“A utility-based dynamic model used to predict abnormalities in diffusion over time”

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A utility-based dynamic model used to predict abnormalities in diffusion over time

Abstract

We model the diffusion of new products and assert that their adoption is motivated by the utility level customers enjoy from a product. The products we consider have attributes that change with the number of users. We incorporate two factors: market growth due to improved utility and improved utility due to market growth. This leads to a dynamic model that is able to provide new insights into adopters' characteristics and is able to predict abnormalities in diffusion, such as decline in sales during take-off.

A comparison of the proposed approach with appropriate benchmarks shows that our model includes previous results as 'special cases', and provides new insights into other situations.

Keywords: diffusion, utility, forecasting, chasm, conjoint analysis.

Introduction

The current paper deals with the adoption of new products, driven by the utility[1] level customers enjoy from a specific product. The idea that potential users are influenced in their adoption of a new product by the utility level they derive from the product is not new. The entire foundation of product design literature, where a manufacturer's product strategy decisions are based on the perceived customers' utility of the product, relies on this idea (for a good review, see Lilien et al., 1992). On the other hand, a number of models, among others, those of Katz and Shapiro (1985, 1986), Loch and Huberman (1999), Thun et al. (2000) and Haruvy et al. (2004) show that customers' product utility depends on the installed base, due to externalities. Bowman and Gatignon (2000) claim that managers frequently justify the development of new features, accessories and attributes[2] as a means of drawing new buyers to a product category. Cerquera (2005) claims that R&D activities – once again product improvement activities – are not exogenous[3], but rather are influenced by the market. The announcement of Ofto's acquisition[4] by Kodak on May 2nd 2001 exposes the way managers consider market size when making R&D spending decisions. We can also learn from Nikon's 2004 annual report that the spending on digital imaging R&D was consistently around 4% of last year's annual sales. Telelogic's Focal-Point management decision supporting tool[5] demonstrates how market attractiveness of each feature is weighed against the R&D cost required for adding that feature. Such considerations have been involved in managers' decision making process for a long time but recently, following the development of tools like Telelogic Focal-Point, became part of the structured decision flow. While R&D results, in terms of technology progress at the individual firm level, are influenced by creativity, innovation, efficiency and luck; at the macro level, R&D product improvement results are a function of investment. Given an R&D budget, experienced managers can set goals and provide an achievable roadmap for technological progress. Sensing (predicting) market growth and preferences can be achieved by market surveys or by analyzing sales data after product models have been launched and adjustment measures have been taken.

In this paper, we incorporate two factors: market growth due to improved utility and improved utility due to market growth. This leads to a dynamic model that is able to provide new insights into adopters' characteristics and is able to predict abnormalities in diffusion, such as decline in sales during take-off.

The most prominent model for forecasting market acceptance of consumer durables is the Bass (1969) diffusion model. The Bass's model was later extended by many researchers, among them, Robinson and Lakhani (1975), Feichtinger (1982), Kalish (1985), Jones and Ritz (1991), Bass et al. (1994) and Shih and Venkatesh (2004) in an attempt to incorporate the influence of a marketing

[1] In economics, utility is a measure of the relative satisfaction gained by consuming different bundles of goods and services.

[2] A specific set of characteristics that identify the visual, physical and behavioral traits of the product.

[3] A variable that is not caused by another variable in the model.

[4] Wednesday, 2 May 2001 – 04:00 GMT (ROCHESTER, N.Y. -- (BUSINESS WIRE).
Today Kodak has announced it is acquiring Ofoto. Kodak, obviously realizing that a large chunk of their future is reliant on consumer digital imaging has signed a "definitive agreement" to buy the online photofinishing giant Ofoto. "The acquisition enhances our leadership in the growing market for online photo services. By combining Kodak's and Ofoto's technology, marketing and distribution assets, we will be able to deliver the most comprehensive, easy-to-use online photography services to customers and consumers", said Shih. "This will accelerate Kodak's growth and drive more rapid adoption of online photography".

