Diffusion and Growth of New Products: A Critical Review of Models and Findings

Deepa Chandrasekaran and Gerard J. Tellis

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Deepa Chandrasekaran is a PhD candidate and Gerard J. Tellis is Director of Center for Global Innovation, Neely Chair of American Enterprise, and Professor of Marketing at the Marshall School of Business, University of Southern California, Los Angeles, CA 90089. (Email: tellis@usc.edu). Phone: 213 740 5031.

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Abstract

This article critically reviews research that models various aspects of the evolution of new products. We classify the research in this domain based on which aspect of the life of a new product it covers: the takeoff, growth, or slowdown. The literature on takeoff provides insights on the duration and characteristics of the introductory stage (or the 'time-to-takeoff') and the key determinants and patterns of takeoff. The literature on slowdown provides insights about the determinants of slowdown and the characteristics of the Early Maturity stage. The bulk of the literature focuses on the Growth stage by providing models of new product growth.

The review considers all aspects of alternate models of new product growth, including the various functional forms, specifications, and estimation methods. It also focuses on phenomena besides growth such as the takeoff and slowdown of new products. It also focuses on focuses on phenomena besides growth, such as takeoff, and slowdown. The review includes important generalizations about the shape of the growth curve, speed of diffusion, determinants of growth, variations and biases in parameter estimates, and processes during the growth stage based on findings with substantial support. The review also covers generalizations in the findings about time to, patterns in and determinants of both takeoff and slowdown. Finally, the review compares the key findings on the duration, growth rates and price declines across the various stages and transition points of the product life cycle.

Introduction

This article critically reviews research that models various aspects of the evolution of new products. This is a vast literature dating back at least as early as the appearance of the Fourt and Woodlock (1960) and Bass (1969) models. We can conveniently classify the research in this domain based on which aspect of the life of a new product it covers: the takeoff, growth, or slowdown.

In order to better elucidate these phenomena, we use the definitions of the four stages of a product's life cycle provided by Golder and Tellis (2004). They define *Introduction* as the period from a new product's commercialization until its takeoff. *Growth* is the period from a new product's takeoff until its slowdown. *Early maturity* begins with the year sales slow down and continues until sales grow to the previous local peak. Hence, *takeoff* marks the transition from introduction to growth and *slowdown* marks the transition from growth to maturity.

Following these definitions, we divide our review into three sections, each of which focuses on one of these three phenomena, ordered in terms of extent of research. The literature on takeoff provides insights on the duration and characteristics of the introductory stage (or the 'time-to-takeoff') and the key determinants and patterns of takeoff. The literature on slowdown provides insights about the determinants of slowdown and the characteristics of the Early Maturity stage. However, the bulk of the literature focuses on the Growth stage by providing models of new product growth. We divide this section into two, one focusing on models of diffusion, particularly the Bass model, and the second on alternate models of growth.

Prior reviews address various aspects of this domain, especially of the growth stage. For example, Mahajan, Muller & Bass (1990) provide an excellent overview of the Bass model, its extensions, and some directions for further research. Sultan, Farley, and Lehmann (1990) metaanalyze 213 estimates of innovation and imitation parameters of the Bass model. Parker (1994) provides an overview of the Bass model and evaluates the various estimation techniques, forecasting ability, and specification improvements of the models used. Mahajan, Muller and Bass (1995) summarize the empirical generalizations from applications of the Bass model. Van den Bulte and Stremersch (2004) meta-analyze the variation of the ratio of the innovation to imitation parameters of the Bass model across different countries of the world.

The current review differs from prior reviews in four important characteristics. First, the prior reviews focus only on growth. This review focuses on phenomena besides growth, 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 growth. Third, some of the prior reviews are over a decade old (e.g. Sultan Farley and Lehmann 1990; Mahajan, Muller and Bass 1990). This review is more recent than any prior review, covering all marketing studies until 2004. Fourth, the prior reviews focus on specific aspects of the literature, such as just models, or generalizations, or meta-analyses of parameters. This review considers all aspects of all models of new product growth, including their functional forms, specifications, estimation methods, parameter estimates, potential generalizations, and future directions. Thus, it encompasses all the above reviews.

We organize the rest of the paper as follows. The second and third sections focus on two alternate approaches to modeling the growth of new products: the Bass Model and alternate models of Growth. The fourth and fifth sections focus on two other phenomena that comprise the domain of this review: takeoff and slowdown of new products. The sixth and final section summarizes the findings from this body of research and suggests directions for future research.

The Bass Model of New Product Growth

The bulk of the literature on new product models focuses on the evolution of aggregate sales *during* the growth stage of the product life cycle. Much of the literature has been highly paradigmatic, following an early model by Bass (1969). This section discusses the functional form of the Bass (1969) model, evaluates its strengths and weaknesses, and discusses improvements in specification and estimation.

Functional Form

The Bass model (Bass 1969) 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). In management parlance, the word ‘diffusion’ has replaced the word ‘contagion’ to denote the communication between adopters and potential buyers (Golder and Tellis 1998, Rogers 1995). In this review, we will follow this tradition.

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 initial purchase occurs at time T, given that no purchase has occurred, is a linear function of the number of previous buyers, i.e.

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

where P(t) is a hazard rate, which depicts the conditional probability of a purchase in a (very small) time interval (t, t+Δ), 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) defines the cumulative fraction of adopters at time t and f(t) is the likelihood of purchase at time t. By re-arranging equation (1),

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

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:

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

Since $f(t) = dF(t)/dt = (p + qF(t))[1-F(t)]$ -(4)

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

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

to obtain

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

Hence, the cumulative adoptions are

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

Fig 1 gives the plot of cumulative adoptions over time and Fig 2 gives the corresponding plot of marginal adoptions over time (Rogers 1995, Mahajan, Muller and

Bass 1990). In Fig 2, the peak is reached at time T*, which is the point of inflexion of the corresponding cumulative adoptions curve.

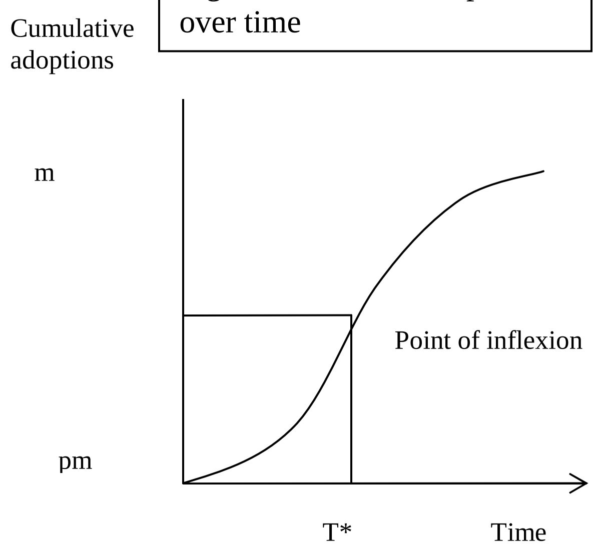


Fig 1: Cumulative adoptions over time

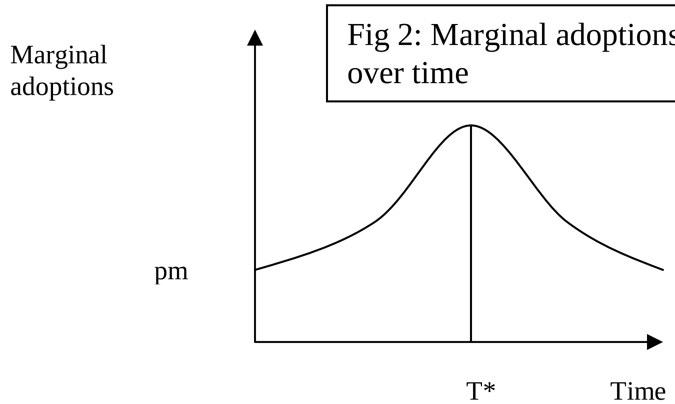


Fig 2: Marginal adoptions over time

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

$$S_t = a + bY_{t-1} + cY^2_{t-1}, \ t=2,3... \qquad - (8)$$

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

$a = p*m,$ - (9)

