Innovation Diffusion and New Product Growth Models: A Critical Review and Research Directions

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Abstract

In this paper we review the diffusion modeling literature since the early 1990s and analyze how diffusion research has broadened its scope to describe the richness and phenomena related to new product growth. We focus on studies that explore six questions related to (a) the drivers of growth, (b) the shape of the product life-cycle curve, (c) the relationships between individual adoptions and aggregate growth, (d) marketing mix influences, (e) cross-country influences, and (f) the effect of competition on growth.

Anticipating market trends such as opening up of markets in developing countries, Web-based services, virtual social networks, and complex product-service structure, we offer directions for further research related to the six aforementioned questions. Based on the proposed research directions, we conclude that in order for diffusion to remain a state-of-the-art modeling framework for market evolution, its scope should be broadened to: include additional growth drivers other than interpersonal communications; reexamine the metrics to describe both the level and variety of usage; and extend the range of data sources to include services, individual-level data, and data from developing countries.

Introduction

At the end of 2007, 3.29 billion people around the world were using mobile phones (ITU report 2007). Mobile phone services were commercially launched in Scandinavia in 1981, and since then have become a part of everyday life for over 49% of the world's population in 211 countries. Mobile telephony is not exceptional: Many now commonly used products and services such as DVDs, personal computers, digital cameras, online banking, and the Internet were not known to consumers three decades ago, and firms invest continuous efforts in further developments of product and service innovations.

The spread of an innovation in the market is termed *diffusion*. An accepted definition of diffusion of innovations is "the process by which an innovation is communicated over time among the members of a social system" (Rogers 1995). Diffusion processes evoke a variety of possible research questions; one might wonder what drives growth, what will be the shape of an innovation's life-cycle curve, and what is the relationship between individual adoption decisions and aggregate market growth. These issues lead to significant implementation-related questions such as the influences of marketing mix variables on the growth pattern of the industry and brand, the interactions between growth processes in various countries wherein the firm has presence, and the effect of competition on growth.

Diffusion research is the branch of marketing that aims to answer such questions through modeling the life cycle of new products. Since its start in the 1960s, diffusion research has been, and still is, the only modeling framework in marketing that is targeted at modeling the entire life-cycle course of an innovation from the perspective of communications and consumer interactions. Traditionally, the main thread of diffusion models has been based on the model developed by Bass (1969). This model, which will be discussed later in this paper, and many of the models that followed it, considered the case of a monopoly of a durable good, and investigated the aggregate first-purchase growth of the category in a single market (see the review by Mahajan, Muller, and Bass 1990). The social network was assumed to be fully connected and homogenous. An individual in this network adopts the innovation as a result of two types of influences: external influences, i.e., advertising and other communications by the firm; and internal market influences, resulting from interaction between adopters and potential adopters in the social system. These interactions were mostly regarded as based on word of mouth and interpersonal communications (Mahajan, Muller, and Wind 2000; Mahajan, Muller and Bass 1990). This literature has been surveyed in review papers and books such as Mahajan, Muller, and Wind (2000), Parker (1994), and Mahajan, Muller, and Bass (1990).

The growing number of newly introduced information, entertainment, and communication products and services, as well as the development of market trends such as globalization and increased competition, has led diffusion processes beyond the classical scenario of a single-market monopoly of durable good in a homogenous, fully connected social system. For example, many communication innovations such as the Internet or mobile phones have network externalities, that is, their utility for the individual depends on the number of other individuals who have already adopted the product. Thus, one may look for growth drivers that go beyond word-of-mouth or direct customer interactions discussed so far in diffusion models.

Similarly, the sophistication and high-tech nature of innovations today serves to increase the gap between the technology-oriented early adopters and the main market. This fact, in addition to the rapid replacement of products by newer technological generations, causes one to wonder whether the penetration curve is indeed smooth and monotonically increasing. Choice processes have also become more complicated than previously: Innovations such as mobile phones or satellite radio involve choice of both product and service providers; the definition of category is sometimes ambiguous (is iPhone a mobile handset, a music player, or PDA?). Thus, zooming in from the aggregate description to tracking individual-level decision processes and their influence on aggregate behavior becomes more acute. Regarding marketing mix, traditionally marketing mix decision questions (mainly pricing) were treated under the rubric of economies of scale and progress along the learning curve. Is this context still relevant to markets wherein many innovations are services, and long-term relationships might play a role in the firm's budget allocation?

Market trends such as globalization and increased competition can also lead to extending classical diffusion questions. While traditional approaches dealt with a single market, many products penetrate simultaneously in more that one country. Mobile phones, for example, were launched throughout Scandinavia within a single year. Simultaneous penetration in turn raises the question of how the diffusion in a given country is influenced by interaction with individuals in other countries. Regarding competition, modeling the category level or regarding the innovation as a monopoly are not sufficient, since products today enjoy shorter monopoly periods. Thus the product category consists of a portfolio of brands that penetrate the market. The resulting question is how interactions between brands in a portfolio influence the growth of each brand and of the entire category.

Loyal to its mission to provide a comprehensive description of life-cycle processes, diffusion modeling has followed the market trend and concerned itself with answering the above questions. Although two recent books relate to complex diffusion scenarios and recent innovations (Chandrasekaran and Tellis 2007; Mahajan Muller and Wind 2000), the times call for a new review that will tie all these studies together, and specifically will identify gaps, i.e., questions that have not yet been explored and that should be addressed in further research. In this paper we review the diffusion literature since the early 1990s, which was the turning point when the literature started its substantial shift from investigating the basic diffusion scenario to exploring more complex market structures. Due to the volume of diffusion research, we focus on the diffusion literature in marketing, and do not survey operations research, technological forecasting, behavioral diffusion theory, and economics growth literature.

Table 1 illustrates the developments in diffusion research during the past two decades as compared with the papers reviewed in Mahajan, Muller, and Bass (1990). The literature is grouped into six major questions on which we found that diffusion research currently focuses: The first three deal with growth mechanisms, and the last three with managerial implementation issues. This paper is organized according to the six major research questions described in Table 1. For each question, we review the major research issues, methods, and main results. In the discussion session, we identify gaps and suggest topics for further research.

- insert Table 1 around here -

What Drives Growth?

A fundamental question in understanding and modeling growth processes concerns the market mechanisms that generate and enhance growth. In this section we discuss the diffusion modeling literature that relates to growth drivers. We begin with the classical approach, represented by the Bass model, whose main interpretation is that growth is driven by interpersonal communications, and then review studies that have proposed alternative approaches and additional growth mechanisms. The approaches and the amount of interpersonal communications they involve are illustrated in Figure 1.

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Interpersonal Communications: The Bass Model

The best-known model in diffusion research is the Bass model (Bass 1969). Since its publication in *Management Science*, it has been cited over 600 times, and it forms the basis for nearly all the models reviewed in this paper, see also the review papers by Mahajan, Muller and Bass (1995; 1990); Meade and Islam (2006; 1998); Hauser, Tellis, and Griffin (2006); and Chandrasekaran and Tellis (2007). Assume a single innovation penetrating a market with potential *m*. At each point in time, new adopters join the market as a result of external influence (*p*), and internal influence (*q*). The parameter *p* captures the activities of firms in the market, mainly advertising, and any other time-invariant element affecting the diffusion, such as the appeal of the innovation. The parameter *q* refers to the magnitude of influence of an adopter on a non-adopter. Thus, the social network is assumed to be fully connected and homogenous, meaning that *p* and *q* do not vary between individuals.

If $N(t)$ is the cumulative number of adopters at time *t*, and $x(t)$ is the adoption proportion at time *t*, then ($x(t) = N(t) / m$) (for consistency, we will use these notations throughout the paper, even if it changes the notation of the paper under review), of new adopters at time *t* can be described by the following differential equations:

(1) $$\frac{dN(t)}{dt} = p \cdot (m - N(t)) + \frac{qN(t)}{m}(m - N(t))\text{; or}$$

$$\frac{dx(t)}{dt} = p \cdot (1 - x(t)) + qx(t)(1 - x(t))\text{, where } x(t) = N(t) / m.$$

Equation (1) is a non-linear first-order differential equation that can be solved analytically using separation of variables. If $N(0) = 0$, then the solution for Equation (1) is given by:

(2) $$N(t) = m\frac{1 - e^{-(p+q)t}}{1 + (q / p)e^{-(p+q)t}}.$$

While the above initial condition is the most commonly used, complex diffusion scenarios such as early and late entry, multinational diffusion, and technological generations sometimes require the more general initial condition $N(0) = N_0$. In this case, the solution is given by:

$$(3)\ \ N(t) = m\frac{S - e^{-(p+q)t}}{S + (q/p)e^{-(p+q)t}}\text{, where } S = \frac{m + (q/p)N_0}{m - N_0} = 1 + \frac{(1 + (q/p))N_0}{m - N_0}$$

The term S, which we term the *seeding factor*, represents the influence of the initial seed of adopters. If $N_0 = 0$ then $S = 1$ and Equation 3 reduces to the zero condition solution of Equation 2. As illustrated in Figure 2, the cumulative adoption curve $N(t)$ is S-shaped, while the new adoptions curve $dN(t)/dt$ is bell-shaped, and approaches zero when the entire market potential has adopted the innovation. The Bass model parameters p, q, and m can be estimated from adoption data, usually by using non-linear least squares. The average values of q and p for durable goods were found to be $p = 0.03$ and $q = 0.38$ (Sultan, Farley, and Lehmann 1990). Estimation issues are also discussed in Jiang, Bass, and Bass (2006), Stremersch and Van den Bulte (2006), Boswijk and Franses (2005), Van den Bulte and Stremersch (2004), and Van den Bulte and Lilien (1997).