[5] See details at http://www.telelogic.com/products/focalpoint/index.cfm

mix. Norton-Bass (1987, 1992), Mahajan, Muller and Bass (1993), Mahajan and Muller (1996), Maier (1996) along with Bass and Bass (2001), developed the diffusion models for substitution of successive generations. Weerahandi and Dalal (1992) present a choice-based diffusion model, indicating product attributes as a factor that causes adoption.

Most of the current existing diffusion models are based on biological and sociological research. On this basis, Rogers (1983) defined *diffusion* as *the process whereby innovation is communicated by the members of a social system*. Therefore, diffusion models describe how communication drives diffusion. Nevertheless, these kinds of models provide no explanation for how the diffusion process can be influenced by the utility levels offered by a product with varying attributes (attribute evolution). In the current study, to deal with this challenge, we change the philosophy, which states that the motivating force that creates the desire to buy a product is due to communication. Instead, we assume that the driving force to adopt a product is a function of the utility that customers derive from the product. In other words, we assume that potential users (who are assumed to be rational) are influenced by the utility level they derive from the product. Knowledge about the product has to be distributed through the social system, by media and word of mouth, and usually spreads fast. Still, many people know many products in depth and never purchase them. The dominant factor that drives actual purchase is, for many products, the utility the customers receives from it. This assumption is consistent with Weerahandi and Dalal (1992). Differently from Weerahandi and Dalal (1992) and Marez and Verleye (2004), we consider the product's evolutionary path endogenously, i.e., we argue that product evolution is not dictated by external forces, but rather is influenced by market development. Moreover, we capture all possible sources of improved utility, such as direct and indirect externalities, price decline and product improvements. Focusing more specifically on high-technology products, we link product improvement to R&D activities, rather than extend the product variety as in the mini-van case discussed by Bowman and Gatignon (2000).

The rest of the paper is organized as follows. In Section 1 we present the model, while in Section 2 we present the new insights revealed by our model. In Section 3 we compare our model with appropriate benchmarks. The last section concludes the paper.

1. The utility-based dynamic model

We consider a product with attributes that change with the number of users[1]. We have two basic assumptions that are consistent with broad empirical observations. The first is with respect to the motivation to purchase, the second deals with firms' desire to improve their products.

Assumption 1. One of the observed phenomena (c.f. the conjoint analysis and product design literature) is that potential product users are influenced by the utility levels they enjoy from the product. This leads us to the assumption that consumers' major driving force to purchase is *utility level*.

Assumption 2. Other observed phenomena (c.f. Bowman and Gatignon, 2000; and Cerquera, 2005) show that a growing market pushes firms and service providers to improve products in order to deploy the market opportunities. This leads us to the assumption that product attributes depend on market growth.

Let A denote the vector of the product's attributes, and $f = f(t)$ be the adoption fraction at time t. Based on Assumption 2,

$$A = A(f). \tag{1}$$

Let

$$u = u(A) \tag{1a}$$

be the utility level of an average consumer[2] of this product, thus consistent with the definition in Footnote 1, is a function of the product's features. Considering (1) and (1a),

$$u = u(f). \tag{1b}$$

The function $u(f)$ can be either linear or non-linear.

Based on Assumption 1, potential product users are influenced by the utility level (or satisfaction, see footnote 1) they enjoy from the product. In other words, the *driving force of potential users is a function of the product utility*, say, $\Phi(u)$ The function Φ can be either linear or non-linear. Then,

the change in the adoption fraction, $\dot{f} = \frac{df}{dt}$, becomes,

[1] Our consideration includes products that are characterized by direct network externalities like mobile phones, fax machines, e-mail, etc. but goes beyond this; we also include products with complementary services (indirect externalities), such as, printer paper, memory cards for digital cameras, car insurance, video libraries for DVDs, etc. Both types of externalities are incorporated in earlier diffusion studies, such as, Katz and Shapiro (1985, 1986), Loch and Huberman (1999) and Thun et al. (2000). Bowman and Gatignon (2000) and Cerquera (2005) argue that product utility improvement can also stem from market acceptance; in other words it behaves like indirect network externalities.