$b = q-p,$ - (10)

$c = -q/m$ - (11)

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

$p = a / m$ - (12)

$q = - cm$ - (13)

m= (–b ± (b2 – 4ac)1/2) / 2c - (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, 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 (1969) 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, i.e., 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,

$$t^* = (1/ (p + q))^* \ln (q/p) \quad -(15)$$

$$S(t)^* = (m^*(p+q)^2)/ 4q \quad -(16)$$

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 (Van den Bulte 2000, Fisher and Pry 1971, Mansfield 1961). If q = zero, the Bass model reduces to an exponential function assumed to be driven by only innovative processes (Fourt and Woodlock 1960, Bernhardt and Mackenzie 1972)[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.

[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 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 US, capture these growth processes by a Gompertz curve.

Limitations

Despite its strengths and strong appeal, the Bass diffusion model 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 the current one.

First, Bass (1969) uses 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). One, there is likely to be multi-collinearity between Y_{t-1} and Y^2_{t-1} making the parameter estimates unstable. Two, 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. Three, there is a time interval bias because the model uses discrete time series data to estimate a continuous model.

Second, 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.

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 however assumes that the coefficients m or p captures the effect of such external influences.

Fourth, the model's parameters are unstable and fluctuate with the addition of new observations prior to the first peak in sales (Golder and Tellis 1998, Van den Bulte and Lilien 1997, Mahajan, Muller and Bass 1990, Heeler and Hustad 1980). This variation in estimates for small changes in observations leads one to question whether the parameters really capture the underlying behavior (imitation and innovation). Indeed, researchers question the basic assumption that diffusion is indeed essentially a communicative process (Van den Bulte and Stremersch 2004, Golder and Tellis 1998). One of the strengths of the model may account for this instability in parameters. The quadratic function fits the sales curve so well that it sacrifices estimating the true underlying behaviors (Golder and Tellis 1998).

Fifth, this tradition of research suffers from several problems with measuring the dependent variable (sales) and determining the starting and ending points of the time interval sampled. For one, 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. Two, 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. Three, 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 last 35 years, a vast body of literature has sought to enrich the model by including marketing variables, supply restrictions, multi-product interactions (such as the presence of competitive products, complementary products, and newer technological generations), incorporating time-varying parameters, replacement purchases, multiple purchases and trial-repeat purchases and by analyzing cross-country diffusion patterns. The subsections evaluate the literature in each of these improvements concluding with an overall evaluation of this stream of literature.

Including Marketing Variables

Many authors consider the impact of marketing variables on new product diffusion (Robinson and Lakhani 1975, Bass 1980, Kalish 1985, Kamakura and Balasubramanian 1988, Jain and Rao 1990, Horsky 1990, Bhargava, Bhargava, Jain 1991). 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. In a comparison of both these types of modeling for incorporating price, Kamakura and Balasubramanian (1988) find that price seems to influence only the probability of adoption and that only for relatively high priced 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 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). 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 in the absence of diffusion, i.e., when the *consumer* adoption curve is exponential, if initial level of distribution is limited, then the pattern of consumer adoptions takes an S-shaped curve similar to that obtained from a Bass model.

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

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

where x(t) is the current marketing effort such that

$$x(t) = 1 + \beta_1 \,\Delta Pr(t)/ Pr(t-1) + \beta_2 \,\Delta A(t)/ A(t-1) \qquad -(18)$$

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 as percentage changes in price and advertising remain the same from one period to the next. 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 only 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 itself 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 non-marketing factors that influence product growth such as income changes.

Including 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:

$$dA(t)/dt = (p+ (q_1/m)A(t) + (q_2/m)\ N(t))\ (m-A(t) - N(t)) - c(t)A(t) \qquad -(19)$$

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

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 at time t on adoption rate. The growth process of the total number of new applicants is given by

$$dZ(t)/dt = dA(t)/dt + d\ N(t)/dt = p+ q_1/mA(t) + q_2/m\ N(t)\ (m-A(t) - N(t)) \qquad -(21)$$

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 order 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 of both demand and supply dynamics. They model the demand process similar to the Bass formulation. In the supply side, the firms choose the sales rate to maximize profiles for fixed values of capacity and launch time. 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 this 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 tacking of competitive effects.

Including 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: one, it could increase the entire market potential for the category due to increased promotion or product variety. Second, it could compete for the same market potential and hence slow down the diffusion of the existing brands.

For instance, from an empirical application of the model to the instant camera market, Mahajan, Sharma and Buzzell (1993) find that Kodak drew more than 30% 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 seems 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.

Including Complementary Products

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, i.e., 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 hard ware 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, UPC code and scanners. The authors find from their analysis of the two categories 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, software attributes, and competing products. Complementor (suppliers of digital programming) response is modeled as a function of the consumer demand for digital TV and regulatory scenarios.

Lehmann and Weinberg (2000) focus on sequentially released products i.e., where new products 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 since there is a possibility of cannibalization across the channels. 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 that being done in practice.

These models reflect the growing effort 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 so successful as to become a competitive product. An example is mobiles phones growing to be competitive with landlines (Shocker, Bayus, Kim 2004). A related issue is modeling the evolution of successive generations of products.

Including 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

$$S_1(t) = m_1F_1(t) – m_1F_1(t)\, F_2(t- r_2) \qquad \text{-(22)}$$

The diffusion equation for the second-generation product is

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

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, 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 semi-conductor 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 where they determine that the optimal decision rule for a firm introducing a new generation of a technological durable good is to either introduce it as soon as possible or to delay its introduction till 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 the 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 between pagers, analog and digital cellular phone and cordless telephone 2 in the wireless telecommunications market in Hong Kong. Their results indicate that the earliest introduced category of pagers 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.

Allowing Time-Varying Parameters

The parameters of the Bass model could 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.

Mahajan and Peterson (1978) model the market potential as a function of time-varying exogenous and endogenous factors such as socio-economic conditions, population changes, and government or marketing actions. Easingwood, Mahajan and Muller (1983) develop a non-uniform influence model where they allow the coefficient of imitation to be time varying. They use the specification

$$dF(t)/dt = (p + q\,F(t)^{\delta}\ (1- F(t)) \qquad \text{-(24)}$$

Where δ is called the nonuniform influence factor. If the value of δ equals one, it indicates that diffusion takes place with uniform influence, similar to the Bass model. Values of δ between zero and one 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 one 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 non-uniform 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 non-uniform influence model where not only is the influence of previous adopters considered non-uniform, but also adopters who have adopted in the recent past are considered more influential than those who had adopted much earlier.

Several researchers propose alternate functional forms capable of allowing for dynamic formulation of the parameters. Lavaraj and Gore (1990) demonstrate the use of the IDB distribution to model an adoption function flexible enough to incorporate increasing, decreasing, constant or bathtub shapes, and non-uniform parameters. Xie et al (1997), Bretschneider and Mahajan (1980), and Bretschneider and Bozeman (1986) 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, they also help examine the causes of accelerating or decelerating influences over time. However, the gain of accuracy and insights from the model come 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 of both replacement and multiple purchases. A few papers in the diffusion literature cover these phenomena (Steffens 2002, Bayus, Hong and Labe 1989, Kamakura and Balasubramanian 1987, Olson and Choi 1985).

