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Evaluating the market potential of innovations: A structured survey of diffusion models

Alexander Frenzel Baudisch* **and Hariolf Grupp****

Abstract

This paper provides a systematic methodology to identify general innovation diffusion patterns in a given case study: First, an analytical framework is introduced which structures a review of innovation diffusion research. This framework may be used to structure the analysis of a case study. Second, a classification of innovation diffusion models is developed by focusing on the analytical hypotheses and stylized facts, which they assume. This categorization allows selecting appropriate models for a given case study based on the matching of the model's hypotheses and case study's characteristics. This provides an structured approach to allow innovators to evaluate ex-ante the market potential and the diffusion process, i.e. commercial success of their new product or practice. The paper concludes with critical recommendations on the use of innovation diffusion models. Based on the systematic approach to survey diffusion models, future research opportunities are outlined.

Keywords

Innovation diffusion model, case study methodology, taxonomy, forecasting

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1 Introduction and structure

This paper provides a systematic methodology to apply models of innovation diffusion to any given case study: The introduced structure of innovation diffusion (section 2) helps to structure a case study analysis ex-ante. The categorization of diffusion models according to their underlying analytical hypotheses and stylized facts (section 3) allows to select appropriate models for a given case study; the categorization provides the basis to match model hypotheses and case study characteristics. Therefore the addressees of this paper are marketing specialists or engineers who want to analyze markets relevant for their new products based on appropriate existing theories of innovation and diffusion research.

Structure and methodology

The literature on innovation diffusion is vast, and it spills over many conventional disciplinary boundaries. Rogers' definition exhaustively describes the diffusion of innovation and identifies mutually exclusive elements interacting to constitute this process (Rogers, 1995):

> **"Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system." (p. 5)**

This definition is chosen as the basis for the analytical framework with four elements – innovation, communication channels, time and social system – that are successively introduced and then supplemented by theoretical findings. Diffusion processes can vary considerably as can be seen in figure 1 in terms of the number of adoptions over time. The three diffusion curves A, B, and C differ substantially in shape and pattern, they differ in final number of adoptions or the penetration level. These differences exist because the constellation of the four identified elements for each of these three diffusion processes differs.

Appropriation of theoretical findings

The use of Rogers' above definition demands for an logical appropriation of the diffusion of innovation along the four identified elements, interacting in the diffusion process. This appropriation is conducted by finding a effect-cause-relationship between the phenomenon observed and one of the four elements or to a variation of one of them – innovation itself, the communication channels used, the time or the involved social system. The varying element then identifies the category in the framework, to which the observed phenomenon is assigned.

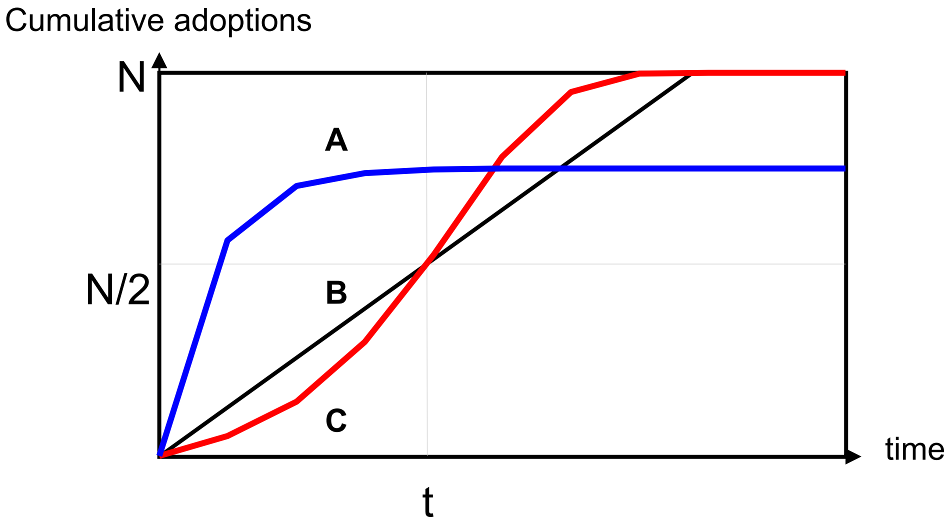

Figure 1: Plots of three diffusion processes of innovation A (modified saturation function), B (linear function) and C (logistic function).