[2] We assume that the market is homogeneous in its perception of the product's utility. However, as we will see, this market is heterogeneous in the preferences on minimal utility that a product needs to have in order to buy it.

$$\dot{f} = \Phi(u)(1\text{-}f). \quad (2)$$

Differently said, equation (2) claims that the satisfaction (utility) gained from the progressive improvements in the product attributes drives the diffusion process. We term equation (2) as the *utility-based dynamic model*, meaning that potential users motivated by the utility level u gained from progressive improvements in the product attributes result in a change in the adoption fraction, $\dot{f}$.

Substituting (1b) in (2), we obtain,

$$\dot{f} = \Phi[u(f)]\cdot[1-f] = \psi(f)\cdot(1-f), \quad (3)$$

where $\Psi(f)$ is the composition $\Phi\,[u(f)]$.

A simple example for $u(f)$ and $\Phi(u)$ is when they are both linear, i.e.

$$u(f) = P + b\cdot f \text{ and } \Phi(u) = \alpha + \beta + u. \quad (3a)$$

Considering (3a), the utility at launch (when $f = 0$) is P, and the increase in utility is proportional to the increase of the adoption fraction with the factor b. The increase in the purchase driving force is proportional to the increase in utility with the factor β. At launch, when $u = P$, the purchase driving force is, which is $\Phi\,(P) = \alpha + \beta\cdot P$, the sales volume for the first period.

By determining $\Phi(u)$ and $u(f)$, equation (3) can be used to forecast market acceptance. Next we present an algorithm that leads to the determination of these functions.

1.1. Determination of $\Phi(u)$ and $u(f)$. To determine $\Phi(u)$ and $u(f)$ we suggest to conduct a conjoint analysis procedure. This procedure should comprise three stages. At the first stage, to design the study by conducting a survey on a target group composed of customers, manufacturers and service providers. At the second stage, to obtain preferences and purchase intentions data from a sample[1] of respondents, which represents the target market segment. At the third stage, to show how to use the data obtained at Stage 2 to determine the functional forms of $u(f)$ and $\Phi(u)$ (see Table 1).

Stage 1. Designing the conjoint study

Steps 1.1 and *1.2:* Select the relevant attributes and attributes levels, which may be identified by a target group, composed of customers, manufacturers and service providers as in the standard conjoint study. For example, if we consider the case of a digital camera, assume that in Step 1.1, we find 3 attributes (resolution, zoom, printing service), and in Step 1.2 the following corresponding levels, such as (2Mpixel, 4Mpixel), (2x, 6x), (20% service[2], 50% service, full service).

Table 1. Steps in designing and executing a conjoint study

Stage 1 – Designing the conjoint study (by conducting a survey on a target group composed of customers, manufacturers and service providers):
Step 1.1: Select attributes relevant to the product and valued by customers.
Step 1.2: Select levels for each attribute.
Step 1.3: Select the relations between the attribute levels and the number of users.
Step 1.4: Develop the product bundles to be evaluated.
Stage 2 – Obtaining data from a sample of respondents from the target market of customers:
Step 2.1: Design a data collection procedure.
Step 2.2: Select a computational method for obtaining part-worth functions.
Step 2.3: Obtain data on purchase intention for each respondent.
Stage 3 – Determine the functional forms of $u(f)$ and $\Phi(u)$:
Step 3.1: Determine the functional form of $u(f)$.
Step 3.2: Compute the sequence of driving forces.
Step 3.3: Determine the functional form of $\Phi(u)$.

Step 1.3: Select the relationship between the attributes levels and the adoption level, A(f). One way to identify these relationships is by asking manufacturers and service providers about the levels added to the basic level of the product at the introduction of different adoption levels in the market. Another option is to perform an analysis of the firms' policies, industry structure and technology and estimate the relations between market growth and product evolution. For each adoption level f, we list the services/attributes that have been added and offered. In this way, we can determine the relationship between the attribute level determined in Step 1.2 and the level of f. For example, in the case of the digital camera, let's say, $f = 0$ (at launch time) corresponds to 2Mpixel, for resolution, to 2x for zoom, and to 20% service for printing service; $f = .2$ corresponds to 4Mpixel resolution, 2x for zoom, and 50% service for printing service and so on. Thus, A(0) becomes (2Mpixel, 2x, 20% service), and A(.2) becomes (4Mpixel, 2x, 50% service).