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

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

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, while α refers to the ultimate penetration. They demonstrate the incorporation of replacement purchases into a diffusion setting even when replacement data is 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 these adopters to making multiple purchases giving the model for multiple unit adopters M(t) as

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

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 adoption is modeled as a fixed proportion $\prod_2$ of multiple unit adopters M(t). The model for subsequent multiple unit adoptions Q(t) is

$$dQ(t)/dt = (\prod_2 M(t) - Q(t))\,((a_2 + b_2 M(t)) \qquad \text{-(27)}$$

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 drives replacement demand. Other factors such as ability to pay could determine also replacement demand (Bayus and Gupta 1992).

Trial and Repeat Purchases

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

Hahn et al (1994) develop a four-segment trial-repeat purchase model where the four segments comprise of non-triers, triers, post trial non-repeaters 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.

Models of Cross Country Diffusion

The initial application of the Bass diffusion model was limited to the study of diffusion of new products within the United States. Initially researchers included socio-economic variables to explain differences in diffusion across countries (Helsen, Jedidi and Desarbo 1993, Takada and Jain 1991, Gatignon, Eliashberg and Robertson 1989). Researchers have since examined the influence of wealth, social system heterogeneity, cosmopolitanism, activity of women, mobility, mass media availability and learning on cross-country diffusion (Talukdar, Sudhir and Ainslie 2002, Dekimpe, Parker and Sarvary 2000, 1998, Kumar and Krishnan 2002, Tellefsen and Takada 1999, Kumar, Ganesh and Echambadi 1998, Ganesh, Kumar and Subramaniam 1997, Putsis et al 1997, Ganesh and Kumar 1996, Helsen, Jedidi and Desarbo 1993, Takada and Jain 1991, Gatignon, Eliashberg and Robertson 1989).

One problem in modeling cross-national diffusion is that the samples of countries are often not comparable. Dekimpe, Parker and Sarvary (1998), propose a *sample matching* procedure to solve this problem. In the first step, the researchers conduct an external estimation and validation of the social system size, which is the population within which the innovation diffuses, and the long run adoption ceiling (to account for the fact that the intrinsic utility of the innovation will be zero for some portion of the population). In the second step, they calculate the intercept term by dividing the number of adopters who purchase the product in the first year by the social system ceiling size (ceiling size multiplied by the social system size). In the third step, they estimate each country's growth parameter. The authors model the intercept and growth terms as a function of exogenous or endogenous variables. The diffusion parameter estimates are more robust than those derived from the Bass model. However, the estimated parameters of ceiling size and social system size are fixed in the third stage not allowing for growth dynamics (Putsis and Srinivasan 2000). In addition, there are some counter-intuitive results in the empirical application to cellular diffusion across 184 countries. For instance, the value of the intercept parameter, which is similar to the coefficient of innovation, is higher for Algeria (0.004) or Egypt (0.0008) than for Japan (0.0001) though Japan is likely to be much more innovative than either country. The authors do not discuss these counter-intuitive results.

Evaluation

Though these various extensions have individually addressed various limitations of the Bass diffusion model and developed modifications, there is no one integrated model incorporating all these extensions. As a result, the contributions remain separate. While a model, which considers all these different dimensions, would no doubt enable a richer and more comprehensive analysis, this benefit would likely come at the cost of parsimony. In the meantime, managers and analysts can use any one of these models that address the limitation that is most salient for the product and category they are modeling. In addition, all of these models assume that the underlying behavior that drives the process is one of knowledge diffusion through the population of consumers. In actual markets, this assumption itself might not hold, requiring alternate models to capture the growth of new products. We describe such models in the next major section.

Improvements in Estimation

A flood of articles since the Bass (1969) model attempt to better estimate the parameters of these models (Schmittlein and Mahajan 1982, Srinivasan and Mason 1986, Lenk and Rao 1990, Xie et al 1997, Venkatesan, Krishnan and Kumar 2004). Schmittlein and Mahajan (1982) propose 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 non-linear least squares approach. We classify subsequent improvements as belonging to one of four approaches: non-linear least squares approach, hierarchical Bayesian methods, adaptive techniques, and genetic algorithms.

Non-Linear Least Squares Approach

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

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

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

$$S(i) = m\,[(1- e(-(p+q)\,t_i))/(1+ (q/p)\,e(-(p+q)\,t_i))$$
$$-(1- e(-(p+q)\,t_{i-1}))/(1+ (q/p)\,e(-(p+q)\,t_{i-1})] + u_i \qquad \text{where } i=1,2,\ldots \qquad -(29)$$

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

However, researchers have determined that non-linear 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) show that there could be a downward bias in the estimates of m and p and an upward bias in the estimates of q due to an omission of time-varying variables. For instance, as price falls, lower income households may be more able to afford the new products, increasing the market potential while the non-linear least squares estimation would provide a downward biased estimate of m. The implication is that the bias may result in managers under-investing in advertising and external media and overestimating the impact of the social contagion. 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. The next section examines attempts by researchers to incorporate Bayesian updating procedures with the non-linear 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, Hauser 1996) to develop pre-launch 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. One, how can products be classified as similar/dissimilar? Two, what happens when there are dissimilar products? Bayus (1993) proposes a solution to the first question by developing a product segmentation scheme using demand parameters, marketing and manufacturing related variables and demonstrates its application to generate forecasts for high-definition TV prior to launch.

[2] Urban, Weinberg, 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.

As a solution to the second question i.e., 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, Talukdar, Sudhir and Ainslie 2002, Neelamegham and Chintagunta 1999, Lenk and Rao 1990). 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 pre-launch forecasts for the focal product, updating them when sales information about the focal product does become available (Putsis and Srinivasan 2000). The approach helps obtain more stable forecasts (Talukdar, Sudhir and Ainslie 2002, Neelamegham and Chintagunta 1999, Lenk and Rao 1990).

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

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

Where the subscripts pr and c refers 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 to either models that estimate the parameters of the Bass model for one product across many countries (Gatignon, Eliashberg and

Robertson 1989) and 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 dynamically over time to model new product growth. These techniques use feedback filters and Bayesian techniques to update the parameters over time (Xie et al 1997, Bretschneider and Bozeman 1986, Bretschneider and Mahajan 1980).

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

$$dn/dt = f_n\,(n(t), u(t), \beta, t) + w_n \qquad \text{-(31)}$$

$$d\beta/\,dt = f_{\beta}\,(\beta, n(t), t) + w_{\beta} \qquad \text{-(32)}$$

$$z_k = n_k + v_k \qquad \text{-(33)}$$

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 given 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 actual 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 non-linear least squares and the OLS, and can estimate time varying parameters. This technique is however not as easy to use as either the non-linear regression or ordinary least squares regression.

Genetic Algorithms

Venkatesan, Krishnan and Kumar (2004) propose the use of estimation of the Bass model by Genetic Algorithms. They find that since this technique combines the advantage of both systematic search and random search, it has a better chance to reach the global optimum as compared to sequential search based non linear least squares. Using simulations, the authors find that this technique does not suffer from bias and systematic change in parameter values as more observations are added, as does the non linear least squares method. 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, it does not allow for the fact that the parameters could 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, there has not been much effort in predicting the turning points in sales, such as slowdown and especially takeoff. For these critical events, researchers have proposed entirely new models, which a subsequent section describes. The improved methods of estimation also do not overcome the limitation of excluded managerial variables from the Bass model. The following section describes efforts to overcome this limitation.