- insert Figure 2 around here -

Additional Consumer Interactions

In the original article by Bass, as well as many of the diffusion studies that followed it, the internal parameter q was interpreted as representing the influence of word-of-mouth, or other personal influences between individuals. Recent diffusion modeling literature has extended the discussion to differentiate between types of social interactions, as well as including additional types. We will discuss below two types of additional social interactions which are gaining recent interest: network externalities, and social inferences.[1]

Network externalities exist when the utility of the product to a consumer increases as more consumers adopt the new product (Rohlfs 2001). Network effects can be direct, wherein utility is directly affected by the number of other users of the same product, such as in the case of telecommunication products and services, i.e., fax, telephone, and the Internet. Network externalities can be also indirect, if utility increases with the number of users of another, complementary product, such as DVD players and DVD (Stremersch et al. 2007). Indirect externalities exist both between software, or content and hardware, and vice versa (Stremersch and Binken 2009). No interpersonal communication is necessarily needed for network externalities to work. Potential adopters can find out the penetration level from the media, or simply by observing retail offerings. Intuitively, network externalities are considered to have a positive influence on a product's sales and penetration (Nair, Chintagunta, and Dube 2004; Tellis Yin and Niraj 2009). However, some recent studies show a negative effect of network externalities, either on early-stage growth (Goldenberg, Libai, and Muller 2007), or on the survival of pioneers (Srinivasan, Lilien, and Rangaswamy 2004).

Social inference relates to the social signals that individuals infer from the adoption of an innovation by other adopters. Through their purchases, individuals seek to either maintain social differences or to signal group identity (Bourdieu 1984). These signals are transmitted to other individuals who follow the consumption behavior of people in their aspiration group (Simmel

[1] Several classifications were proposed for social influence mechanisms. For example, Stremersch and Van den Bulte (2004) discuss learning under uncertainty, normative pressure, competitive concerns and network externalities. While their classification focus on motivations, our classification focuses on growth mechanisms according to the level of interpersonal communications they involve (see also Van den Bulte and Wuyts 2007). Thus mapping these two classifications might group learning and normative pressure under interpersonal communications, and competitive concerns under social inferences.

1957, Van den Bulte and Wuyts 2007, Van den Bulte and Joshi 2007). Recent research indicates that competition for status is an important growth driver, sometimes more than interpersonal ties (Burt 1987), and that the speed of diffusion increases in societies which are more sensitive to status differences (Stremersch and Van den Bulte 2004). When formal status hierarchy does not exist, adoption of certain products may signal group identity. Thus, the adoption of an innovation by people in the "right" group signals members in this group to adopt it, and members of other groups to avoid adoption (Berger and Heath 2007). Social signals could be transmitted via word-of-mouth or advertising but not necessarily. They do not require interpersonal ties, but are observed by potential adopters who infer from them on the social consequences of the adoption.

Do social inference and network externalities contradict the Bass framework? The Bass model and most papers built on its foundation traditionally expressed the effects of current sales on previous cumulative adopters in terms of personal communications (Mahajan Muller and Bass 1990). However, word-of-mouth interpretation is just that: interpretation. All that the classical diffusion model is saying is that *current sales are a function of cumulative adoption*, yet the model is silent with respect to the reasons. Thus, the growth drivers of network externalities and informational cascades certainly fit the framework, as well as do other possible growth drivers, as long as they imply that the probability of purchase is increasing in the number of previous adopters.

Communications vs. Heterogeneity

As an alternative to consumer interaction-based diffusion, a new research branch has emerged that presents a divergent point of view. This viewpoint argues that the major driver of growth of new products is consumer heterogeneity, rather than consumer interaction. The heterogeneity approach claims that the population is heterogeneous in innovativeness, price sensitivity, and needs, leading to heterogeneity in propensity to adopt. Thus innovators are the least patient in adopting, whereas laggards are the most patient. Often patience is inversely related to affordability, willingness to pay, or reservation price (Song and Chintagunta 2003; Golder and Tellis 1998). The dynamics of market volume are determined by the shape of the distribution of the "patience" as it faces falling prices. If incomes are log-normally distributed in the population, then growth is S-shaped (Golder and Tellis 1997). This line of research implies that the current diffusion-based research has overemphasized the influence of word-of-mouth communication (see Van den Bulte and Stremersch 2004; Van den Bulte and Lilien 2001).

What is the shape of the life-cycle curve?

Temporally, the basic diffusion scenario starts with spontaneous adoption by an initial seed of customers due to advertising or sampling, then continues through the combination of external and internal influences until the market saturates. An exciting study emerged in the past decade on turning points in the product life cycle that are not included in the classic smooth adoption curve (see illustration in Figure 3). We chose to review papers dealing with three turning points in the product lifecycle: takeoff - at the beginning, saddle - during early growth, and technological substitution - at the late stages of growth.

- insert Figure 3 around here -

Takeoff

The classic Bass model starts with the adoption of an initial group of adopters, yet does not provide explanations as to the mechanisms that led to this adoption. Studies on takeoff focus on this initial stage, and explore its market behavior and its interface with the start of communication interactions; these are summarized in Table 2.

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The paper that initiated the takeoff literature was that of Golder and Tellis (1997), who defined takeoff time as *the time at which a dramatic increase in sales occurs that distinguishes the cutoff point between the introduction and growth stage of the product lifecycle*. The importance of takeoff time to the firm is quite clear: Rapid increase in sales requires substantial investments in production, distribution, and marketing, most of which require considerable lead time to be put into place successfully.

Golder and Tellis applied a proportional hazard model to data that included 31 successful innovations, and found that the average time to takeoff is six years, and average penetration at takeoff is 1.7% of market potential (equivalent to $p = 0.017$ in the Bass model). Other studies investigated factors influencing time to takeoff. As Table 2 illustrates, factors found to have a positive influence on takeoff are price, product category (brown goods such as CDs and TVs take off faster) and cultural factors such as low uncertainty avoidance and masculinity.

The basic assumption of most takeoff studies is that takeoff does not require any consumer interactions, but rather is a result of heterogeneity in price sensitivity and risk avoidance, i.e., as the innovation price is reduced, and is associated with less risk, the product takes off. Therefore, if one believes that both heterogeneity and communication play a role in new product adoption, then takeoff is an excellent example for an interface point: Heterogeneity is dominant prior to takeoff, while consumer interactions start immediately afterwards. However, the takeoff studies so far have been mostly descriptive. As had already been stated by Mahajan, Muller and Bass in their review from 1990, there is a need for a comprehensive theory that delves deeper into early market growth up to takeoff.

Saddle

Following takeoff, the classic diffusion model predicts a monotonic increase in sales. However, in some markets, this increase might be non-monotonic, and a sudden decrease in sales may occur after an initial rise. This decrease in sales was first observed by Geoffrey Moore (1991), a Silicon Valley consultant (who denoted it as *chasm* between the early and main markets), and was later formalized and explored by Mahajan and Muller (1998), Goldenberg, Libai, and Muller (2002), Golder and Tellis (2004), Muller and Yogev (2006), and Van den Bulte and Joshi (2007). Goldenberg, Libai, and Muller (2002) referred to the phenomenon as a *saddle*, and defined it as a pattern wherein *an initial peak predates a trough of sufficient depth and duration, followed by sales that eventually exceed the initial peak*. Table 2 summarizes the papers on saddles.

While a saddle can be attributed to many causes, including stockpiling, changes in technology, industry performance, or macroeconomic events, it can be also explained by consumer interactions: Golder and Tellis (2004) as well as Chandrasekaran and Tellis (2006) claimed that the saddle phenomenon could be explained using the informational cascade theory. Small shocks to the economic system such as a minor recession can temporarily decrease adoption rate, a decrease which is magnified through the informational cascade.

Another explanation is based on heterogeneity in the adopting population, and its division into two distinct groups. If these two groups adopt the innovation at widely differing rates, (e.g., because of weak communication between the two), sales may show an interim trough (Van den Bulte and Joshi 2007; Muller and Yogev 2006; Goldenberg et al. 2002). These papers demonstrate how combining heterogeneity (in this case, the division into two markets) and consumer interactions can explain a phenomenon that is not a part of the classical bell-shaped sales curve.

Technological Substitution

The classical diffusion process is terminated by saturation of the market potential. However, in practice, new products are substituted with more advanced products and technological generations. New product growth across technology generations occupies a growing interest among marketing scholars (Pae and Lehmann 2003; Kim Chang and Shocker 2000; Mahajan and Muller 1996; Bayus 1994; Norton and Bass 1992). These papers are summarized in Table 3.

- insert Table 3 around here -

The papers in Table 3 reveal intergenerational adoption processes not found in a single generation diffusion: First, the entry of a new generation is usually considered to *increase the market potential to new buyers* who were not included in the old market potential; in addition, customers can *upgrade* and substitute old technology with new. On the other hand, individuals who belong to the increased market potential can decide eventually to adopt the older generation, hence they *cannibalize* the new technology's potential. If there are more than two generations, adopters can skip a generation and *leapfrog* to advanced versions. This means that the entry of a new technology reveals heterogeneity in the adopting population that was not realized in a single-generation scenario.

An important intergenerational effect discussed in the papers of Table 3 is whether diffusion parameters accelerate between technological generations. This question has practical importance for forecasting, due to the need to forecast the growth of advanced generations in very early stages of their penetration, or even before launch. As Stremersch, Muller, and Peres (2008) pointed out, in contradiction to common wisdom, most of Table 3 papers studies found (or achieved good fit when assuming) that growth parameters are constant across technology generations. They further show that while diffusion parameters do not accelerate, time to takeoff does, which might be the source for this common wisdom

How do individual adoptions affect aggregate growth?