Step 1.4: Develop the product bundles to be evaluated. This step is standard to conjoint analysis. Note that using Step 1.3, we also have the product bundles in terms of f.

Stage 2. Obtaining data from a sample of respondents

Steps 2.1 and *2.2*: Design a data collection procedure and select a computational method for obtaining part-

[1] The sample should be representative for the entire potential market across all social dimensions (income, age etc.). Respondents should be educated about the benefits of the new product, its limits and how it is used. The size of the sample depends on the complexity of the conjoint study. When there are more attributes and more levels, a larger sample is required for guaranteeing a reasonable error of market preferences and purchase intentions estimation.

[2] This means that 20% of available photo shops provide digital photo printing services.

worth functions. These steps are standard in conjoint analysis.

Step 2.3: Obtain data on purchase intention for each respondent. In addition to selected product bundle evaluations, we ask the respondent to compose a profile of a product with minimal levels that would still drive a purchase; in contrast with the usual conjoint where such a composition is made under price constraints. To prevent the customer from creating a non-realistic product, we use an implicit time constraint. A product with low utility will be available earlier than a product with high utility. This part is done as UD (User Design) selection where the respondent selects the levels of the product he/she desires (Dahan and Hauser, 2002). At this stage, for each respondent i, we have the bundle B_i with minimal levels that drive a purchase. By Step 2.2, we can also calculate the utility that corresponds to B_i, u_i. If for example B_i = (4Mpixel, 2x, 50% service) and if, in Step 2.2, we calculated $u(B_i) = 30$ then $u_i = 30$ will represent the minimal purchase driving utility of customer i.

We also ask the respondent to estimate the average time between the availability of the desired product on the market to an actual purchase. Let t_i be customer i's, average time, for example, 4 months. We will assume for the sake of simplicity that t_i is the same for all customers, thus $t_i = \tau, \forall i$. If this is not the case, we either average the time over all the customers or we segment the customers along the time parameter.

Stage 3. Determining the functional forms of $u(f)$ and $\Phi(u)$

Step 3.1: Determine the functional form $u(f)$. From Step 1.3, we have determined the relationship between each attribute level and the market adoption fraction, while Step 2.2 gives us the part-worth of each attribute level. Thus, by combining these two steps, we achieve the utility that corresponds to each market adoption fraction. For example, being consistent with our example above, the utility that corresponds to $f = .2$ is $u = 30$. In this way, we obtain a list of utilities that correspond to a list of adoption fractions. By a linear or non-linear regression, we determine $u(f)$.

Step 3.2: Compute the sequence of driving forces. In this step, we proceed according to the following sub-steps:

1. We arrange the values of minimal utility to purchase of the respondents into a non-decreasing sequence, i.e., we generate $u_1, u_2, \ldots, u_m$, where $u_1 \leq u_2 \leq \ldots \leq u_m$, and m is the number of respondents.
2. We calculate the adoption fraction in periods $t = n\tau$, $n = 0,1,2,\ldots$[1]. Let us denote this sequence of adoption fractions by $\{f_n\}_{n=0,1,2,\ldots}$, where $f_n = f(t)$. We calculate f_n iteratively by the formula
$$f_n = f_{n-1} + \Delta f, \; f_0 = 0, \qquad (4)$$
where Δf represents the difference between the fraction of adopters between the periods $t-1$ and t. To calculate Δf, we count the difference between the number of people, out of the sample size, that purchase at $u(f_{n-1})$[2] and at $u(f_{n-2})$; this is because the customers who are satisfied with $u(f_{n-2})$ have already adopted the product in period $n-1$. The customers who are satisfied by $u(f_{n-1})$ adopt during period n. Along with earlier adopters, they create the adoption fraction f_n at the end of period n. The utility $u(f_n)$ drives purchase at period $n+1$. This process continues until we reach the value 1 for f_n.
3. By discretizing (2), we obtain
$f_n - f_{n-1} = \Phi(u(f_{n-1})(1-f_{n-1})$ or
$$\Phi(u(f_{n-1})) = \frac{\Delta f}{(1-f_{n-1})}, \qquad (5)$$
where Δf is as in (4). To obtain the sequence of potential users' driving force $\Phi(u(f_{n-1}))$, we need to calculate the RHS of (5), which can be obtained from sub-step (2), above.