Alternate Models of New Product Growth

Due to the many limitations of the Bass model, especially its reliance on a process of diffusion, several other researchers have departed from the framework and proposed entirely new models. Four of these are particularly important and are reviewed here: Affordability models, individual level models, sales models for entertainment products, and spatial diffusion models

Affordability Models

The assumption of diffusion 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 learn of the product, either from the firm or from other adopters, at different times. We review models that question this assumption.

Horsky (1990) develops a model that incorporates the role of price and income (affordability) 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 S(t) as a logistic function, thus:

$$S(t) = [\theta\, M(t)/(1+ e^{-}\,(K + \acute{w}\,(t) - k\, p(t)\, /\delta(\, t)) - Q(t)]\; [\alpha + \beta\; Q(t)] \qquad -(34)$$

where M(t) refers to the number of households in the population, with an average wage $\acute{w}(t)$, its dispersion being δ (t). p(t) refers to the average price of the durable. θ refers to the fraction of the population who will buy the product. 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

$$S(t) = [N - Q(t)]\; ([\alpha + \beta\, Q(t)] \qquad -(35)$$

Where N(t) equals θM(t), 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.

Golder and Tellis (1998) propose an alternate model based on the idea of A*ffordability*. Their model recognizes that consumers may delay their purchases until prices decline or incomes rise sufficiently for them to afford the new product. Hence, they model product sales as a function of price, income, consumer sentiment and market presence, in a Cobb-Douglas multiplicative manner. Their model is

$$S = P^{\beta_1} * I^{\beta_2} * CS^{\beta_3} * MP^{\beta_4} * e^{\epsilon} \qquad -(36)$$

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.

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 that are the key benefits of the Bass model.

Individual Level Models

Individual level models of *adoption* of new products focus on the fact that consumers do not adopt immediately on coming into contact with information on the product. Rather, the adoption decision is a decision problem under uncertainty. As the diffusion process continues, the consumers obtain new information that helps reduce their uncertainty. The consumers are also expected utility-maximizers and choose products that maximize benefit or utility. Hence, these individual level models provide a behavioral basis for understanding the consumer’s decision of whether to adopt a new product or defer purchase for later, based on uncertainty reductions and expectations of price declines or quality improvements over time.

Individual level models first originated in the economics literature (Hiebert 1974, Stoneman 1981, Feder and O’Mara 1982). In the marketing context, Roberts and Urban (1988) assume that individual consumers chose 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. One, word of mouth communications (positive or negative reviews) may change the estimated mean attribute levels of the brand. Two, 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 pre-launch 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 product with uncertain performance and a currently available product with certain performance where 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 (rather than market penetration).

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), Fourt and Woodlock (1960) models. The authors obtain individual level parameters for price, risk and uncertainty by means of a survey of respondents.

Building on work by Bemmaor (1994), Bemmaor and Lee (2002) demonstrate the derivation of an aggregate level diffusion model from individual level heterogeneity assumptions. They assume that the individual level model of adoption timing is consistent with a 2-parameter shifted Gompertz distribution whose cumulative distribution function is as follows:

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

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. Here, small values of α indicate greater heterogeneity. The authors derive an aggregate level distribution of adoption times given by

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

This is the G/SG model. Here, if α = one, b= p+q and β = q/p, equation 38 reduces to the Bass model and if α = zero, equation 38 reduces to the exponential model. The authors test the model by forecasting the sales of 12 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.

In high technology markets, consumers are often not myopic and consider their expectations of changing price and quality levels while making their adoption decisions.

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. The difference from previous research is that 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 to either buy or not buy a product in each period and chooses 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.

Evaluation

Aggregate diffusion models provide a crude understanding of how sales of new products evolve over time. In contrast, individual level models show us why individual consumers adopt new products. Thus, in one sense, the latter models complement the former by revealing the behavioral process of how people adopt innovations and change their judgments over time.

However, individual models suffer from some limitations. One, most individual models lack the parsimony and ease of understanding that are the strengths of aggregate level models. Two, they need to have aggregate level interpretations to be of use to new product marketing managers who are interested in serving segments or populations as a whole. Three, these models suffer from data availability, as individual level data is harder to obtain than aggregate data (Mahajan, Muller and Wind 2000). Some researchers

(Roberts and Urban 1988, Chatterjee and Eliashberg 1990) measure the individual level parameters prior to launch. However, *actual* behavior might provide more insights into consumer behavior than *stated* intentions. In addition, these models typically do not incorporate the consumers' expectations of changing levels of price and quality in the future. The model developed by Song and Chintagunta (2003) addresses this issue by allowing for aggregate level estimation and dynamic expectations. However, it is complicated to understand or estimate and cannot help forecast sales before the product launch.

Overall, while individual-level models lead to a better behavioral understanding of the process of adoption and can help understand why some consumers adopt earlier than others do, the predictive ability of these models to forecast aggregate level adoption still seems limited.

Models for New Entertainment Products

Recently, researchers have focused on modeling and forecasting the sales of entertainment products that typically follow a pattern of exponential decay rather than the bell-shaped pattern of durable goods sales. The bulk of this research has focused on the movie industry though recent research has also looked into forecasting sales of other entertainment products. This section reviews the important models in this area. We divide the review into models that examine box office patterns and forecast movies sales, models that examine optimum selection, scheduling and distribution of movies and models that forecast the growth of other entertainment products.

Forecasting Movie Sales

The earliest marketing model looking at the movie industry seems to be that by Eliashberg and Sawhney (1994) who develop a model to predict individual differences in movie enjoyment. In the first model that looks at modeling box office, 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 related to distribution intensity. Both these processes are assumed to be exponentially distributed with the stationary parameters λ and γ. The authors find that their model can determine three classes of adoption patterns that can represent all the 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 by attempting 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 there is little insight on how the box-office performance is spread over time.

Subsequent researchers of entertainment products show how to develop better pre-launch 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 the advertising and word of mouth effects, there is a behavioral transition from the Undecided to the ‘Considerer’ (one who eventually sees the movie) or a ‘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 pre-release experiments. This model is simple, 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 of a movie 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), Shugan and Swait (working paper) demonstrate how researchers can utilize consumer intent-to-see measures in developing pre-release forecasts.

Movie Selection, Scheduling, and Distribution

Krider and Weinberg (1998) develop a game theoretic analysis to investigate competitive dynamics in release timings of movies with each firm deciding whether to opt for an early release or delay the release. Swami, Eliashberg and Weinberg (1999) develop a two-tier decision support system for a multiple screens theater to better select and schedule movies in order to maximize profits.

Forecasting Sales of Other Entertainment Products

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 pre-launch forecasts of new product sales of entertainment goods such as music CDs, based on patterns of advance purchase orders. Lee, Boatwright and Kamakura (2003) develop a hierarchical Bayesian model to develop pre-launch 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 pre-launch 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 non-entertainment products. In contrast, the strength of the Bass model, in contrast, is that it is generalizable beyond the durable goods settings.

Spatial Diffusion

Most models described so far give an idea of how products diffuse over *time* but not how they diffuse over *space.* Spatial diffusion models address this latter problem, Though not considered explicitly in the field of marketing, spatial diffusion has had a long tradition of research in the field of geography and agricultural history, originating from the seminal work of Hagerstrand (1953) [3].