The classic treatment of growth processes has been at the aggregate level, i.e., the overall diffusion pattern was explored rather than individual choice processes. Aggregate diffusion models have advantages as well as disadvantages (Parker 1994): While they are parsimonious and require little data for parameter estimation, they provide little intuition as to how individual interactions are linked to global aggregate market behavior. Using aggregate models is especially justified if the social network is assumed to be homogenous and fully connected, and thus aggregate effects are just the average of local effects. The increasing complexity of choice processes, together with the extensive recent research on social networks that confirmed that they are neither homogenous nor fully connected (e.g., Kossinets and Watts 2006) has motivated diffusion researchers to zero in on and inspect the relationships between individual decision-making and aggregate market demand.

Some empirical studies investigated these relationships through exploration of the influence of the social network structure on growth (see Van den Bulte and Wuyts 2007 for an overview). Much of the research attention was on the role of central individuals (influentials, social hubs) on the overall growth process (e.g. Goldenberg *et al*. 2009; Iyengar, Van den Bulte and Valente 2008). One well-known modeling technique for generalizing empirical finding and modeling their aggregate effects is agent-based models, which describe the market as a collection of individual elements (termed *units*, *agents*, or *nodes*), interacting with each other through connections (termed *links*). Their behavior (in our case adoption) is determined by a decision rule. Neural networks, cellular automata, and small-world models are examples of agent-based modeling techniques.

A typical agent-based model is Goldenberg et al.'s (2001) cellular automata. As illustrated in Figure 4, each unit in such a model represents an individual consumer, and has a value of "0" if it has not yet adopted the product, and a value of "1" if it has adopted the product. Units adopt due to the combination of external influence (parameter p), and internal influence (parameter q). Time is discrete, and if in period t, an individual i is connected to $N_i(t)$ adopters, then the probability of adoption by that individual is shown by the following:

$$\text{(4)} \qquad \Pr(\text{adoption } \mid t)_i = 1-(1-p_i)(1-q_i)^{N_i(t)}$$

Such a simulation model overcomes some of the limitations of aggregate-level diffusion models. Firstly, it enables distinguishing between growth drivers: For example, Goldenberg, Libai, and Muller (2007) used it to explore network externalities by adding a threshold to the decision rule. Secondly, this model allows heterogeneity by making p_i and q_i differ between units, or by setting differing link structures to each unit. Heterogeneity can be incorporated into nearly every aspect of the model, including responsiveness to price and advertising (Libai, Muller, and Peres 2005), intrinsic innovativeness (Goldenberg Libai and Muller 2002), and role in the social network (hubs, connectors, or experts).

- insert Figure 4 around here -

Conceptually, aggregate diffusion models represent the overall results of individual-level processes. Hence, some studies have proposed methods of aggregating individual-level behavior based on assumptions regarding customer heterogeneity and calculation of time to adoption (Van den Bulte and Stremersch 2004; Chatterjee and Eliashberg 1990). In the specific case of cellular automata, this equivalence was demonstrated by Goldenberg, Libai, and Muller (2001a) and Shaikh, Rangaswamy, and Balakrishnan (2006).

Agent-based models are very useful in exploring the spatial structure of the market, using a variation called *small world*, which are cellular automata models that allow various strengths of links. Goldenberg, Libai, and Muller (2001a) studied spatial issues of the market through the relative influence of strong ties – the ties with neighboring units, and weak ties, which are ties with remote units. They used the model to measure the total effect of weak ties, and showed that consistent with Wuyts, Stremersch, Van den Bulte, and Franses (2004) and Rindfleisch and Moorman (2001), the cumulative influence of weak ties has a strong effect on the growth process. Garber, Goldenberg, Libai, and Muller (2004) suggested a measure for the spatial density of adoption, in order to predict the product's success / failure.

What are the marketing mix influences on growth?

Marketing activities of firms have a considerable influence on the growth process: Developing an innovation into a product, price changes, advertising, and setting the distribution channels all influence the success of a new product, as well as its rate of growth. Quantifying and understanding these influences can help firms to achieve better control of the growth process and optimize their investments accordingly. The basic Bass model does not contain marketing mix variables. This omission raised a conceptual conflict, since the model provides a high level of fit and forecasting power even without incorporating marketing mix variables; however, it is intuitively evident that marketing mix decisions do have considerable influence on the growth process. Bass, Krishnan, and Jain (1994) proposed a resolution to this conflict by introducing the Generalized Bass Model (GBM), which assumes that the effect of marketing mix variables vector $z(t)$ can be described by a non-negative function $\phi(z(t))$ that multiplies the basic curve of Equation (1) as follows:

$$(5) \qquad dx/dt = \left(p + qx(t)\right)\left(1 - x(t)\right)\phi(z(t))$$

$$\text{where} \quad \phi(z(t)) = 1 + \beta_1 P'(t)/P(t) + \beta_2 A'(t)/A(t)$$

P and A are the pricing and advertising expenses; $P'(t)$ and $A'(t)$ are the rates of change in price and advertising at time t. When the percentage change in price and advertising is constant, $\phi(z(t))$ is constant, and the GBM reduces to the original Bass model (Equation (1)). The authors tested several categories of durable goods, and found that constant rate change is a reasonable assumption, which explains why the original Bass model provides a high fit and forecasting capability even without marketing mix variables. Studies that followed the GBM compared its performance to that of the original Bass model, and their general conclusion was that both models provide a similar fit (Karine, Frank, and Laine 2004; Danaher, Hardie, and Putsis 2001; Bottomley and Fildes 1998). A limitation of the GBM is that the marketing mix variables have an equal effect on parameters p and q. This assumption is in contrast to some of the earlier work that modeled advertising as affecting only the external coefficient (see also Mesak 1996 and Feichtinger 1992); however, it is very much consistent with pricing assumptions such as those of Robinson and Lakhani (1975), who use such a multiplicative model based on the exact same assumption.

A considerable number of studies on marketing mix influences are normative (that is, they explore how marketing mix variables should be optimally used). A typical normative model maximizes the discounted profit π over a planning horizon T. The objective function can generally be described by

$$(6) \qquad \pi = \int_{t=0}^{T} (g_1 \frac{dN(t)}{dt} + g_2 N(t) - A(t))e^{-rt} dt ,$$

where r is the discount rate, $A(t)$ is the expenditure on advertising, g_1 is the profit margin on first purchase, and g_2 is the profit margin on repeat purchase, and both are a function of price. Models differ in their choice of growth function $N(t)$, and in what way it depends on the marketing mix (see Mesak and Darrat 2003; 2002; and Krishnan, Bass, and Jain 1999).

- insert Table 4 around here -

The normative studies since the early 1990s, summarized in Table 4, elaborated on those from the 1980s (see the review by Mahajan, Muller and Bass 1990), and explored optimal allocations under various market conditions. While studies in the 1980s dealt mainly with advertising, most studies from the 1990s onward relate to pricing decisions. Decisions on pricing get more complex as heterogeneity and complex penetration patterns are considered. An example is discussed by Lehmann and Esteban-Bravo (2006), who explored the influence of consumer heterogeneity on optimal pricing. They used a variation on the GBM to investigate the question of whether and how a firm should subsidize its early adopters in order to enhance adoption. Their conclusion demonstrates the direct negative effect of level of heterogeneity: As long as communication between adopter categories (early and main market) exceeds a certain level, the firm benefits from subsidizing the early adopters.

Research so far has focused mainly on price and advertising; little attention has been paid to the other two elements of marketing mix, namely product and distribution channels. Regarding product, empirical evidence indicates that product characteristics have influence on the growth pattern (e.g., Henard and Szymanski 2001). Tellis, Stremersch, and Yin (2003) found that brown goods (e.g., CDs, camcorders, and other entertainment electronic appliances) take off faster than do white goods (e.g., refrigerators and dishwashers). Following the increasing economic power of new product types such as services and entertainment products, diffusion research is now developing to enhance the diffusion framework in order to describe products' specific nature and growth pattern (see Libai Muller and Peres 2009b for services; and the review by Eliashberg, Elberse, and Leenders 2006 on films).

Despite the frequent use of marketing channels in innovation marketing, the topic of diffusion through marketing channels is way under-researched. Examples are the models by Jones and Ritz (1991) or Mesak and Darrat (2002), which described diffusion through channel as a double diffusion process of two layers: the distributors, and the end users. Only when a distributor adopts does the product become available to its assigned end users. Lehmann and Weinberg (2000) elaborated on this basic concept and induced technological substitution into the distribution channel. They inspected the issue of sequential channels through the question of the optimal timing of the video release of a movie after it has been shown in cinemas. Their empirical observation was that films are usually released to video later than is optimal.

How do cross-country interactions influence growth?

A growing number of papers since 1990 have been following the global trend of the increasing importance of multinational product acceptance, extending the traditional single-market scope to explore problems and issues related to international diffusion (Dekimpe, Parker, and Sarvary 2000a). A key issue in multinational diffusion, particularly with respect to order of entry, is the **mutual influences** of diffusion processes across countries. One of the major findings of the studies on cross-country influences (with few exceptions such as Desiraju, Nair, and Chintagunta 2004, or Elberse and Eliashberg 2003), is that entry time lag has a positive influence on the diffusion process. That is, countries that introduce a given innovation later show a faster diffusion process (Tellis, Stremersch and Yin 2003; Dekimpe, Parker, and Sarvary

2000b; 2000c; Ganesh, Kumar, and Balasubramanian 1997; Takada and Jain 1991) and a faster time-to-takeoff (Stremersch, Van Everdingen, and Fok 2008). This cross-country influence is occasionally termed *lead - lag effect*; however influence can be multi-directional, and a-symmetric. Thus, one can distinguish between the *clout* of a country on other countries and its *susceptibility* to foreign influences (ibid.)