Step 3.3: Determine the functional form of $\Phi(u)$. From Step 3.2, we obtain a list of points of driving forces that correspond to a list of points of utilities at certain adoption fractions. By a linear or non-linear regression, we determine $\Phi(u)$.

Combining $\Phi(u)$ and $u(f)$, obtained from the algorithm described above, leads to the dynamic model (3), thus to the specification of $\Psi(f)$.

2. Implications of the utility-based dynamic model

2.1. New insights – product adopters' profiles. The utility-based diffusion model can be used to shed new light on product adopters' profiles. As it appears in our model, early adopters (innovators of the Bass's model) are driven by acute needs to purchase the product even when it has a lower utility level and a higher price. Thus, they are influenced not by mass media, which is a low involvement media, but by specific needs. This also explains why innovators are product-specific. In our model, late adopters (imitators of the Bass's model) are consumers who are satisfied with the cur-

[1] The sequence ends for n at which $f = 1$.
[2] Thus, this is composed from all customers with utility, which is less or equal to $u(f_{n-1})$. This number is obtained from sub-step (1), above.

rent alternatives. They will adopt the product only when it improves to provide more benefits than the currently existing alternatives. The new product has to compete not only with the existing technological attributes, but usually also with a well-deployed infrastructure that supports the well-established technology. The late adopters or laggards are those who are heavily invested in the old technology. Those who had a large library of vinyl records were not enthusiastic about switching over to CDs. The benefits of better sound and a compact package were negated by the need to re-purchase a new inventory of music records. The same is true for professional photographers and photography hobbyists who had their own dark room, developing equipment, lenses and other paraphernalia for film photography and development, all of which became obsolete with the invention of the digital camera.

In our model, knowledge about the product (which is a precondition for considering a purchase) spreads, as shown by Midgley (1976), at a faster rate than adoption and is available to potential adopters before the product's utility has reached the level of their demands. We describe the process of adoption in Figure 1.