Classification of models

A classification of innovation diffusion models will be introduced by means of some underlying dichotomies in the analytical hypotheses and stylized facts, which they assume (Dosi, 1991). This is needed to group models into categories according to common hypotheses and for matching models to a case study, which can substantiate or models hypotheses with real world observations. The models are collected according to quality and recency and are introduced by 'model families', i. e. by groups with the same underlying principles and assumptions. These model families are introduced in section 3 by giving an example of one representative model of this family; reference to other models of that family is given. These model families are classified according to whether they assume or do not assume ten stated hypotheses in section 3; the models' data requirements are also circumscribed.

Case study analysis

A potential application of the categorization of diffusion models is to use it as the basis for a selection method, i.e. to select certain models for an ongoing case study according to their hypotheses. To do so, the case studies are qualitatively analyzed to prove or disprove the ten stylized facts and hypotheses of innovation diffusion models. Empirical data on the diffusion of the case study innovations have to be assessed. If the case study environment substantiates the hypotheses of a model, this model is appropriate to be applied to the case study for an ex-ante evaluation of its potential success.

2 Innovation diffusion

The goal of diffusion research is to explain the process of an innovation spreading among adopters, i.e. to explain the form of the diffusion curve of an innovation. Our approach is based on the analysis of the four elements constituting the diffusion process, the innovation, communication, time, the social system, and their interactions, which are now subsequently introduced.

Innovation

Having reviewed numerous different definitions of innovation (Hauschildt, 1997a, pp. 6 onwards; Grupp, 1998, pp. 18), the following common aspects are detected: Innovations are products or processes of a new quality, which differ significantly – however that is defined –

from their preceding state. The novelty has to be perceived as combining ends and means in a way unknown up to that date. This combination has to survive the test in a market or a business application. The sole creation of an idea is not enough; sales and use distinguish innovation from invention – in an ex-post perspective. Hauschildt (op. cit.) structures the differences between the New and the Old into four dimensions: (1) the dimension of the content (What is new?), (2) the subjective dimension (New to whom?), (3) the process dimension (Where does the new start and end?) and (4) the normative dimension (Is the new successful?). Until all four dimensions are considered, the definition of what is or is supposed to be innovative is incomplete. Grupp (op. cit. chapter 2.4) points likewise to the importance of demand when judging innovativeness.

Most common is the distinction between product and process innovations (OECD, 1992). An argument against the distinction between process and product innovation is the fact that a process innovation is often manufactured somewhere else in the economic system: The product innovation of one firm is the process innovation for another one. Therefore, making distinctions between process and product innovation is a difficult task, if more than one industry sector is being observed. Process innovations, which are only cost efficient, can be described as a product innovation, which affects nothing but the price among the product's attributes (Grupp, op. cit., p. 77).

Products differ, according to how they are made ('process technology'), the benefits they yield for consumers (attributes), how they are used or perceived (consumer behaviour) or how the product is integrated with other products or systems (architecture). Thus, innovations can be classified focusing on significant discontinuities ('radical') or change ('incremental') in any or all of the above four aspects constituting the product quality.

