnan, Trichy V., Frank Bass, and V. Kumar. (2000) "Impact of a Late Entrant on the Diffusion of a New Product/Service." *Journal of Marketing Research*, 37 (2), 269–278.

Kumar V., and Trichy V. Krishnan. (2002) "Multinational Diffusion Models: An Alternative Framework." *Marketing Science*, 21 (3), 318–330.

Kumar, V., Jaishankar Ganesh, and Raj Echambadi. (1998) "Cross National Diffusion Research: What Do We Know and How Certain Are We?" *Journal of Product Innovation Management*, 15, 255–268.

Lavaraj, U.A., and A.P. Gore. (1990) "On Interpreting Probability Distributions Fitted to Times of First Adoption." *Technological Forecasting and Social Change*, 37, 355–370.

Lee, Jonathan A., Peter Boatwright, and Wagner A. Kamakura. (2003) "Bayesian Model for Prelaunch Sales Forecasting of Recorded Music." *Management Science*, 49 (2), 179–196.

Lehmann, Donald R., and Charles B. Weinberg. (2000) "Sales Through Sequential Distribution Channels: An Application to Movies and Videos." *Journal of Marketing*, 64 (3), 18–33.

Lenk, Peter J., and Ambar G. Rao. (1990) "New Models from Old: Forecasting Product Adoption by Hierarchical Bayes Procedures." *Marketing Science*, 9 (1), 42–53.

Lilien, Gary I., Ambar G. Rao, and Shlomo Kalish. (1981) "Bayesian Estimation and Control of Detailing Effort in a Repeat-Purchase Diffusion Environment." *Management Science*, 27 (5), 493–506.

Mahajan, Vijay, and Eitan Muller. (1996) "Timing, Diffusion and Substitution of Successive Generations of Technological Innovations: The IBM Mainframe Case." *Technological Forecasting and Social Change*, 51, 109–132.

Mahajan, Vijay, Eitan Muller, and Frank M. Bass. (1990) "New Product Diffusion Models in Marketing: A Review and Directions for Research." *Journal of Marketing*, 54, 1–26.

———. (1995) "Diffusion of New Products: Empirical Generalizations and Managerial Uses." *Marketing Science*, 14 (3), Part 2 of 2, G79–G88.

Mahajan, Vijay, Eitan Muller, and Rajendra K. Srivastava. (1990) "Determination of Adopter Categories Using Innovation Diffusion Models." 27 (1), 37–50.

Mahajan, Vijay, Eitan Muller, and Yoram Wind. (2000a) "New Product Diffusion Models: From Theory to Practice." In *New Product Diffusion Models*, ed. Mahajan, V., Eitan Muller, Yoram Wind, pp. 3–24, Boston: Kluwer Academic.

Mahajan, Vijay, Eitan Muller, and Yoram Wind. (2000b) *New Product Diffusion Models*. Boston: Kluwer Academic.

Mahajan, Vijay, and Robert Peterson. (1978) "Innovation Diffusion in a Dynamic Potential Adopter Population." *Management Science*, 24 (15), 1589–1597.

———. (1979) "Integrating Time and Space in Technological Substitution Models." *Technological Forecasting and Social Change*, 14, 231–241.

Mahajan, Vijay, Subhash Sharma, and Robert D. Buzzell. (1993), "Assessing the Impact of Competitive Entry on Market Expansion and Incumbent Sales." *Journal of Marketing*, 57, 39–52.

Mansfield, Edwin. (1961) "Technical Change and the Rate of Imitation." *Econometrica*, 29, 741–766.

Moe, Wendy, and Peter Fader. (2002) "Using Advanced Purchase Orders to Forecast New Product Sales." *Marketing Science*, 21, 347–364.

Moore, Geoffrey A. (1991) *Crossing the Chasm: Marketing and Selling Technology Products to Mainstream Customers*. New York: HarperCollins

Morrill, Richard, Gary L. Gaile, and Grant Ian Thrall. (1988) *Spatial Diffusion*. Newbury Park, CA: Sage.

Neelamegham, Ramya, and Pradeep Chintagunta. (1999) "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets." *Marketing Science*, 18 (2), 115–36.