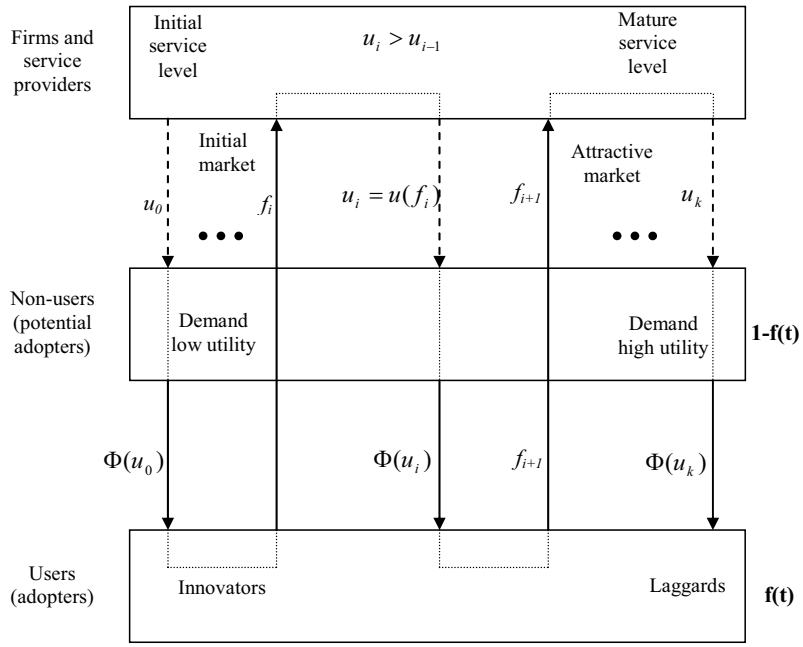

Fig. 1. The utility-based dynamic model

2.2. Prediction of abnormalities in diffusion. Moore (1991) discusses a decline in sales that occur, for many products, during the period of rapid growth[1]. This effect is mentioned also by Goldenberg et al. (2002). This phenomenon was ignored by earlier researches and considered a random interference. Moore indicates that such a phenomenon, which he called a 'chasm'[2], exists for many products, resulting in diverse managerial implications. Understanding the chasm may avoid investors' disappointment and encourage the required patience that is necessary for "crossing the chasm". Moore explains that there is a distinction between early adopters that have certain needs and the early majority who is more conservative. In order to cross the chasm, firms have to adjust their products to the demands of the early majority. Our model can provide an explanation for the chasm phenomenon. To be more specific, we next present some illustrative examples for a case where *u(f)* is linear, as in (3a).

Example 1. Consider that *Φ(u)* is also linear, as in (3a). The increase in the purchase driving force is proportional to the increase in utility with the factor *β*. At launch, when *u* = *P*, the purchase driving force is $\Phi(P) = \alpha + \beta \cdot P$, which is the sales volume for the first period. Consider the following values for our parameters,

$$(P,\ b,\ \alpha,\ \beta) = (1.053,\ 0.64,\ -0.76,\ 0.728). \qquad (6a)$$

The diffusion curves, for both cumulative and periodical sales, which are identical to the usual diffusion curves, are shown in Figure 2.

[1] It is interesting to note that a chasm phenomena is seen at Bass (1969) sales data of TVs and washing machines. Bass focused capturing the long-run sales trend, which was unknown before, leaving the chasm analysis to followers.

[2] This term was coined by Geoffrey A. Moore in his seminal work on marketing for technology startups, "Crossing the Chasm"; a phrase referring to the challenging strategic and marketing process by which technology startups transition from selling their products and/or services to innovators and early adopters to selling to the early majority, a.k.a. pragmatists; this transition ("crossing the chasm") entails a dramatic shift in mentality for the startup, best understood by reviewing Moore's book.

Example 2. Now we consider that the driving force *Φ(u)* has the following non-linear form,

$$\Phi(u) = \begin{cases} \alpha + \beta u & u < 1.1 \\ \alpha + 1.1\beta & 1.1 \le u < 1.16 \\ \alpha + (u - 0.06)\beta & 1.16 \le u \end{cases}, \qquad (6b)$$

with (*P, b, α, β*) as in (6a). According to (6b), the attractiveness of the product or the purchase driving force does not grow for all utility values *u*, but remains the same for a certain utility range. In this case, the periodical sales curve shows a chasm. This decline in sales can be explained by the purchase driving force function *Φ*(*u*), which is constant for $1.1 \le u \le 1.16$. This means that although the utility *u* increases, the number of potential customers that are interested in the product at this utility range, and represented by *Φ*(*u*), does not increase.