There may be various types of spatial diffusion (Morrill, Gaile, Thrall 1988). *Contagious* diffusion occurs when the distance or adjacency is the controlling factor, for instance, the spread of infectious diseases. *Expansion* diffusion describes the process similar to that of a wildfire, when there is a source, and the diffusion occurs outwards from the source. *Hierarchical* diffusion occurs when diffusion progresses through an ordered series of classes, such as the phenomenon being first 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

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

spatial location or as the trait passes on to additional agents, it is lost in the original agents.

Hagerstrand (1953) conducts a detail 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 area observed. Typically, diffusion seems to have the following spatial regularities: At first, there is a local concentration of initial acceptance followed by a radial dissemination outwards 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 on clear-cut lines. For instance, he observes that the acceptance of state-subsidized pastures acceptance spread from the west to the eastern part of the area. In contrast, the initial acceptance is more dispersed and the subsequent dissemination less orderly for general indicators.

Much of Hagerstrand’s work has relevance to marketing. For instance, he pioneered the notion of a ‘mean information field’ where the frequency of contacts in a social network is assumed to diminish with distance. He also finds through his simulations that potential adopters seem to vary in their ‘resistance’ to the innovation, which explains the longer period of incipient growth and greater degree of spatial concentration evident in the diffusion of some products.

In marketing, a few papers have shown interest in incorporating the notion of space into diffusion models (Garber et al 2004, Mahajan and Peterson 1979). Mahajan and Peterson (1979) introduced the notion of the 'neighborhood effect' in technological substitution models i.e., the further a region is from the 'innovative region', the later it will be before substitution occurs.

In a more recent application, 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, where the discrete cells represent adoption by individuals. Each cell interacts with the other cells, the interactions not being restricted to strictly neighboring cells (in what is termed a 'Small-world' framework). The value '0' represents non-adopters 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 affects by an interaction with a single other individual who has adopted the product. The individual probability of adoption given that the individual has not yet adopted is:

$$\text{Prob}(t) = 1 - (1-p)(1-q)^{v(t)+r(t)} \qquad \text{-(39)}$$

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.

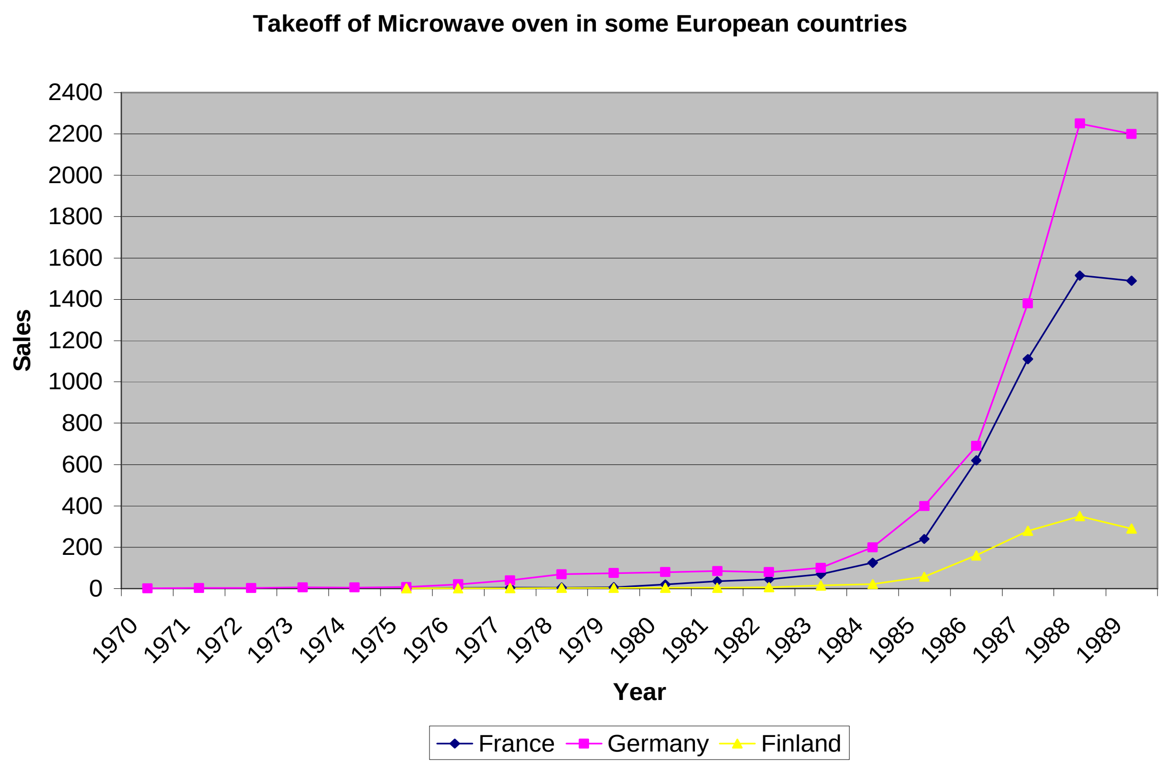
Garber et al (2004) argue that a spatial analysis of diffusion data can help in early prediction of new product success. They state that for a well-received product, word of mouth and imitation will feed the flow of internal influence, leading to the formation of clusters. However if the product is a failure, then internal effects activity will be minimal, and diffusion will be mainly due to external effects, and hence adopters will be randomly distributed. Hence, the distribution in the case of a failure would be closer to a uniform distribution. The authors hence argue that it is possible to predict the success of a new product within a few periods from 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 would have a consistently low cross entropy measure.

Evaluation

The use of complex systems analysis helps provide a micro-view of the patterns of interaction among individuals and an understanding how this influences the diffusion of new products. It highlights the much-ignored spatial dimension of the diffusion process. However, these models seem to follow the Bass model tradition of viewing new product growth entirely as a process of 'diffusion', ignoring alternate explanations such as those studied in previous sections.

Models of Introductory Stage and Takeoff

A key characteristic of new products is that not all consumers accept them instantaneously at the time of introduction. The Bass model assumes a certain number of consumers (p*m) to adopt the product initially. However, most new products have a long period when sales are low. At some point in time, there is a sudden spurt in sales followed by a period of rapid growth. When viewed graphically this trend appears as a sharp bend in the curve or a "takeoff". Fig 3 compares the takeoff patterns of a white good (microwave oven) in various Western European countries. The sharp bend in the curves in the graphs signal 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 discussed 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 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 could 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 to manage the sales and success of a new product. Most importantly, 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 consumers durables in the US. 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% 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 and takeoff. The logistic curve rule is also a continuous rule to measure what is essentially a discontinuity. The maximum growth rule suffers from three limitations. One, the largest sales growth occurs sometimes 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) and Agarwal and Bayus (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 take-off) and annual net entry rates (for firm take-off) for each product. To determine the take-off year for a product, they first 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- take-off periods, respectively. They classify the in-between years based on mean values. This is a method similar to that followed by Gort and Klepper (1982) to identify firm take-off. However, they do not explain this rule very clearly.

Tellis, Stremersch and Yin (2003) propose 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

Goldenberg, Libai and Muller (2001) use a measure that takeoff occurs when 16% of the population adopts. This is similar to Roger's (2003) argument that the S-shaped curve of diffusion 'takes off' at around 10-20% adoption.

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

Model Specification

We consider the literature on takeoff itself to be in the introductory and pre-takeoff stage of its life cycle. Our search revealed only seven studies on this topic, three of which deal specifically with the determinants of takeoff. These three studies reach substantially different conclusions about the determinants of takeoff.

Golder and Tellis (1997) propose that price declines and market penetration are the principle drivers of takeoff. They argue that takeoff occurs when technologically driven prices drops suddenly to render a product affordable to a substantial number of innovative consumers.