Norton, John A., and Frank M. Bass. (1987) "A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products." *Management Science*, 33 (9), 1069–1086.

Norton, John A., and Frank M. Bass. (1992) "Evolution of Technological Generations: The Law of Capture." *Sloan Management Review*, 33 (2), 66–77.

Olson, Jerome, and Seungmook Choi. (1985) "A Product Diffusion Model Incorporating Repeat Purchases." *Technological Forecasting and Social Change*, 27, 385–397.

Oren, Shmuel S., and Rick Schwartz. (1988) "Diffusion of New Products in Risk-Sensitive Markets." *Journal of Forecasting*, 7, 231–287.

Parker, Philip. (1994) "Aggregate Diffusion Forecasting Models in Marketing: A Critical Review." *International Journal of Forecasting*, 10, 353–80.

Parker, Philip, and Hubert Gatignon. (1994) "Specifying Competitive Effects in Diffusion Models: An Empirical Analysis." *International Journal of Research in Marketing*, 11, 17–39.

Putsis, William P. Jr., Sridhar Balasubramanian, Edward Kaplan, and Subrata Sen. (1997) "Mixing Behavior in Cross-Country Diffusion." *Marketing Science*, 16 (4), 354–369.

Putsis, William P. Jr., and V. Srinivasan. (2000) "Estimation Techniques for Macro Diffusion Models." In *New Product Diffusion Models*, ed. Mahajan, V., Eitan Muller, Yoram Wind, pp. 263-291, Boston: Kluwer Academic.

Rangaswamy, Arvind, and Sunil Gupta. (2000), "Innovation Adoption and Diffusion in the Digital Environment: Some Research Opportunities." In *New Product Diffusion Models*, ed. Mahajan, V., Eitan Muller, Yoram Wind, pp. 75-96, Boston: Kluwer Academic.

Redmond, William. (1994) "Diffusion at Sub-National Levels: A Regional Analysis of New Product Growth."