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Table 5 summarizes the papers that have modeled multi-market diffusion with cross-country influences (e.g., Ganesh, Kumar, and Subramanian 1997; Putsis, Balasubramanian, Kaplan, and Sen 1997; Eliashberg and Helsen 1996). Generalizing over the idiosyncrasies of these models, a generic cross-country influence model based on Equation (1) may take the following form:

$$(7) \qquad \frac{dx_i}{dt} = (1 - x_i)(p_i + q_i x_i + \sum_{j \neq i} \delta_{ij} x_j)$$

where x_i is the proportion of adopters in country *i*. The influence matrix δ_{ij} represents the cross-country effects between country *i* and the rest of the countries. It can be interpreted as representing weak ties between adopters in one country who communicate with non-adopters from other countries (Wuyts et. al 2004; Rindfleisch and Moorman 2001). However, even without communicating or imitating other individuals, non-adopters are influenced by diffusion in other countries. The level of acceptance of the innovation acts as a signal for consumers: It can signal a reduced perceived risk, a leakage of advertising messages across borders, or an improvement in the supplier's offering due to its accumulated experience. While several studies state explicitly that the dominant effect is due to communication (Putsis et al. 1997; Eliashberg and Helsen 1996; Ganesh and Kumar 1996), others explore the effect without relating to the specific mechanism (e.g., Dekimpe Parker and Sarvary 2000b; 2000c; Takada and Jain 1991).

Due to heterogeneity between countries in adopting the same products, a large number of studies during the last two decades have focused on describing and explaining inter-country differences; these are summarized in Table 6. Such studies have usually focused on the differences in diffusion parameters *p* and / or *q* (e.g., Dekimpe Parker and Sarvary 1998; Helsen, Jedidi, and DeSarbo 1993; Takada and Jain 1991); the ratio of *q / p* (Van den Bulte and Stremersch 2004); time-to-takeoff (Tellis Stremersch and Yin 2003); and duration of the growth stage (Stremersch and Tellis 2004).

- insert Table 6 around here -

The salient result emerging from all of these papers is that diffusion processes vary greatly between countries, even for the same product, and even within the same continent (Ganesh 1998; Mahajan and Muller 1994; Helsen Jedidi and DeSarbo 1993). In addition to measuring the differences, many of the papers in Table 6 also investigate country-specific factors that generate differences in the growth process. The main factors were found to be entry time, price, product type, cultural sources, and economic causes. Cultural sources relate to the country's cultural characteristics and values, including population heterogeneity, as well as cultural dimensions.

One interesting finding is that population heterogeneity (cultural and socioeconomic) has a negative effect on the speed of diffusion (Talukdar, Sudhir, and Ainslie 2002; Dekimpe Parker and Sarvary 2000c; 2000b; Takada and Jain 1991). Another finding is that the diffusion rate increases as the country is more masculine, collective, and hierarchic in its social structure (Dwyer, Mesak, and Hsu 2005; Van den Bulte and Stremersch 2004). Studies using economic factors generate two main empirical generalizations: First, the **wealth** of the country (usually measured by GDP per capita, but also by lifestyle, health status, and urbanization) has a positive influence on diffusion (e.g., Desiraju Nair and Chintagunta 2005; Van Den Bulte and Stremersch

2004). Second, **access to mass media** (usually operationalized by the penetration of TV sets) has a positive influence on diffusion parameter *p* (e.g., Talukdar Sudhir and Ainslie 2002). In pharmaceutical markets, regulation was also found to influence growth in sales (Stremersch and Lemmens 2009). Tellis, Stremersch, and Yin (2003) and Stremersch and Tellis (2004) distinguished between the influences of cultural and economic factors on the penetration stages, and reported that cultural factors influence time to takeoff, while economic factors influence growth.

Understanding the evolution of a multinational market is also valuable in the context of normative managerial decisions. Some studies have explored the issues of entry strategy, i.e., should a firm enter all its markets simultaneously (a "sprinkler" strategy), or sequentially (a "waterfall" strategy). Kalish, Mahajan, and Muller (1995) demonstrated that when conditions in foreign markets are unfavorable (slow growth or low innovativeness), competitive pressure is low, lead < > lag effect is high, and fixed entry costs are high, then waterfall strategy is preferable. Libai, Muller, and Peres (2005) extended this question to explore responsive budgeting strategies, where firms dynamically allocate their marketing efforts according to developments in the market.

What is the effect of competition on growth?

Most of the existing diffusion modeling deals either with growth of monopolies or with category-level growth. However, although some innovative categories start as monopolies, many quickly develop to include multiple competing brands.

Figure 5 illustrates various competitive effects that modify and influence the growth process, and that do not exist in monopolies. Among these effects are the influences of competition on the category growth rate, and communication transfer within and between brands.

Brands compete for both market potential and customers. Thus, in the presence of competition, one might observe increase in market potential, competition on overlapping market potential, and customer churn between competitors. Competitive effects can emerge from legal brands as well as illegal brands, due to piracy.

- insert Figure 5 around here -

Much of the dynamic modeling literature, which by its nature deals with competitive effects, has focused on mature markets (see Chatterjee, Eliashberg, and Rao 2000 for a review). Since the early 1990s, the diffusion literature has paid increasing attention to the competitive effects on brand and category growth. This is summarized in Table 7.

A basic research question, still at the category level, deals with whether competition enhances or delays category growth. Generally, competition has been found to have a positive effect on diffusion parameters (Van den Bulte and Stremersch 2004; Kim, Bridges, and Srivastava 1999; Dekimpe Parker and Sarvary 1998). An exception is found in Dekimpe, Parker, and Sarvary (2000c), who showed a negative effect of existing installed base of the old technology on the growth process. Studying the impact of late entrants on the diffusion of incumbent brands, Krishnan, Bass, and Kumar (2000) found a mixed effect: With the entry of competition, diffusion is enhanced for some products, and does not change for others.

- insert Table 7 around here -

Related to this effect is the question of to what extent the diffusion mechanisms are also valid at the brand level. The main body of competitive diffusion literature assumes that the fundamental mechanism of the combined effect of external and internal influences applies also at the brand level, and therefore a Bass type model can be used to describe the growth of a brand. There are studies that regard adoption as a two-stage process, wherein adopters first adopt the category, and then choose the brand (Givon, Mahajan, and Muller 1995; Hahn et al. 1994; Weerahandi and Dalal 1992) as a result of factors other than internal communications such as promotion activities, discounts, and special offers.

If indeed brand-level growth results from communication between adopters and the remaining market potential, we should inquire as to the nature of this communication. As illustrated in Figure 5, communication can take place within brands and across brands, where both paths may lead to the adoption of the focal brand. Generalizing over many of the papers listed in Table 5, a diffusion equation for multiple brands that is based on the Bass model (Equation (1)) and that explicitly presents both communication paths (adopted from Libai Muller and Peres 2009b; Savin and Terwiesch, 2005) can take the form:

$$(8) \qquad \frac{dN_i(t)}{dt} = (p_i + q_i \frac{N_i(t)}{m} + \sum_{j \neq i} \delta_{ij} \frac{N_j(t)}{m})(m - N(t))$$

where N is the total number of adopters, and δ_{ij} represents the cross-brand influences.

Many existing brand-level diffusion models are special cases, or variations on this generic model. Some assume that within-brand communication equals that of cross-brand, namely $\delta_{ij} = q_i$ (Krishnan Bass and Kumar 2000; Kim Bridges and Srivastava 1999; Kalish Mahajan and Muller 1995). Their underlying assumption is that there is no relevance of brand ownership to the individual spreading the information. Other models, such as that of Mahajan, Sharma, and Buzzell (1993), assume that communication is solely brand-specific. Two studies tried to examine systematically the distinction between within- and cross-brand communications: Parker and Gatignon (1994) for consumer goods, and Libai, Muller, and Peres (2009a) for cellular services; both conclude that both within- and cross-brand influences exist.

Another competitive effect regards market potential, i.e., do competitors compete for overlapping marketing potential, or does each brand have its own, independent potential? Most studies assume that competition is for the same market potential; however some studies have relaxed this assumption and allowed competitors to develop their own market potential (Parker and Gatignon 1994). The subject was explored empirically by Mahajan, Sharma, and Buzzell (1993), who tested Polaroid's lawsuit against Kodak, and concluded that Kodak did not attract Polaroid's prospective customers to a new brand of digital camera, but rather increased the potential for its own benefit of as well as that of Polaroid.

In addition to competition for market potential, in multi-purchase products such as consumer goods or services, firms can compete for each other's existing customers. Brand switching, also termed *attrition*, *defection*, or *churn*, is a major concern in many innovative industries; for example, Reichheld (1996) reported that the average attrition rate in US companies is around 20% (80% retention). Attrition and its consequences have so far been discussed in the CRM literature in mature markets. However, recent studies demonstrate that customer attrition can have a substantial effect on growing markets (Libai Muller and Peres 2009b; Gupta, Lehmann, and Stuart 2004; Hogan Lemon and Libai 2003).

Directions for Further Research

From its early days, diffusion modeling efforts aimed at offering a comprehensive description of the life cycle of innovative products. In this paper, we document how technological developments and change in the nature of innovations have extended the scope of the classical diffusion questions. Future innovations will broaden this scope even further, and reveal growth patterns that were not observed before. Taking the mobile industry example from the introduction, we expect patterns such as long-term co-existence of multiple technological generations, numerous services offered by various (sometimes competing) service providers on the same handset, and an increasing role of global considerations in the adoption process. The enhanced penetration of communication and other technological innovations in developing countries, with their special constraints and needs, forms a rich substrate for the development of such patterns. In order to remain timely and stay on top of market trends, we suggest below future research directions for diffusion modeling. We go over the six research questions presented in Table 1, discuss relevant market trends, and suggest research directions for each, all of which are summarized in the rightmost column of Table 1. For illustration, we mostly use the penetration of mobile phones referred to in the introduction, as we believe it represents many recent and future innovations.