Agarwal and Bayus (2002) propose that new firm entry (or quality increases) is the primary driver of takeoff. They 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. Hence, an increase in the number of firms leads to a sharp increase in the number of products sold.

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 argue that cultural and economic characteristics of counties should explain inter-country differences in time-to-takeoff.

Estimation Methods

Researchers typically use a hazard function to model takeoff. As such, they assume that takeoff is a time dependent binary event, whose probability increases with the length of time it has not occurred. Both Golder and Tellis (1997) and Agarwal and Bayus (2002) 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:

$$h_i(t) = h_0(t)e(z_{it}\beta) \qquad -(40)$$

Where $h_0(t)$ is an unspecified baseline hazard, z_{it} is the vector of independent variables for the i^{th} 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. The interpretation of equation 40 is that the baseline hazard function is adjusted by the independent variables of each category. The magnitude 100* (e^{β}-1) captures the effect of any independent variable.

In a different study of takeoff of new products across countries, Tellis, Stremersch and Yin (2003) use the parametric log-logistic hazard approach to model time to take-off.

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 have some success at 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).

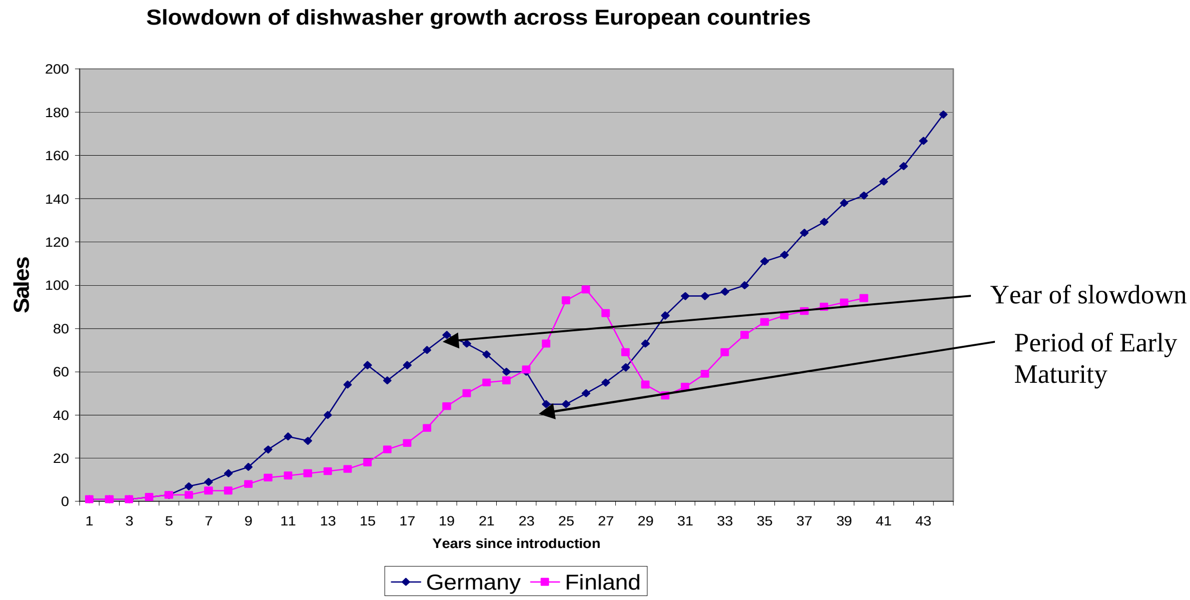
At the same time, the literature suffers from some important limitations. First, it considers only successful innovations. As such, its implications are good for predicting *when* a takeoff might occur. It cannot tell *whether* a takeoff might occur or predict the success or failure of a new product. Second, the empirical applications of takeoff have been over a limited geographic domain (only US and Western Europe). Third, models of takeoff focus on only the growth of the product until takeoff, which on average occurs at 2% 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.

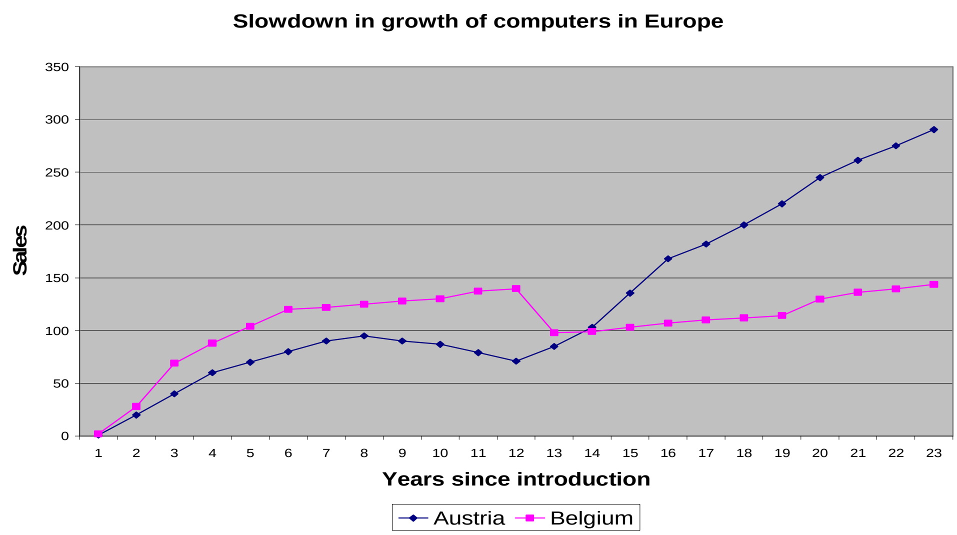
Early Maturity and the Models of Slowdown

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. As early as in the late 1970s, researchers noted that the classic bell shape might not be quite as smooth. For instance, Wasson (1978) argued for a period of *slowdown* in sales, or 'competitive turbulence' that 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 formal 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). *Late Maturity* begins with the first year sales are higher than the local peak and continues until a product's sales begin to fall steadily during the decline stage.

Fig 4 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, witness a sharp and deep decline, and seem to take some time before regaining the initial peak. Fig 5 shows similar patterns for a newer electronic goods category of computers.





Measure of Slowdown

Studies propose different measures for this stage. Goldenberg, Libai and Muller define and measure the saddle as a trough following an initial peak in sales, reaching a depth of at least 20% 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 as the first year, of two consecutive years after takeoff, in which sales are lower than the highest previous sales.

Alternate Theories for Slowdown

What are the reasons for the sudden decline in sales following slowdown? Recent literature in marketing proposes three key reasons on what may be the key processes driving slowdown of new products: heterogeneity in diffusion, informational cascades, and economic affordability.

Heterogeneity in Diffusion

Goldenberg, Libai and Muller (2002) argue that the social contagion process is *broken* at the point of transition from the early adopters to the early majority. The differences between early adopters and early majority create communication barriers between the two segments. The latter segment does not get much information from the early adopters as smoothly as do consumers within each segment.

This theory builds on work by Moore (1991), who argued a *chasm* existed 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, want 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 creates a difference in the adoption rates of both segments, leading to the formation of a saddle.

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 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 thence trigger a negative cascade. Such behavior can account for the common drop in sales of a new product after slowdown.

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 slow down and even subsequent drop in sales that we observe at the end of the growth stage of a new product life cycle.

Models

The two studies of slowdown have conflicting explanations on what determines slowdown and 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, which reveal aggregate patterns based on local interactions between cells. This technique has three benefits. One, 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. Cellular automata modeling helps get around this problem. These models can help validate the assumptions made in aggregate level models (Goldenberg, Libai and Muller 2001 a, b). However, the cellular automata models only consider adoptions in a binary state (0 or 1). There do not seem to be ways of obtaining socio-economic characteristics of these adopters or any such information that aid the modeling of diffusion processes.