According to Henderson and Clark (1990), radical innovation fulfils two necessary conditions: an 'overturned' core concept of the product, and major change in the linkage among the core concept of the product. Moore (1991) focuses on how the product is used, and defines 'discontinuous innovation' as products that require us to change our current mode of behaviour or to modify other products and services we rely on (p.10). As Henderson and Clark (1990) distinguish between product core or component technology and peripheral systems or linkage technology, Grupp and Maital (2001) absorb this and differentiate between incremental innovations whether a new version of an existing product has one, some, or all of its existing attributes improved. A radical innovation is an innovation with an overturned core technology and changed user interfaces. They establish a taxonomy of innovation attributes and their changes synthesizing the premise that products are best seen as combinations of attributes (Grupp and Maital, 2001, p. 24), based on a consumer theory developed in economics (Lancaster, 1971). It can be generally said that managing incremental innovation is a matter of balancing cost and value. In radical innovation, although many new features occur, not all of them seem to be equally important. There are limits for substitution of one achievement by another one if a core feature dominates. The adoption of radical innovations may therefore be hindered by barriers (Christensen, 1997; Moore, 1991; Rogers, 1995).

Crucial is the adoption of an innovation as perceived by the consumer. "Not the technical change is relevant, but the change of awareness" (Hauschildt, 1997b, p. 17). An intelligible, visual, almost classic presentation of this concept of innovation has been proposed by Booz et al. (1982). Product innovations are categorized by identifying the innovative degree to the enterprise, their object innovative degree.

Connecting the innovation's objective nature with the adopters' behaviour towards this innovation offers explanations of its rate of diffusion, being the relative speed (number of adoption per time period) at which members of a social system adopt an innovation. The receivers' perception of the attributes of an innovation, not the attributes of an innovation as classified by experts or scientists, affect the adopter's behaviour and thus the innovation's rate of diffusion (Rogers, 1995).[1] Therefore transforming the objective, measurable innovation attributes into innovation characteristics as perceived by adopters is the subject of this sub-section.

Five different characteristics of innovations are described in the literature. Each is somewhat empirically interrelated with the other four, but they are conceptually distinct. The selection of these five characteristics is based on past research, as well as on a desire for maximum generality and succinctness:

(1) *Relative advantage* is the degree to which an innovation is perceived as being better than the idea it supersedes.
(2) *Compatibility* is the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters.
(3) *Complexity* is the degree to which an innovation is perceived as relatively difficult to understand and to use.
(4) *Trialability* is the degree to which an innovation may be experimented with on a limited basis.
(5) *Observability* is the degree to which the results of an innovation are visible to others.

Bringing together the classification of innovation with the perceived characteristics of the innovation leads to foresight on the diffusion of the innovation in focus. Usually conducting surveys among adopters and non-adopters yields a quantification of these five perceived characteristics.

Many products have little or no value in isolation, but generate value when combined with others. Examples include: nuts and bolts, automatic teller machines (ATM) and ATM cards. These products are strongly complementary, although they need not be consumed in fixed proportions. They form systems, which refer to collections of two or more components together with an interface that allows the components to work together. A conceptual framework for multi-product interaction during the diffusing process is given by Bayus et al. (2000) based on the positive, negative or non-existing influences of the new product on the existing product and vice versa. Diffusion of innovations subject to complementary or substitutive relationships cannot be adequately studied in isolation. Here the diffusion of such innovative systems and market competition between such systems, as opposed to diffusion and competition between individual products, highlight at least three important issues: (1) expectations, (2) coordination and (3) compatibility (Katz and Shapiro, 1994).

A situation in which consumer coordination is essential arises when consumers must choose durable hardware; for example, they purchase a device to play a new format of pre-recorded music. In making such a choice, each consumer will have to form expectations about the availability of software (here, the availability of recordings in that format). In the presence of economies of scale in the production of software, the availability of software will depend on what other consumers do, which gives rise to positive-feedback effects. This “hardware-software” paradigm applies to many markets: computer hardware and software, credit card networks (the card is the hardware, merchant acceptance the software), durable equipment and repair services (the equipment is the hardware, the repair the software) and the typewriter keyboard (the typewriter is the hardware, experience on that keyboard the software). These hardware-software systems can fruitfully be thought of as forming “virtual networks” that give rise to feedback effects similar to those associated with physical networks (Arthur, 1989; Valente, 1995).[2]

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1 By stating this, Rogers (1995) seems to reject the assumption of rational adopter behaviour, but gives no deeper explanation of diffusion patterns.