What drives growth?

The classical diffusion model focused on interpersonal communications as the main driver for growth. As illustrated in Figure 1, current research suggests additional growth drivers: Some, such as informational cascade and network externalities, relate to consumer interactions, while heterogeneity does not depend on internal market dynamics. We expect the penetration dynamics of future innovations to enhance the role of these additional growth drivers, as well as expose new ones. Regarding customer interaction drivers, we are seeing more growth drivers that involve consumer influences other than direct personal recommendation. For example, as innovations become complex and central to everyday activity, they might be associated with a higher perceived risk and need for social approval. A higher number of users signals better product quality, thus the number of previous adopters can signal such social approval and reduce risk. As innovations become global and information is spread widely and quickly (CNN, for example, broadcasts in 200 countries), the success of an innovation in one country can influence adopters in other countries without even engaging in direct communication. The existence of competition and the entry of major players into the market can serve as signals of a new product's (perceived) credibility.

While none of these require interconnections, they all contribute to adoption. We can term all these drivers, including informational cascade, as *signals*. Signals can be transmitted by a variety of means, such as the traditional media, the Web, observations, or even interpersonal communications. However, we distinguish between the message and the medium: *Signals are the bits of information on the product and market status that reach us other than via personal recommendations*. Similar to word-of-mouth, signals can be either positive or negative (Goldenberg et al. 2007). As mentioned above, the classical diffusion approach does not deal explicitly with the various types of consumer interactions; using Bass model terminology, they are all embedded in parameter q. From the modeling point of view, word of mouth and signals are quite different: While word of mouth depends on the number of adopters tied to potential adopters, signals do not require interpersonal ties. We see the need for a unified model, accompanied by empirical studies that explicitly represent each of these growth drivers, and study their antecedents and their influence on market growth; individual-level diffusion models can be an effective tool in doing so.

Future growth trends also emphasize the heterogeneity issue, making it more acute than ever. For example, as added-value telecommunication services are becoming elaborate and costly (making up 10% of household expenditure in Western Europe in 2008), firms face a greater challenge in overcoming heterogeneity and introducing innovations successfully to the market. The sources and metrics for heterogeneity, i.e., price sensitivity and willingness to pay, are also changing. If traditionally, mobile operators avoided entering developing countries because their low GDP could indicate lower propensity to adopt, it appears that individuals therein are actually highly responsive to innovations and advanced services, since they have a high need for communication that is not satisfied by the low level of landline infrastructure (Chircu and Mahajan 2009).

Currently, heterogeneity constitutes an alternative growth driver to consumer interactions. One theory suggests interactions without heterogeneity, while the other suggests heterogeneity without interactions. Obviously there exists substantial evidence for both consumer heterogeneity and communication. Future research should combine both theories into one model and use this model to determine the balance between the two in various stages of the product life cycle, and for various diffusion scenarios.

Another characteristic of innovations today, which we expect to be enhanced in the future, is the existence of parallel "shadow" diffusion processes. Givon, Mahajan, and Muller (1995) termed *shadow diffusion* as *a diffusion process that accompanies the major diffusion growth and influences it, yet is not captured in the adoption or sales data*. Although they used the term to describe piracy, we propose extending its scope to describe a wider spectrum of latent parallel diffusion processes that are part of neither sales nor adoption records. In the mobile industry in developing countries, for example, we see several people using the same handset, or re-assembly and usage of old handsets. Shadow diffusion is also salient in the entertainment industry, wherein films, books, and music CDs are advertised before they are launched, so that adoption decisions are made before the product is available (Hui, Eliashberg, and George 2008). Although some appearances of shadow diffusion have been discussed in current literature, the subject lacks thorough treatment. Future modeling should describe the variety of shadow processes and measure their influence on the parameters and speed of the main diffusion process. In addition, normative implications can be derived regarding firm policy.

What is the Shape of the Life Cycle Curve?

The life cycles of new products and their turning points has gained extensive research attention during the past two decades. One of the main challenges on the path to full understanding of the product life cycle is incorporating pre-takeoff and post-takeoff growth into a single framework. Currently, diffusion models focus on growth after takeoff, while takeoff studies are descriptive by nature and do not provide theoretic explanations of takeoff mechanisms. However, firms do regard takeoff as a major consideration in product growth (average time to takeoff for mobile phones in Europe was 10 years) and invest efforts in controlling it, either through integration of the product development process with the timing of adoption, or by pre-announcements that create pre-launch demand (Wind and Mahajan 1997). The time has arrived for a combined model that suggests a comprehensive theory for all stages of growth, thereby enabling firms to plan penetration and invest marketing efforts accordingly.

Another open issue relates to technological substitution. The traditional view of this subject is that the new generation eventually replaces the older generation, yet this is no longer accurate: For many products, old and new generations coexist for a long time. In the mobile industry, the number of subscribers to analog phones continued to increase long after digital technologies became available. The usage of old models in developing countries challenges handset manufacturers to cope simultaneously with multiple technological generations. We propose that research invest efforts in developing a theoretically reliable, empirically validated model that takes into account the marketing dynamics of technology switch, cannibalization, increase of market potential, and leapfrogging. Such a model can assist in understanding the mechanisms of technological substitution, and in better management of multigenerational products.

How Do Individual Adoptions Affect Aggregate Growth?

Although modeling of individual adoption decisions started in the 1970s (see Mahajan Muller and Bass 1990 for review), individual-level diffusion research is still in its early phases. The reason is mainly because it is hard to map networks and have diffusion tracked at the same time. However, the need for such is increasing: Choice processes become complicated; users have to choose devices and service providers, while category boundaries blur. The online medium offers better research opportunities due to new types of individual-level data in blogs, CRM systems, and sites like LinkedIn and Facebook. We therefore suspect that social networks' perspective on diffusion will be the most significant trend in further research.

Research so far has focused on developing techniques and demonstrating them on sample problems; however, much more should be done to make individual-level models an integral part of the toolkit of diffusion research. Firstly, the individual decision-marking parts of such models should be elaborated on by separating the adoption process into the hierarchy of effects (awareness, consideration, liking, choice, and purchase) and by using methods such as choice modeling and game theory.

Secondly, individual-level models should be extended to better describe partially connected networks, since actual social networks are far from being fully connected, and most individuals are engaged in a limited number of connections (Watts and Dodds 2007). Few studies have focused on breaks in connectivity and their implications (Goldenberg Libai and Muller 2001a, 2002), yet much needs to be done. Specifically, empirical findings on both partial connectivity structures and the role of adopter groups such as experts, mavens, and opinion leaders (e.g., Goldenberg et al. 2009) in diffusion, should be integrated into such models.

Thirdly, individual-level models should allow for flexibility in determining the unit of adoption. Traditionally, it is the individual customer, yet this is often not the case. In the mobile industry of many developing countries, the same mobile handset can serve several family members, each with her own SIM card. Sometimes handsets are given to family members and household staff, yet they can accept only incoming calls or call certain numbers (Chircu and Mahajan 2009). These constraints can either be viewed as a type of network externality, or as an example of collective decision-making. Either way, their effect on the growth process is a promising research topic. As with any new, complex, and data-intensive method, individual-level models are still challenged to show that they can contribute insights that cannot be gained by the simple, parsimonious aggregate-level models.

What Are the Marketing Mix Influences on Growth?

Of the Four P's of the marketing mix, diffusion research has thus far generated a large body of knowledge concerning the effects of price and promotion, yet little has been done concerning the other two elements: product and place.

Regarding product types, the overwhelming majority of the diffusion papers reviewed herein deal with diffusion of durable goods and entertainment products. In practice, many products introduced to the market during the past few years are either services (such as digital cable TV or instant messaging), or combined goods and services as in mobile phones. Service-related behaviors such as attrition, multiple purchase, and ongoing word of mouth should be incorporated into diffusion modeling, first attempts at which have been made by Gupta, Lehmann and Stuart (2004) and Libai, Muller and Peres (2009b). However, modeling should put further efforts into tying diffusion concepts in with CRM literature in order to describe the influence of relationship-related measures on growth and valuation of customers and firms.

Additional product-related modeling questions relate to interdependencies between products. For instance, with Amazon.com offering more than 250,000 music albums as well as various choices of book formats, portfolio decisions become crucial to a new product's success. Allocation of marketing efforts, such as whether to focus on a limited number of blockbusters, or spread efforts over many long-tailed products (Elberse 2008) are of great managerial interest. Extending the basic diffusion model to include multi-product interactions can contribute to the discussion in this dispute.

Another marketing mix element that merits further attention is distribution channels. In addition to traditional distribution systems, novel distribution mechanisms are emerging, some with a complex distribution structure such as service providers and retailers that both distribute mobile handsets, and others representing direct consumer involvement such as eBay, bartering, and Netflix. Diffusion modeling should aim to explore the influence of these novel distribution structures on growth, as well as answer normative questions such as what the optimal distribution chain is under various types of social networks, and extent of firm support of user-involved channels.

How do Cross-country Interactions Influence Growth?