Golder and Tellis (2004) use hazard modeling to determine the impact of covariates such as price declines, income declines, and market penetration on the *time to slowdown*. The formulation is similar to that discusses in the section on takeoff. However, while their specification lends insights on *when* slowdown is likely to occur, it does not *why* slowdown occurs.

Evaluation

Research on the slowdown in new product growth is new. There is yet 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 comparing the relative merits of the proposed processes driving slowdown.

Potential Generalizations

We use the term potential generalization or regularities to describe findings with substantial support. By substantial, we mean that support comes from reviews of the literature, meta-analyses of the literature, or individual studies that had a large sample of over 10 categories or 10 countries (see Table 1).

We report findings in four sections: findings related to the growth, introduction and early maturity stages and findings or comparisons across the stages.

Regularities about the Growth Stage

This section covers important findings about the shape of the growth curve, speed of diffusion, determinants of growth, variations and biases in parameter estimates, and processes during the growth stage.

Shape of the Growth Curve

The most important and widely reported finding about new product diffusion relates to the shape of the growth curve. Numerous studies in a variety of disciplines suggest that sales of new products follow an S-shaped curve (e.g., Bass 2004, Rogers 2003, Mahajan, Muller and Bass 1990). The exception is for frequently purchased grocery products, movies, and by analogy, for other information/entertainment goods, such as CDs, books, etc.

Speed of Diffusion

The next most common finding about new product growth concerns the parameters of the Bass diffusion model. Two meta-analyses of the parameters of the Bass model identify the following consistent patterns about the key parameters (Van den Bulte and Stremersch 2004, Sultan, Farley and Lehmann 1990):

- The coefficient of innovation or external influence (p) has a mean value between 0.027 and .03 and is generally stable.
- The coefficient of imitation of internal influence (q) has a mean value that lies between 0.38 to 0.42, which varies much across contexts.

These findings indicate that imitation is a more important influence on growth than is innovation.

Processes of Growth

Cumulative research suggests a number of processes are responsible for the growth in sales of a new product (Van den Bulte and Stremersch 2004, Golder and Tellis 2004, Golder and Tellis 1998). Specifically,

- Diffusion is an important but not a sole underlying process of new product growth. Within diffusion itself, there could be four underlying processes driving the communication: information transfer, normative pressures, competitive concerns, and performance network effects (Van den Bulte and Lilien 2001). Van den Bulte and Stremersch (2004) determine that social norms and status concerns seem to dominate this process of diffusion.
- Other important processes of new product growth are income heterogeneity and affordability (Van den Bulte and Stremersch 2004, Golder and Tellis 1998).

Drivers of New Product Growth

- Macro level socio-economic factors influence new product growth in the growth stage (Talukdar, Sudhir and Ainslie 2002, Golder and Tellis 1998). For instance, Talukdar, Sudhir and Ainslie (2002) determine that for every 1% change in PPP adjusted per capita income, the market penetration potential is likely to change by about 0.3%. A 1% change in international trade or urbanization is likely to change the penetration potential by about 0.5% and 0.2% respectively.
- Learning occurs in the diffusion process across countries. When an innovation is introduced first in one country with a time lag in subsequent countries, the diffusion rate in the lag countries is faster than the rate in the lead country (Kumar, Ganesh and Echambadi 1998, Ganesh, Kumar, Subramaniam 1997).

Variations in Parameters and Processes during the Growth Stage

Several reviews suggest that the characteristics and parameters of the growth stage vary across countries, categories and time.

Across Countries

- The average parameter estimate for the coefficient of innovation is 0.001 for developed countries, which is higher than the value of 0.00027 for developing countries. The average parameter estimate for the coefficient of imitation is 0.509 for developed countries, while the average value is 0.556 for developing countries (Talukdar, Sudhir and Ainslie 2002).
- The coefficient of innovation is higher for European countries than for the US (Sultan, Farley and Lehmann 1990).
- The average market penetration potential ceiling is 0.52 for developed countries, around three times higher than the average penetration potential for developing

countries, which is 0.17. It also takes developing countries 19 years to reach peak sales, which is on average 18% longer than the average of 16 years for developed countries (Talukdar, Sudhir and Ainslie 2002).

- The average length of the growth stage is 8 years for Scandinavian countries and the U.S., and 10 years for other West European countries (Stremersch and Tellis 2004, Golder and Tellis 2004).
- The average growth rate during the growth stage also varies across countries with an average of 45% per year in the US, 46% for the Nordic countries, 41% for Mid-European countries and 36% for Mediterranean countries (Stremersch and Tellis 2004, Golder and Tellis 2004).

Across Categories

- Industrial/medical innovations have a higher coefficient of imitation than durables and other innovations (Sultan, Farley and Lehmann 1990)
- Timesaving products are associated with longer growth stages and lower growth rates while leisure-enhancing products are associated with shorter growth stages and higher growth rates (Golder and Tellis 2004).
- Products that tend to have large increases during takeoff also seem to have large declines at slowdown (Golder and Tellis 2004)

Across Time

- Some stages of the new product growth seem to be getting shorter over time (Golder and Tellis 2004, Van den Bulte 2000, Golder and Tellis 1997). Overall, a new product reaching 5% household penetration in 1946 in the U.S. took about 14 years to go from 10% to 90% of its estimated maximum adoption ceiling. In 1980, that time has dropped to about half, at 7 years (Van den Bulte 2000). The average time to takeoff is 18 years for categories introduced before World War II, but only 6 years for categories introduced after World War II (Golder and Tellis 1997). Golder and Tellis (2004) find that the duration of the introduction and early maturity stages are getting shorter over time, but not the duration of the growth stage

Biases in Parameter Estimation

- The non-linear 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 m can be underestimated by 20%, the coefficient of innovation can be underestimated by 20% and the coefficient of imitation can be overestimated by 30% (Van den Bulte and Lilien 1997).

Regularities in Takeoff

This section describes findings about time to, determinants of, and penetration at takeoff.

Time-to-Takeoff

- Estimates of the average time-to-takeoff vary from six to ten years (Golder and Tellis 1997, Kohli, Lehmann and Pae 1999, Agarwal and Bayus 2002).
- The average time-to-takeoff varies across products and across countries (Tellis, Stremersch and Yin 2003).
    - Brown goods take off faster (with an average of two years) than white goods (with an average of eight years).
    - For time-to-takeoff, Scandinavian countries average four years, mid-European countries average six years, and Mediterranean countries average eight years.

Determinants of Takeoff

- Price reduction is an important factor associated with takeoff, with every 1% decrease in price being associated with a 4.2% 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% (Golder and Tellis 1997). This finding is consistent with Roger's (1995) estimate that innovators make up 2.5% of the population and Mahajan, Muller and Srivatsava's (1990) upper bound of 2.8% for innovators.

Regularities in Slowdown

Pattern of Slowdown

- Slowdown in sales occurs after a period of rapid growth. For many product categories, sales after slowdown tend to drop below the peak reached at slowdown. Goldenberg, Libai and Muller (2002) call the decline in sales a saddle. Golder and Tellis (2004) call the period where sales after slowdown are below peak sales as early maturity.
- The saddle or trough in sales occurs in around 50% to 95% of categories studied (Golder and Tellis 2004; Goldenberg, Libai and Muller 2002)
- Sales decline on average of 15% to 32% during early maturity (Golder and Tellis 2004, Goldenberg, Libai and Muller 2002)

Determinants of Slowdown

Price declines and market penetration seem to have some influence on the probability of slowdown (Golder and Tellis 2004). In particular, these authors find that:

- Every 1% increase in price is associated with a 5% increase in the probability of slowdown
- Slowdown occurs on average at 34% penetration
- The sales decline at slowdown is higher than the GNP decline during the same period.