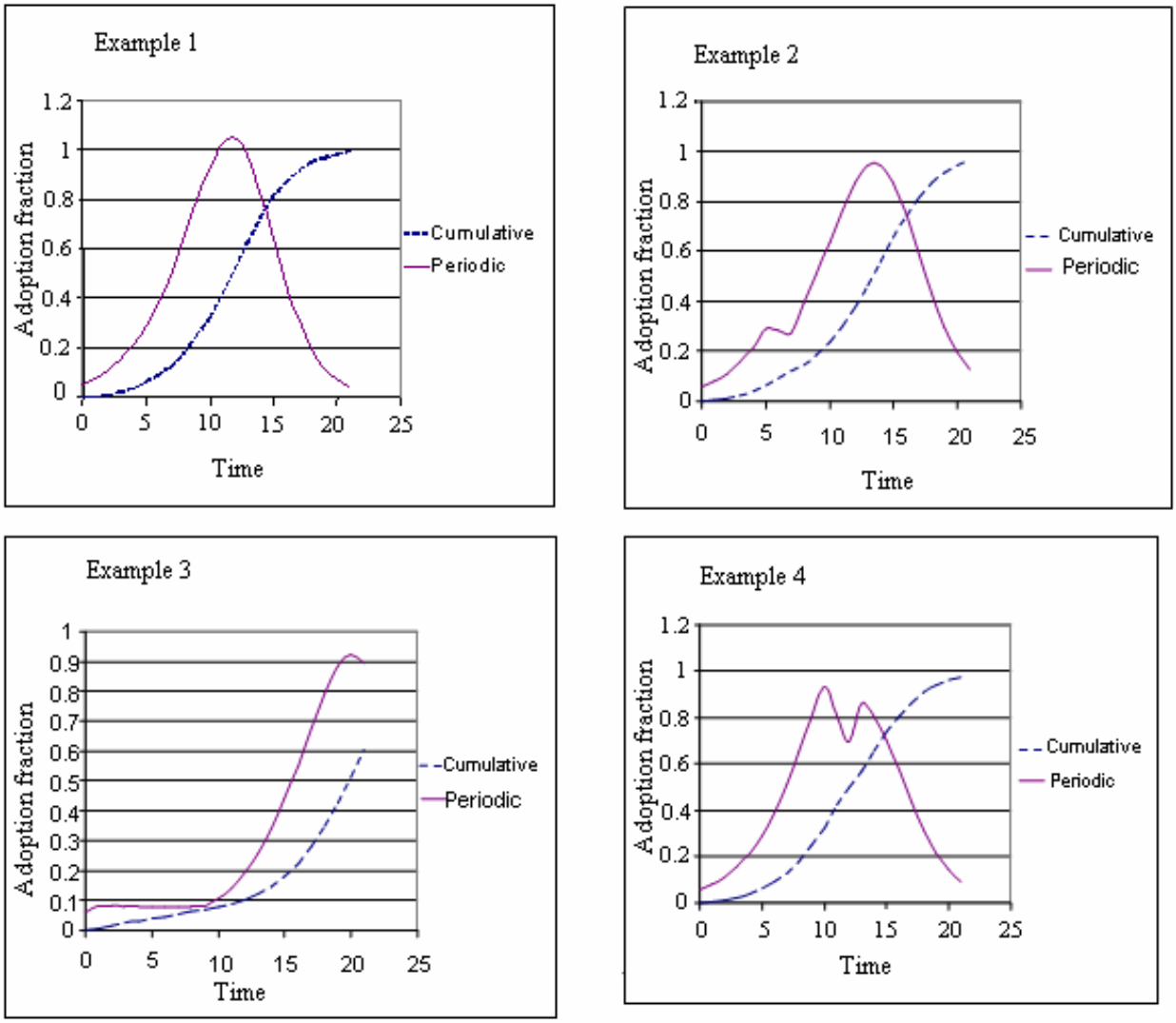

Fig. 2. Possible marketing phenomena explained by the utility-based model

Note that sales are a multiplication of *Φ*(*u*) by *(1-f)*, which represents the saturation effect. This saturation causes sales to decline. When *Φ*(*u*) increases again (for *u > 1.16*), the saturation effect is compensated by the growing potential market, represented by *Φ*(*u*), and sales rise. This rise is described by Moore (1991) as: "crossing the chasm".

Example 3. Now we deviate from the previous example by considering:

$$\Phi(u) = \begin{cases} \alpha + \beta u & u < 1.06 \\ \alpha + 1.06\beta & 1.06 \le u < 1.12 \\ \alpha + (u - 0.06)\beta & 1.12 \le u \end{cases}. \qquad (6c)$$

The deviation means that the slowdown in product attractiveness or the purchase driving force happens a little earlier. Again we use (*P, b, α, β*) as in (6a). Following Figure 2, the periodical sales show that for a long time the sales volume is small until it rapidly takes off. The impact on sales is that the product has a long runway before take-off. It might be interesting to see if this example can explain the behavior of a product like HDTV, which has not yet taken off.