2 A survey of the literature on network externalities is given in Farrell and Saloner (1986).

The two pioneering empirical studies by Griliches (1957) on the diffusion of hybrid corn in different states of the US and by Mansfield (1963) on the diffusion of twelve innovations in the US manufacturing industry mark the entry of economics into this research field. Both authors pioneered a two-step econometric procedure, which has since dominated empirical studies of diffusion. The first step consists of collecting and processing data m_i of more than one innovation's diffusion path i. Those paths can refer to the same innovation diffused in different markets or industries or different innovations diffused in the same industry. The adoption data over time of the innovation usually describes an S-shaped curve as indicated in figure 1. Both authors used a logistic function to fit the data sets to the S-shaped diffusion, therefore the model is also called logit model. As the diffusion paths of the innovations were different, the parameters of the logistic curves fitted to the data differently. Parameters q_i for all the m_i diffusion paths fitted to set of i curve shapes measure the different 'diffusion speeds'. In the second step, Griliches and Mansfield explained diffusion speed with a linear regression over independent variables characteristic to the innovations analyzed.[3]

Communication

Communication is the process by which participants create and share information with one another in order to reach mutual understanding. Diffusion is a particular type of communication in that the messages are concerned with new ideas, which is discussed in this sub-section.

Mass media channels are often the most rapid and efficient means to inform an audience of potential adopters about the existence of the innovation, to make them aware of it. Mass media channels are all those means of transmitting messages that involve a mass medium, such as radio, television, newspapers etc., which enable a source of one or a few individuals to reach an audience of many. However, mass media channels are deemed to lead to changes only in weakly held attitudes. Interpersonal channels, however, usually accomplish the formation and change of strongly held attitudes. Interpersonal channels involve a face-to-face exchange between two or more individuals. Communication via these channels is more effective in persuading an individual to accept a new idea, especially if the interpersonal channel links two or more individuals who are similar in socioeconomic status, education or other important ways.

A technology usually has, as already mentioned, a *hardware* aspect and a *software* aspect (Rogers, 1995, p. 12). The software information embodied in a new technology serves to reduce one type of uncertainty which is concerned with the cause-effect relationships involved in achieving a desired outcome. But a technological innovation also creates another kind of uncertainty because of its newness to the individual and motivates him or her to seek information by means of which the new ideas can be evaluated. Rogers, (1995 p.14) calls this the "innovation-evaluation information" which leads to a reduction in uncertainty about an innovation's expected consequences when obtained. The main questions that an individual typically asks in regard to software information are: "What is the innovation?", "How does it work?" and "Why does it work?". Besides, an individual usually wants to know such innovation-evaluation information as: "What are an innovation's consequences?" and "What will its advantages and disadvantages be in my situation?".

The main issue of most discussions of technology diffusion is the apparently slow speed at which individuals or firms adopt new technologies. If a new technology offers a significant improvement over existing technologies, the question is why some adopters shift over to it more slowly than others. Possibly, the most obvious explanation is that they find out about the new technology later than the others (Bass, 1969). If this is true, one is likely to learn a lot about the time path of technology diffusion by studying the spread of information about it, i. e. the communication mode of the innovation. This basic hypothesis is explored by epidemic

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[3] Dholakia and Krish (1990) provide a survey of facilitators and barriers to diffusion.

diffusion models: it takes time for information about an innovation to reach all potential users, but as soon as it reaches one of them, (s)he adopts as if (s)he was infected by an epidemic. Two different mechanisms of knowledge transfer – information spread from a common source and by word-of-mouth – affect the pattern of diffusion over time. The latter communication is called “external” as it comes from a source external to the supplier, which is termed “internal” (Bass, 1969). However, this model is based on a flow of information between individuals with homogenous probabilities of adoption when they come in contact with the innovation, i. e. all potential adopter behave in the same manner. This communication effect accounts for the first convex part of the S curve. The most prominent epidemic diffusion model, the Bass model, provides a symmetric S-shaped curve because of the assumed homogeneity of adopters. It further assumes a fixed market potential, which when being approached by the number of adopters, creates saturation effects, which in turn account for the second concave part of the S-curve. Epidemic models are parsimonious in parameters and easily fitted to empirical data of adoption numbers, which is why they have be widely applied in marketing and economics (Dholakia and Krish, 1990; Mahajan et al., 2000).