Findings across the Stages and Phenomena

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

Duration of Stages

- 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 (Stremersch and Tellis 2004, Golder and Tellis 2004, Tellis, Stremersch, and Yin 2003, Goldenberg, Libai and Muller 2002, Bayus and Agarwal 2002, Golder and Tellis 1997)

Role of Price

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

Comparisons of Growth Rates

- The mean growth rate of sales differs substantially across stages of the product life cycle. The mean growth rate is 31% during Introduction, 428% during takeoff, 45%

during growth, -15% during slowdown, -25% during early maturity and 3.7% during late maturity (Golder and Tellis 2004).

- The mean economic growth rate is 1% during introduction, 4.3% during takeoff, 3.1% during growth, 0.86% during slowdown, 2.4% during early maturity and 3.1% during late maturity of new products (Golder and Tellis 2004).

Future Research

Despite decades of research on modeling new product growth and despite a large body of emerging generalizations, 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 important problem of measurement. Yet, measurement plays a critical role in documenting the phenomena under study. Measurement is also an important pre-requisite for modeling. For example, no clear rules are available for the measurement of the start of the product life cycle or the year a new product is introduced. Most researchers consider the date from which data becomes 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. Now, using the date of availability of sales as a surrogate for the start date may grossly under estimate 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.

The literature contains several competing measures for takeoff. There is a need for a careful evaluation of the merits and costs of each of these methods. Measures for slowdown and the saddle or trough in sales are still tentative and there has not been any validation on a substantial scale.

Although under researched, measures for the key phenomena under study 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 at least three theories or processes that can be responsible for the takeoff, growth and slowdown in sales of new products. We classify these theories as diffusion, informational cascades, and economic affordability. There is scattered empirical support for each of these theories. However, no researcher has developed either an integrated theory that explains new product growth, an integrated model than can differentiate between these three theories, or a comprehensive test that can show which theory is most important in which context.

This issue is of primary research importance, because theory constitutes the key explanation for a phenomenon and informs good models and good managerial practice.

Models

In the area of modeling, there are five pressing issues. First, there is a need to develop an integrated model of sales before takeoff, during growth, and after slowdown, which can also predict takeoff and slowdown. Second, research in marketing has focused extensively on modeling the growth of new consumer durables. There is a need to consider other categories of products such as software, services, agricultural products, and medical products. Third, research has focused on sales growth through traditional brick and mortar distribution channels. The process of adoption, diffusion and growth can be quite different for the sale of products via non-traditional mediums, such as the Internet (Rangaswamy and Gupta 2000). Fourth, researchers are realizing that network effects can play a key moderating role in the takeoff or success of a new product. Yet that issue has not yet permeated most aspects of modeling. There is a need to explore and incorporate the role of network effects in new product takeoff, speed of diffusion speed, and growth. Fifth, the Bass model has long been the bulwark of diffusion research in marketing due to many of its strengths. Researchers can explore other models or combination of models that have the strengths of the Bass model but avoid at least some of its limitations to forecast new product growth.

Findings

While research in this area has led to some preliminary generalizations, further research can help to ascertain to what extent these generalizations are universal or vary by context. In particular, research could address the following five 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* a broad population where we are likely to see faster growth. Some preliminary studies (Redmond 1994, Omrod 1990) indicate that local conditions and demographics influence diffusion patterns across subgroups within a country. There is also a need for further integration of time and space in diffusion models.

Second, most of the empirical applications, such as those on takeoff deal with successful products. There has been little analysis of the diffusion process of failed products. In addition, researchers need to determine to what extent takeoff is a predictor of ultimate success.

Third, new product research typically does not analyze decisions beyond the adoption decision of consumers. Lately, there has been more interest on use diffusion. For instance, Shih and Venkatesh (2004) segment users into four groups based on the variety of use and rate of use of a new product. There is a need to study the dynamics of usage diffusion over time, and determine how this varies across products.

Fourth, studies of diffusion speed have been largely limited to the US. By examining whether diffusion speed has accelerated in multiple countries, one can possibly draw more substantive conclusions on whether new products do indeed tend to diffuse faster over time. In addition, there is a need to understand how a firm's technological choices and entry strategy affect the speed of diffusion (Kuester, Gatignon and Robertson (2000).

Fifth, apart from a lot of consensus, there are some unresolved conflicts in the findings from this literature. Though researchers tend to agree on the appropriateness of a waterfall strategy of new durable launch, they do not seem to agree on the sequence of launch. For instance, Tellis, Stremersch and Yin (2003) recommend that managers planning new products launches in Europe target Scandinavian countries initially, as they are the most innovative, followed by Western European countries and Mediterranean countries. Note that this is contradictory to the recommendation of Putsis et al (1997) to first target Mediterranean countries. Hence, there is a need to develop a consistent measure of innovativeness, possibly by including a larger sample of countries and product categories.

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Table 1: Studies Included for Assessing Generalizations

Authors	Dependent variable	Model estimation	Categories	Countries
Sultan, Farley and Lehmann (1990)	Bass model parameters	Bayesian updating in meta analysis	213 applications of diffusion models	US, Europe
Ganesh, Kumar, Subramaniam (1997)	Learning model		4 consumer durables	11 to 16 countries
Golder & Tellis (1997)	Time-to-takeoff	Proportional hazard model	31 consumer durables	USA
Van den Bulte, Lilien (1997)	Bass model parameters	NLS estimation of Bass model	12 innovations	US
Kumar, Ganesh and Echambadi (1998)	Bass model parameters	Simultaneous estimation of diffusion model parameters with covariates, using GLS for each innovation	5 consumer durables	14 W. European countries
Golder and Tellis (1998)	New product growth	Affordability model	10 product categories	USA
Kohli, Lehmann and Pae (1999)	Incubation time	Bass with NLS	32 appliances, house wares and electronics	USA
Tellefsen, Takada (1999)	Bass parameters p and q	Based on Meta analysis of 47 cross country diffusion studies		14 European and 2 Asian countries
Van den Bulte (2000)	Diffusion speed	Logistic distribution to derive diffusion speed which is then modeled as a function of various covariates	31 electrical products	USA
Talukdar, Sudhir, Ainslie (2002)	Parameters of Bass model p, q and m	Nonlinear Bass model with Hierarchical Bayesian estimation	6 consumer durables	31 developing and developed countries
Agarwal and Bayus (2002)	Time-to-takeoff	Proportional hazard model	30 innovations	USA

Bemmaor, Lee (2002)	**Parameters of G/SG model**	**Bass model; G/SG model**	**12 innovations**	**USA**
Tellis, Stremersch and Yin (2003)	**Time-to-takeoff**	**Parametric hazard model**	**10 products**	**16 European countries**
Golder and Tellis (2004)	**Time to slowdown**	**Proportional hazard model**	**30 products**	**USA**
Stremersch and Tellis (2004)	**Duration and growth rate of growth stage**	**Parametric Hazard model**	**10 products**	**16 European countries**
Van den Bulte and Stremersch (2004)	**q/p ratio (shape of diffusion curve)**	**Multilevel model with random effects estimated by residual maximum likelihood**	**293 observations on 52 consumer durables**	**28 countries**