As presented in our review, multinational diffusion has received massive research attention over the past two decades. Current demographic changes affect cross-country influences and raise new challenges for global marketers. With large immigration waves, many families - representing strongly tied units in the social network - are dispersed between remote geographic locales. Thus, the traditional association of strong ties with geographical proximity is called into question. This dispersion influences both launch policy (should Bollywood films be launched simultaneously in India and outside India?) and product design and offering (should a cellular price deal include long-distance air time that enables calling relatives overseas?). Diffusion of innovations in emerging countries is an increasingly important managerial interest, especially in industries such as telecommunications where market potential in the developed world is about to almost reach its limit. Issues that are ubiquitous in the developing world , such as multiple users for the same hand-set, adoption of used sets to buy pre-paid phonr cards, can act as a springboard to larger questions such as how prepaid services versus postpaid or packages effect consumer choices and penetration (Iyengar, Koenigsberg and Muller 2009; Mahajan 2009). Diffusion modeling can contribute to these questions by placing further emphasis on the spatial aspects of growth. Through an explicit representation of weak and strong ties, as well as international influences in the form of signals and network externalities, new insights on these problems can be gained.

What is the Effect of Competition on Growth?

The previous emphasis placed by diffusion research on the category level is slowly giving way to brand-level diffusion and competitive effects. As competitive structures become complex, brand-level decision-making takes on importance to the understanding of growth. We see three optional research questions regarding competitive effects, to which diffusion modeling can contribute: First, the market potential issue: Is there one market potential from which the brand draws, or is a reasonable working hypothesis that each brand has its own market potential? While we believe the former, models of both scenarios should be empirically compared on a large set of data to resolve this issue. Second, the influence of competition along the distribution chain: In the mobile industry, while competing operators distribute the same handset model, third parties offer customers auto-selection of the network with the best rate. Besides the complex cross-firm dynamics, such scenarios bear heavy implications for the customers' brand perception in such an environment, and in turn the brand strategy that will optimize growth. Extending the basic diffusion model to be both multi-layer and competitive can help in descriptive and normative investigation of this question. Third, the question of whether brand choice is a single- or a two-step process remains open. If brand choice is a two-stage process, wherein consumer interactions are dominant in category choice and special offers and advertising are dominant in choosing the brand, then straightforward application of a standard diffusion model on brand-level data is problematic. Although some work in this realm is obviously behavioral, diffusion modeling can contribute its insights by constructing a combined choice and individual-level decision model, and estimating the relative importance of each stage.

Conclusions

After intensive review of the diffusion modeling literature in the past two decades and our view of future market trends and suggested research directions, we see a need to extend the scope of diffusion modeling, and update the metrics and data sources used therein. We believe that the nature of diffusion processes today requires broadening the scope of diffusion modeling from focusing on interpersonal communications (Mahajan Muller and Wind 2000; Mahajan Muller and Bass 1990) to include other social interactions among consumers. We therefore define diffusion of innovations so as to describe *the growth of new products and services driven by interactions among consumers* as discussed earlier and depicted in Figure 1. Development of such a framework and model would assist in deciphering the relative importance of each of the various growth drivers.

The metrics used by diffusion modeling should also be updated; traditionally, sales or adoption over time were used. However, these metrics are not enough to describe the full dimensionality of the penetration process. As suggested by Chircu and Mahajan (2009), diffusion might be measured in two dimensions: depth and breadth. *Depth relates to the level of penetration*, or the number of individuals who adopt given products. Depth is captured by sales data if each individual purchases a single unit. However, if there are multiple users of the product or service, the product is purchased but not used, the product or service is purchased repeatedly, or in the presence of shadow diffusion, then sales data do not reflect true acceptance of the product. In most such cases, adoption or subscription data (for services) provide a better measurement. Luckily, the increasing number of service and combined product-service innovations facilitates obtaining and using subscription data. In cases of massive shadow diffusion, approximations should be made as to the true number of users represented by each paying adopter.

Breadth relates to the usage of the innovation; while it constitutes the level and intensity of usage, it also encompasses the number of features of the product and service used by the customer. In developing countries, for example, mobile penetration might not be deep, but it is wide: Consumers use many mobile add-on services since they lack other information and communication means (Chircu and Mahajan 2009). For service innovations, breadth information is available through billing systems, which indicate usage of service features and usage. Introducing the breadth dimension opens up a wide range of research questions regarding the relative importance of various growth drivers to depth and breadth, and the optimal strategy firms should apply for optimizing depth and breadth.

One major challenge we see in diffusion modeling is to revolutionize its approach to data and data sources. The overwhelming majority of the papers we reviewed use aggregate (mostly annual), category-level sales or usage data of durable goods in Western countries. Such data are barriers to further development of the field, since they do not enable thorough investigation of many of the above open issues. Much more data should be collected on services, and at the individual level. Special emphasis should be placed on obtaining data from developing countries. Besides the importance of these countries in terms of growth (Mahajan and Banga 2006), growth patterns therein have unique characteristics such as leapfrogging, shadow diffusion, use of disruptive technologies, and unique patterns of the social network, each of which can isolate and illuminate certain aspects of growth and thereby contribute to a better understanding of growth mechanisms.

The Internet can be a useful source of rich and high-volume data. Internet social communities such as Facebook, blogs, forums, and customer communities can serve to explore the structure of social networks, as well as communication and adoption dynamics. Data collected from consulting firms who develop brand communities can be used to explore influence mechanisms and efficiency of marketing mix. These data are now more accessible than ever due to the development of advanced search engines and available software for content analysis, which can be used to measure communication, brand perception, and competitive effects simultaneously in multiple geographical regions. We believe that extending the scope of research questions, metrics, and data sources will enhance our understanding of growth process and maintain the role of diffusion modeling as a powerful tool in the path toward a comprehensive understanding of the evolution of markets for new products.

Figure 1: Growth drivers for the diffusion of an innovation

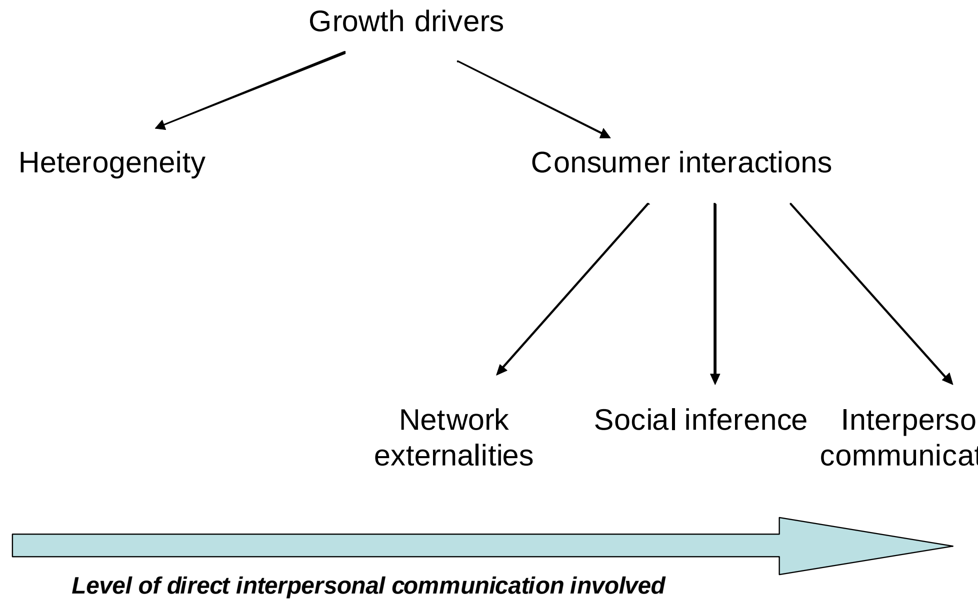


Figure 2: The Bass penetration curve for two initial conditions. p = 0.03, q = 0.38, m = 1.