Two main points of criticism to the the Bass model are now addressed: It has to be emphasized that one rarely encounters symmetric S curves in the actual diffusion of new technology. Asymmetry arises when populations are heterogeneous and the infection probabilities of certain groups differ from each other. The Non-Symmetric Response Logistic (NSRL) model by Easingwood et al. (1981) based on the logistic function and the Non-Uniform Influence (NUI) model by Easingwood et al., (1983) based on the Bass Model account for asymmetry in the S-shaped diffusion path by implementing parameter variations over the time of the diffusion process. The other main point of criticism to epidemic modelling is that it takes the adopter population as fixed. The total pool of potential adopters is usually not fixed but increases over time. Parker (1993) accounts for the criticism of the fixed market potential as he extends the NUI model by making the market potential flexible and concomitantly introducing a penetration level parameter to the market potential.

The importance of the role of marketing-mix variables such as advertising, price, promotion and personal selling in understanding diffusion dynamics has been repeatedly emphasized by diffusion scholars (Bass et al., 1994; Bass et al. 2000; Horsky and Simon, 1983; Mahajan et al., 1990; Robinson and Lakhani, 1975). Bass et al. (2000) provide an excellent survey on modelling marketing-mix influence in innovation diffusion. A statistically flexible way of incorporating marketing variables are proportional hazard models which will be introduce in a general form (Haldar, 1998). Chatterjee et al. (2000) review on marketing efforts and pricing over the diffusion process.

Time

Contrary to the notion underlying the epidemic model, social scientists agree that the adoption of an innovation is not an instantaneous decision, it is a process over time, like most decisions. The innovation-decision process is the process through which an individual (or another decision-making unit) passes (1) from first knowledge of an innovation, (2) to forming an attitude towards the innovation, (3) to a decision to adopt or reject, (4) to implementation of the new idea and (5) to confirmation of this decision. This process consists of a series of actions and choices over time through which the adoption unit evaluates the new idea and decides whether or not to incorporate the innovation into ongoing practice (Rogers, 1995, pp. 161 onwards). This process consists in creation of utility expectations of the innovation, the overcoming of the uncertainty of these expectations and the creation of pre-conditions to adoption. The model describes this series of actions and decisions in the innovation-decision-process; its conceptualization consists of five stages:

(1) *Knowledge* occurs when an individual (or another decision-making unit) is exposed to an innovation’s existence and gains some understanding of how it functions.

(2) *Persuasion* occurs when an individual (or another decision-making unit) forms a favourable or unfavourable attitude toward the innovation.
(3) *Decision* occurs when an individual (or another decision-making unit) engages in activities that lead to a choice to adopt or reject the innovation.
(4) *Implementation* occurs when an individual (or another decision-making unit) puts an innovation into use.
(5) *Confirmation* occurs when an individual (or another decision-making unit) seeks reinforcement of an innovation-decision already made, or reverses a previous decision to adopt or reject the innovation if exposed to conflicting messages about the innovation.

The innovation-decision period is the length of time required for an individual or organization to pass through the innovation-decision process. The length of this period is usually measured from the point in time an individual becomes aware of an innovation to the point that the same individual adopts the innovation. An often observed discrepancy between the wide spread awareness of an innovation combined with the favorable attitude towards it and lacking seemingly consequent action of adopting an innovation has been called KAP gap (knowledge-attitude-practice gap). Shortening this innovation-decision period is one of the main interests in speeding up the diffusion of innovation. Models with various stages have been recently surveyed by Roberts and Lattin (2000). Multiple-Stage models are somewhat cumbersome, as data is merely available for these stage transitions over time, but the notion of stages in the adoption process yields further insights into consumer behaviour, which can be used for targeted communication efforts.