Example 4. Now we consider another deviation of *Φ(u)* (with a slowdown at a later stage):

$$\Phi(u) = \begin{cases} \alpha + \beta u & u < 1.27 \\ \alpha + 1.27\beta & 1.27 \le u < 1.33 \\ \alpha + (u - 0.06)\beta & 1.33 \le u \end{cases}, \quad (6d)$$

using (P, b, α, β) as in (6a). We maintain that the periodical sales show a double-hump curve (decline and revival) (see Fig. 2).

Similar effects happen when the driving force is linear, but the firms fail to increase the utility at a constant rate. We demonstrated the effects of a slight distortion of a linear dependency. Other forms of diffusion can be explained by different $u(f)$ and $\Phi(u)$ functions.

3. The utility-based dynamic model vs. previous related literature

In this section, we want to compare our model vs. previous related literature. For this purpose, we consider the dynamic model in (3) for a number of special cases.

1. $\Psi(f)$ is linear in f, thus
   $$\psi(f) = p + qf, \quad (7)$$
   where p and q are the *innovator* and *imitator* parameters of Bass. This special case represents the diffusion of a conventional product and thus, in this case, model (3) is equivalent to the Bass's (1969) model or some of the examples presented by Van den Bulte and Joshi (2006).
2. $\Psi(f)$ is quadratic in f, thus
   $$\psi(f) = p + qf + \hat{q}f^2, \quad (8)$$
   where p and q are the innovator and imitator parameters of Bass, and $\hat{q}$ represents the cross-effect interaction between adopters (in the case of products characterized by a network externality that follows Metcalf's law[1]). Thus, for this special case, model (3) represents the diffusion model for products with direct and indirect network externalities that follow Metcalf's law. Other forms of externalities can be captured by different non-linear functions of f, c.f., Katz and Shapiro (1986), Loch and Huberman (1999), Thun and Milling (2000).
3. If u represents the utility of a product with changing attributes as a result of augmented service, price decline or brand reputation that is a result of advertising, and $\phi(u)$ represents the decision factors of the customers, we maintain that (3) represents a diffusion model that includes marketing mix and decision variables, c.f. Feichtinger (1982), Kalish (1985), Weerahandi and Dalal (1992), Dockner and Fruchter (2004), Marez and Verleze (2004), Shih and Venkatesh (2004).
4. If u represents the step-wise utility function of a product with changing attributes as a result of successive generations, we maintain that (3) represents a successive generation diffusion model, c.f. Norton and Bass (1987), Mahajan and Muller (1996), Maier (1996), Bass and Bass (2001), Goldenberg et al. (2002).

Note that while generations' substitution models require a set of at least three parameters per generation, the utility-based diffusion model describes the entire lifetime with a single function.

5. When u or $\Phi(u)$ has a non-linear form such as (6b) the diffusion curve will show a chasm or a saddle as described by Moore (1991) and Goldenberg et al. (2002). Other "abnormalities" described by Van den Bulte and Joshi (2006) as caused by certain relationships between influences and imitators can be alternatively explained by our model using (6b) or (6c).

Conclusion

In this paper, we develop and analyze a dynamic model for forecasting sales. In contrast to the usual diffusion models, in our model the potential adopters are driven by the increasing utility that customers perceive in the product, which stems from its improved attributes and accompanied services. The growing market drives manufacturers and service providers to further improve their offerings. The new model provides an explanation for certain aspects of diffusion, which other models lack. It explains why early adopters of one product will not necessarily be early adopters of other products. Furthermore, it provides tools with which to identify early adopters as well as other market segments according to their utility demands. It helps to predict if and when there will be a 'chasm' in sales or other "abnormalities".

[1] Metcalf's law determines the benefit that the user network receives from the number of users. While for a certain user in a network, the immediate benefits that stem from other users are proportional to the number of users (he/she can communicate with N persons), the number of interconnections is αN^2. Thus, the benefit for the network operator is kN^2. If some of the operator benefits are enjoyed by the individual user (through price) then the utility has a component of f^2.

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