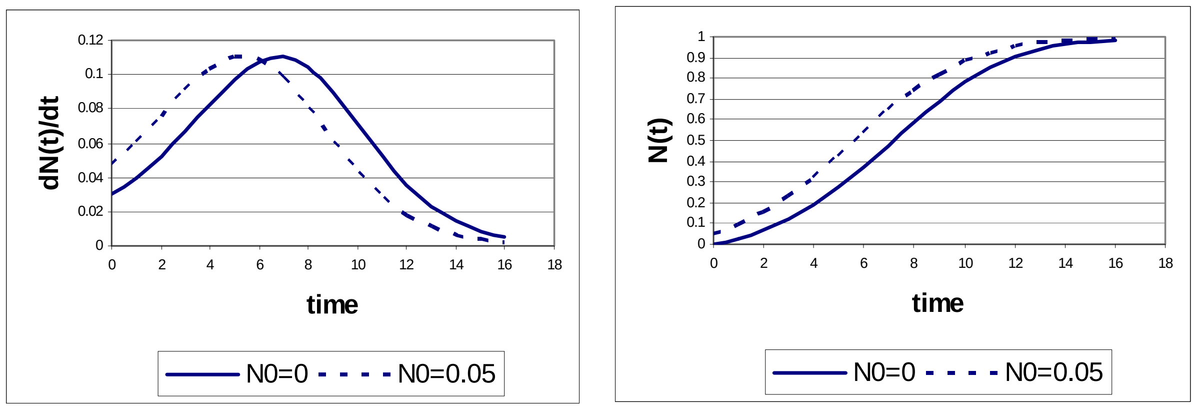


Figure 3: Turning points in the product life cycle

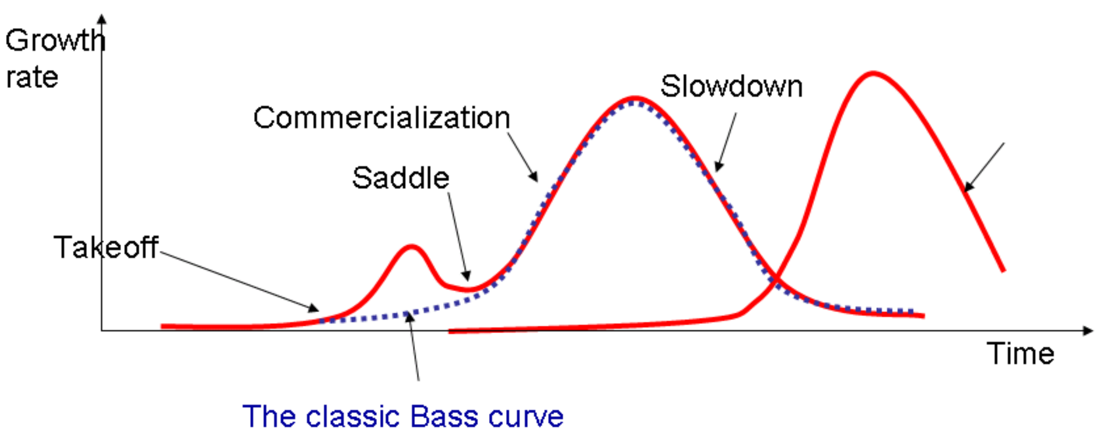
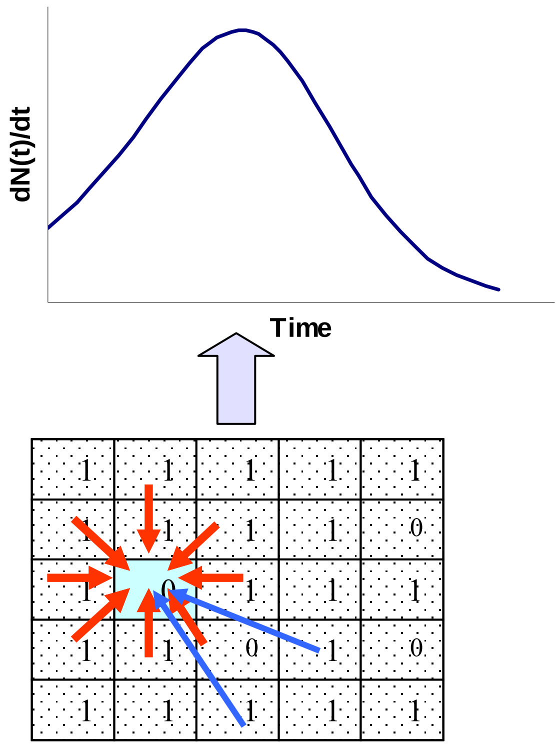


Figure 4: Aggregate-level decisions generate the cumulative adoption curve*



*Based on Goldenberg, Libai and Muller (2001)

Figure 5: Competitive effects on focal brand A of competition for market potential, piracy, cross-brand communication, and churning customers to and from the competitors

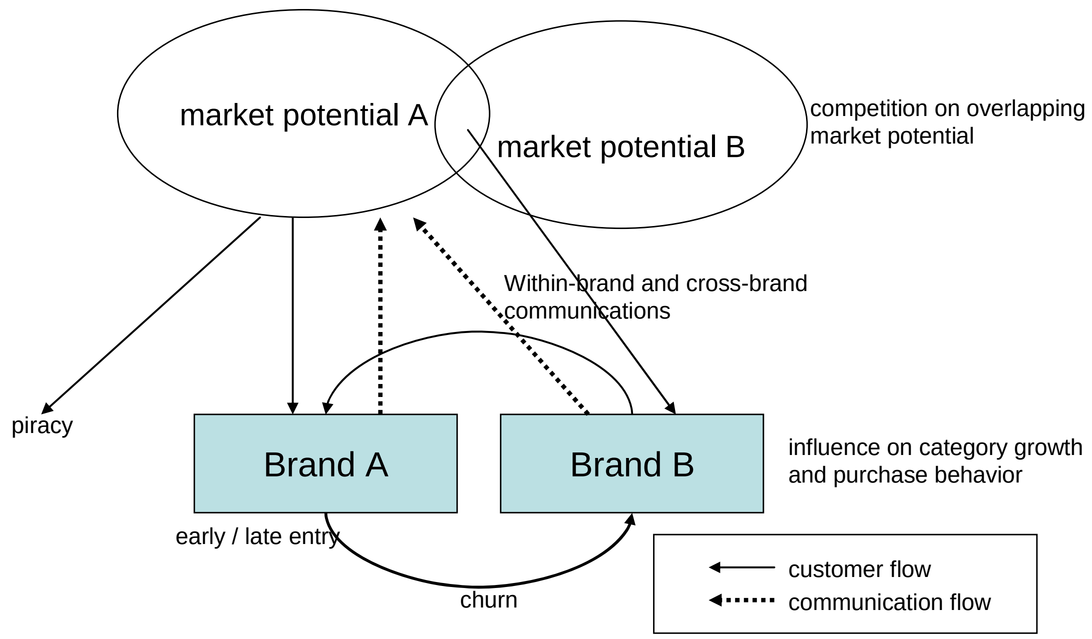


Table 1: Major research trends

	Subject	Research up to 1990	Research since 1990	Directions for further research
Growth mechanisms	What drives growth?	Homogenous social network Word of mouth communications as the main growth driver	Consumer heterogeneity (such as adopter categories and price sensitivity) as an alternative driver, especially during early growth Additional growth drivers: informational cascade and network externalities	A unified framework for heterogeneity and diffusion Variety of growth drivers: communications, signals, network externalities Shadow diffusion processes
	What is the shape of the life cycle curve?	Antecedents and estimation of inflection points and maximum sales in the Bass model	Other turning points: commercialization takeoff, saddles, and slowdown The shape of the growth curve of successive technology generations Acceleration of diffusion processes over time	Takeoff as an integral part of diffusion modeling A comprehensive model for technological substitution
	How do individual adoption decisions affect aggregate growth?	Mainly aggregate-level modeling	Aggregate- and individual-level modeling; use of agent-based modeling and social network concepts	Individual-level and social network models becoming a major trend Networks with partial connectivity Disentangle the hierarchy of effects in adoption Multi-user adoption units
Implementation	What are the marketing mix influences on growth?	Type of products: durables Marketing mix variables are not included in the model. Marketing mix variables: mainly price and advertising	Type of products: durables and services; intensive research on entertainment diffusion Integrated models with marketing mix variables Marketing mix variables: mainly price	Type of products: services, online services Marketing mix variables: product and distribution channels (place)
	How do cross-country interactions influence growth?	Mainly single-market in Western countries	International aspects: differences in growth patterns between countries; cross-country effects Optimal global entry strategies Diffusion of innovations in the developing world	Marketing mix decisions under global awareness Marketing mix decisions under the demographic changes caused by mass immigration waves
	What is the effect of competition on growth?	Category-level models	Models on competitive diffusion and brand-level analysis The effect of disadoption and churn	Do firms compete for the same market potential? Complex competitive structure along the distribution chain The mechanisms of brand choice (1-step vs. 2-step process)

Table 2: Turning points in the product life cycle

Stage in life cycle	Main research focus	Paper	Data	Results
Takeoff	Sources that influence time to takeoff	Golder and Tellis 1997	31 US innovations launched 1898-1990	Price Market penetration
		Agarwal and Bayus 2002	30 US innovations launched 1849-1984	Entry of firms (a proxy for demand side) Price decline Demand-side explanation dominant
		Tellis, Stremersch, and Yin 2003	10 durables in 16 European countries	Region (Scandinavia faster than Mediterranean) Product type (brown goods (CD, TV) take off faster) Cultural factors (uncertainty avoidance and masculinity) Later entry time (leads to shorter takeoffs)
		Foster, Golder, and Tellis 2004	40 US innovations	Time frame (WWII, 1965, 1980) Category Price
		Goldenberg, Libai, and Muller 2007	Fax machines, CB radios, CD players, and DVD players in the US	Network externalities
Saddle	Saddle occurrence and its explanation as a dual-market phenomenon	Goldenberg, Libai, and Muller 2002	32 US consumer electronic innovations launched 1950-1985	A saddle exists in between 1/3 and ½ of the cases. Average relative depth is 25%, with duration of four years. Saddle is created by cross-market communication gap.
		Muller and Yogev 2006	35 US consumer electronic innovations launched 1950	Dual markets (early and main market) were reported in 26 of the 35 cases. Average adoption at time wherein early and main market curves intersect is 16%.
		Van den Bulte and Joshi 2007	33 data sets of three categories: antibiotics; music CDs; high-tech products.	A dual-market model can predict saddles.
Other turning points	Incubation time (the time between invention and launch)	Kohli, Lehmann, and Pae 1999	32 US durables in three categories, USA, 1922-1992	Incubation time has a chilling effect on the p and q of the category.
	Commercialization, takeoff, and slowdown	Golder and Tellis 2004	30 US innovations launched 1929-1990	Both diffusion and informational cascade were found to be significant. In the average sales figures, a saddle was observed.

Table 3: Multi-generational diffusion

Paper	Data	Intergenerational process	Intergenerational effect
Bayus 1994	Four generations of PC computers from 1974 to 1992 worldwide, for 20 manufacturers	Year of entry and technology facilitate the growth of later generations.	Acceleration of the new generation life cycle
Norton and Bass 1992	Up to four generations of six electronic products, three pharmaceuticals, two consumer goods, and one industrial good, 1960-1987	Adopter groups: new buyers and upgraders Market potential increases with generation	No acceleration in growth rate
Mahajan and Muller 1996	Four generations of IBM mainframe computers, 1955-1978	Adopter groups: new buyers, upgraders, cannibals, and leapfroggers Market potential increases with generation	No acceleration in *p* and *q*
Kim, Chang, and Shocker 2000	Three categories: pagers, two generations of cell phones, and CT2 in Korea, 1984-1994	Adopter groups: new buyers and upgraders Market potential increases with generation	No acceleration in *p* and *q* Similarity in growth rate between product categories
Van den Bulte 2000	31 product categories in consumer electronics and household products	Adopter groups: Only new buyers for each generation; generations develop independently. Market potential increases with generation	2% annual increase in diffusion speed (parameter *q*)
Pae and Lehman 2003	45 generations in 15 product categories, 1868 - 1994	Adopter groups: Only new buyers for each generation; generations develop independently. Market potential increases with generation.	Late entry of the new generation is negatively correlated with *p* and *q*.