Journal of Product Innovation Management, 11, 201–212.
Reinganum, Jennifer F. (1981) "Market Structure and the Diffusion of New Technology." *Bell Journal of Economics*, RAND, 12 (2), 618–624.
Roberts, John. H., and James L. Lattin. (2000) "Disaggregate-Level Diffusion Models," In *New Product Diffusion Models*, ed. V. Mahajan, Eitan Muller, and Yoram Wind, pp. 207- 236 Boston: Kluwer Academic.
Roberts, John H., and Glen Urban. (1988) "Modeling Multivariate Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice." *Management Science*, 34 (2), 167–185.
Robinson, Bruce, and Chet Lakhani. (1975) "Dynamic Price Models for New Product Planning." *Management Science*, 21, 1113–1122.
Rogers, Everett. (1995) *Diffusion of Innovations*. New York: Free Press.
Sawhney, Mohanbir S., and Jehoshua Eliashberg. (1996) "A Parsimonious Model for Forecasting Gross Box-Office Revenues of Motion Pictures." *Marketing Science*, 15 (2), 113–131.
Schmittlein, D., and Vijay Mahajan. (1982), "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance." *Marketing Science*, 1 (1), 57–78.
Sharma, Praveen, and S.C. Bhargava. (1994) "A Non-Homogeneous Non-Uniform Influence Model of Innovation Diffusion." *Technological Forecasting and Social Change*, 46, 279–288.
Shocker, Allan D., Barry L. Bayus, and Namwoon Kim. (2004) "Product Complements and Substitutes in the Real World: The Relevance of Other Products." *Journal of Marketing*, 68 (1), 28–40.
Shugan, Steven. (2000) "Recent Research in the Motion Picture Industry." *available at http://bear.cba.ufl.edu/shugan/profile/RRMPI.pdf, last accessed April 4 2006.*
Shugan, Steven, and Joffre Swait. (n.d.) "Enabling Movie Design and Cumulative Box Office Predictions Using Historical Data and Consumer Intent-to-View." University of Florida, working paper.
Simon, H., and K. Sebastian. (1987) "Diffusion and Advertising: The German Telephone Company." *Management Science*, 33, 451–466.
Sinha, Rajiv K., and Murali Chandrashekaran. (1992) "A Split Hazard Model for Analyzing the Diffusion of Innovations." *Journal Of Marketing Research*, 29 (1), 116.
Song, Inseong, and Pradeep Chintagunta. (2003) "A Micromodel Of New Product Adoption with Heterogeneous and Forward Looking Consumers: Application to the Digital Camera Category." *Quantitative Marketing and Economics*, 1, 371–407.
Srinivasan V., and Charlotte Mason. (1986) "Nonlinear Least Squares Estimation of New Product Diffusion Models." *Marketing Science*, 5 (2), 169–178.
Srinivasan, Raji, Gary L. Lilien, and Arvind Rangaswamy. (forthcoming) "The Emergence of Dominant Designs." Journal of Marketing.
Steffens, Paul R. (2002) "A Model of Multiple Ownership as a Diffusion Process." *Technological Forecasting and Social Change*, 70, 901–917.
Stoneman, Paul. (1981) "Intra-Firm Diffusion, Bayesian Learning and Profitability." *Economic Journal*, 91, 375–388.
Stoneman, Paul (2002). *The Economics of Technological Diffusion*. Cambridge, MA: Blackwell.
Stremersch, Stefan, and Gerard J. Tellis. (2004) "Managing International Growth of New Products." *International Journal of Research in Marketing*, forthcoming.
Sultan, Fareena, John U. Farley, and Donald R. Lehmann. (1990) "A Meta-Analysis of Diffusion Models." *Journal of Marketing Research*, 27, 70–77.
Takada, Hirozu, and Dipak Jain. (1991) "Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries." *Journal of Marketing*, 55, 48–54.
Talukdar, Debabrata, K. Sudhir, and Andrew Ainslie. (2002) "Investigating New Product Diffusion Across Products and Countries." *Marketing Science*, 21 (1), 97–114.
Tellis, Gerard J., Stefan Stremersch, and Eden Yin. (2003) "The International Takeoff of New Products: The Role of Economics, Culture and Country Innovativeness." *Marketing Science*, 22 (2), 188–208.
Urban, Glen L., Bruce D. Weinberg, and John R. Hauser. (1996) "Premarket Forecasting of Really-New Products." *Journal of Marketing*, 60, 47–60.
Urban, Glen L., John R. Hauser, William J. Qualls, Bruce D. Weinberg, Jonathan D. Bohlmann, and Roberta A. Chicos. (1997) "Information Acceleration: Validation and Lessons from the Field." *Journal of Marketing Research*, 34, 143–153.
Van Den Bulte, Christophe. (2000) "New Product Diffusion Acceleration: Measurement and Analysis." *Marketing Science*, 19 (4), 366–380.

Van Den Bulte, Christophe, and Gary Lilien. (1997) "Bias and Systematic Change in the Parameter Estimates of Macro-Level Diffusion Models." *Marketing Science*, 16 (4), 338–353.

———. (2001) "Medical Innovation Revisited: Social Contagion Versus Marketing Effort." *American Journal of Sociology*, 106 (5), 1409–1435.

Van Den Bulte, Christophe, and Stefan Stremersch. (2004) "Social Contagion and Income Heterogeneity In New Product Diffusion: A Meta-Analytic Test." *Marketing Science*, 23 (4), 530–544.

Venkatesan, Rajkumar, Trichy V. Krishnan, and V. Kumar. (2004) "Evolutionary Estimation of Macro-Level Diffusion Models Using Genetic Algorithms: An Alternative to Nonlinear Least Squares. *Marketing Science*, 23 (3), 451–464.

Wasson, Chester. (1978) *Dynamic Competitive Strategy and Product Life Cycles*. 3d ed. Austin, TX: Austin Press.

Webster's New World College Dictionary (2004), 4th Edition, Cleveland: Wiley.

Xie, Jinhong, Michael Song, Marvin Sirbu, and Qiong Wang. (1997) "Kalman Filter Estimation of New Product Diffusion Models." *Journal of Marketing Research*, 34, 378–393.

Zufryden, Fred S. (1996) "Linking Advertising to Box Office Performance of New Film Releases: A Marketing Planning Model." *Journal of Advertising Research*, 36 (4), 29–41.

———. (2000) "New Film Web Site Promotion and Box Office Performance." *Journal of Advertising Research*, 40 (1/2), 55–64.