Table 4: Marketing mix decisions

Marketing mix variable	Paper	Research question	Data	Results
Price	Krishnan, Bass, and Jain 1999	Optimal pricing strategies for new products using the GBM	Theoretical	1. For high price sensitivity and high discount rate, the optimal price is monotonically decreasing over time. 2. For lower price sensitivity and discount rate, optimal price has a ceiling.
	Mesak and Darrat 2002	Optimal pricing of services in a market with service providers and consumers.	Optimal control	When discount rate is high (myopic industry), optimal price decreases with time. For low discount rate, optimal price increases with time.
	Lehmann and Esteban-Bravo 2006	Should a firm subsidize its early adopters to speed adoption?	Theoretical	In many cases, it is logical to subsidize innovators, main market, or both. When inter-segment influence is very weak, there is no point in subsidizing.
Price of successive generations	Bayus 1992	Optimal pricing for successive generations (Switching to the 2nd generation is done either by replacement when the product is worn out, or by upgrading.)	Theory + empirical support from durable goods sales data	1. For upgrading only, optimal price decreases for 2nd generation and increases for 1st generation. 2. For on-time replacement only, optimal price decreases for both generations.
	Padmanabhan and Bass 1993	Optimal pricing of successive technological generations	Theory	When generations belong to different firms, the optimal price for the 1st generation is higher than when they belong to the same firm. Price of 2nd generation is equal between scenarios.
	Danaher, Hardie, and Putsis 2001	The effect of price on the diffusion of technological generations Dual price structure: first-time purchase and subscription renewal	Cellular penetration in a European country, two generations	1. A price decrease of 2nd generation increases its demand, yet decreases demand for 1st generation. 2. A price decrease of 1st generation increases both its sales and sales of 2nd generation.
Advertising	Feichtinger 1992	What is the diffusion pattern under the “constant percentage of advertising to sales” rule?	Theoretical	Adoption moves periodically between low and high customer numbers, depending on the interplay between acquisition and loss of customers.
	Mesak 1996	Optimal advertising	US cable TV	For static price, distribution, and advertising elasticities, optimal advertising is a percentage of sales.
	Libai, Muller, and Peres 2005	Dispersion vs. focus of marketing efforts in international entry	Formal analysis and cellular automata simulations	Dispersing marketing efforts yields faster penetration. Moderators: entry costs, level of responsiveness to advertising
Product	Jain, Mahajan, and Muller 1991	How do supply restrictions affect new product growth?	Data on applicants and subscribers for landline telephone service in Israel, 1949-1987	Supply constraints bring about negatively skewed diffusion patterns; the waiting list creates negative w-o-m.
Distribution channels	Jones and Ritz 1991	Incorporating distribution into the diffusion model	Movie-goers and theater owners in the US	Two levels of adopters: retailers (adopt through a Bass-type process); consumers (a fixed adoption rate). Each retailer opens the market to k consumers.
	Lehmann and Weinberg 2000	Optimal entry time of a channel introduced second in a sequence (e.g., movies and video release) Video entry time to maximize joint profits	35 films in the US: movie and video release	Assumption: video release brings down movie sales Tradeoff: early video entry leads to higher video revenues, lower film revenues. Movies are released to video later than the optimal.

Table 5: Multinational Diffusion – Cross country influences*

Research focus	Paper	Description / Model	Data	Results
Existence of cross-country influences	Elberse and Eliashberg 2003	An econometric model testing the connection between a film's performance in the domestic market and its performance in foreign markets	164 films. Domestic: US; foreign: France, Germany, Spain	1. Domestic performance influences foreign availability and revenues. 2. This influence decreases with the time lag between domestic and foreign launches.
Multinational diffusion models	Eliashberg and Helsen 1996	$\frac{dx_i}{dt} = (1 - x_i)(p_i + q_i\, x_i + \delta\, x_j)$	VCRs in 13 European countries; sales data of a single firm	1. Mostly δ < q, might be negative. 2. There is a flow from big countries to small countries.
	Ganesh and Kumar 1996	$\frac{dx_i}{dt} = (1 - x_i)(p_i + q_i\, x_i + \delta\, x_j)$	B2B durables: supermarket scanners in US, Japan, and eight European countries	Cross-country influence δ is positive and significant.
	Ganesh, Kumar, and Subramanian 1997	What influences Ganesh and Kumar's (1996) δ? Test empirically geographical proximity; cultural similarity; economic similarity; continuous / radical innovation; existence of standards; entry time lag.	Four durables, 15 European countries tested in pairs	The learning effect is influenced by cultural similarity; economic similarity; continuous / radical innovation; existence of standards; and entry time lag. It is not affected by geographic proximity!
	Kumar and Krishnan 2002	$\frac{dx_i}{dt} = (1 - x_i)(p_i + q_i x_i) \cdot \sum_{j=1}^{N} (1 + \delta_{ij} \frac{dx_j}{dt})$	Case studies of three durables in six European countries, tested in pairs	Influences exist in all directions: lead < > lag, lag < > lead, and simultaneous.
	Putsis et al. 1997	$\frac{dx_i}{dt} = (1 - x_i)(p_i + q_i x_i + \sum_{j \neq i} \delta_{ij} x_j)$	Four durables in products 10 European countries	Countries with strong external connections affect other countries. Therefore they should be the first to begin with.
	Van Everdingen, Aghina, Fok, 2005	Use the same model as Putsis et al., but with dynamic parameters	Internet access, landline, and cellular telephony in 15 EC countries	Using dynamic parameters provides better fit and forecast.
Entry Strategy	Kalish, Mahajan, and Muller 1995	A game theoretic optimization model for a monopoly and a competitive scenario, to study which entry strategy is better: simultaneous, or sequential		When conditions in foreign markets are unfavorable (slow growth or low innovativeness), competitive pressure is low, and fixed entry costs are high, then sequential entry is preferable.
	Libai, Muller, and Peres 2005	Compare three types of dynamically allocated budgets		Dispersing marketing efforts (as in support-the-strong and uniform) Moderators: entry costs, level of responsiveness to advertising

* Mathematical expressions are based on Equation (1) formulation: x_i = cumulative adoption proportion in country i; δ_{ij} – influence parameter of country i on country j; p_i, q_i = external and internal influence parameters for country i.

Table 6: Sources for differences in diffusion parameters

	Source	Influence
Entry time	Entry time lag	Mostly positive
Marketing mix	Price	Mixed
	Product type	Positive (Brown goods: CD Players, TVs, camcorders, etc. penetrate faster)
Market related	Existence of competition	Positive
	Regulation	Positive
Demographic and cultural	Population Heterogeneity	Negative
	Population growth rate	Positive
	No. of population centers	Mixed
	Hofstede's dimensions	Positive Direction: less uncertainly avoidance, collectivism masculinity, power distance
Economic	Wealth (GDP, income per capita)	Positive
	Media availability	Mixed
	Income inequality	Positive
	Regulation	Negative

Table 7: Brand level and competition issues studied using diffusion model

Competitive effect	Paper	Research question	Data	Results
Influence of competition	Hahn et al. 1994	The influence of competition on customer trial and repeat purchase	Pharmaceuticals	Repeat purchase depends on competition and product characteristics.
	Kim, Bridges, and Srivastava 1999	The influence of number of competitors and market entries / exits on category growth	Video cassettes, personal computers, and workstations	1. Market potential and external influence increase with the number of competitors. 2. The dependence of entries on number of competitors is complex, and might depend on whether or not a "shakeout" occurred in the market. 3. Exits increase with number of competitors.
Early / late entry	Krishnan, Bass, and Kumar 2000	The influence of a late entrant on diffusion	Minivans and cellular phones in US states	The market potential, q_i, or both increase after entry.
Within-brand and cross-brand influences	Parker and Gatignon 1994	Within- and cross-brand word of mouth during diffusion	Data on sales of nine brands of hair styling mousse	For some brands, there is significant cross-brand communication.
	Libai, Muller and Peres 2009a	The influence of within-brand and cross-brand communications on competitive growth	Cellular markets in Europe	The ratio of the cross- to within-brand influences determines the existence, size, and sustainability of the pioneering advantage.
Competition for market potential	Mahajan, Sharma, and Buzzell 1993	Kodak and Polaroid competitive scope	Digital cameras: An old brand (pack) and a new brand (integral) of Polaroid, vs. a new brand of Kodak	1. Polaroid pack developed mainly its own potential market. 2. Kodak took ~30% of its customers from Polaroid's potential buyers. 3. Kodak expanded the market for Polaroid.
Churn	Libai, Muller and Peres 2009b	The influence of churn on the growth of services	Five service industries	Attrition influences the effective market potential and the time to maximum growth.
Piracy	Givon, Mahajan, and Muller 1995	Software piracy and its impact on diffusion	Spreadsheet software and word processors in the UK	Piracy has an enhancing effect on diffusion.
	Prasad and Mahajan 2003	What is the optimum level of piracy that a firm should tolerate?	Theoretical	For the competitive case, the optimal tolerance of piracy is higher than in monopoly.
Churn + Piracy	Givon, Mahajan, and Muller 1997	The net effect of brand switching and piracy on user-based share and unit sales-based share	Two brands of spreadsheet software and word processors in the UK	Piracy and brand switching have inverse influences on user-based market share and unit sales-based market share respectively. The net effect works in both directions.

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