Social system

A social system is defined as a set of interrelated units that are engaged in joint problem solving to accomplish a common goal. The members or units of a social system may be individuals, informal groups, organizations or subsystems. This sub-section reviews the nature of social systems in order to explain why their members may not adopt an innovation at the same time.

Members of a social system adopt an innovation in a sequence, so that individuals can be discerned in terms of time of adoption (Deroïan, 2002). The term ‘innovativeness’ of an adopter is introduced, being the degree to which an individual or another unit of adoption is relatively earlier in adopting new ideas than other members of a system. Thus innovativeness indicates overt behavioural change. Rogers (1995) uses the time of adoption for categorizing the adopting population. The distribution of adopter adoptions over time is assumed to be normal. The mean μ and multiples of the standard deviation σ of the normal distribution are used to divide a normal adopter distribution into five categories over time starting with the earliest adopters: Innovators 2.5%, early adopters 13.5%, early majority 34%, late majority 34% and laggards 16%. Relative characteristics of adopter categories are briefly introduced as they serve to qualitatively analyze a given diffusion environment (Rogers, 1995, pp. 268).

It follows that differences between individuals may have a potentially important role to play in explaining patterns of diffusion. One way to think about this is by using a probit model to analyze individual adoption decisions, which was first introduced by Davies (1979). An intelligent way to think about an individual choice-based model of diffusion is to suppose that individuals differ in some characteristic x_i which affects the profitability of adopting the innovation. Further, suppose that they will adopt if x_i exceeds some threshold level, x^*. Individuals i differ in their characteristic, and we will suppose that x_i is distributed across the population according to some function f(x). Those agents with levels x_i of larger than x^* choose to adopt, while the rest do not. Clearly, if x^* falls over time, due to exogenously determined improvement of the innovation, the rate of adoption will gradually rise generating an S-shaped diffusion curve again. This model assumes perfect information of these rational, but myopic agents about the innovation as they are optimizing their utility of the adoption. The main limitation of the probit models can be identified in the narrowness of the definition of ‘innovation’. Its impact on adopters' cost and preference structure must be a minor one: In fact, adopters' are supposed not to change their characteristics which must mean that the extra profits derived from adoption are insufficient for the purpose.

Another modelling approach, called individual diffusion model, combines the hypotheses of epidemic and probit models, i. e. information contagion and adopter heterogeneity. Roberts and Lattin (2000) survey these diffusion models using statistical hazard-rate literature to categorize various approaches to the diffusion of innovations between two extremes: market-level epidemic diffusion models, in which all members of the population are assumed to have the same probability of adoption, and individual-level models, in which the hazard-rate of each individual is different and idiosyncratic. On the one hand, aggregate-level diffusion models, e. g. the Bass model, are easy to use and parsimonious in parameters, but in many ways too simple (Bass, 1969). On the other hand, individual-level models, which assume population heterogeneity resulting in individual hazard-rates and updating mechanism like Bayesian learning, require a lot of data and are therefore seldom used, have been made more parsimonious by assuming that some parameters will be common across the population. Chatterjee and Eliashberg (1990) provide an interesting example of this group of models.

Modelling the adoption behaviour of firms, i. e. diffusion on the supply side, more influence factors have been identified. Like for probit models, which are also called rank effect models, its is common to the two models that the cost of acquiring new technology (or at least a quality adjusted price, i. e. the technology) changes (falls) over time and that adopter are perfectly informed about the number, the effects of an innovation and other adopter’s reactions to their actions.

So-called “rank” or probit models as introduced are premised on the observation that, given differences in capital vintage, size, access to technical information, labour productivity and environmental regulatory costs, some firms will get a higher return from a new technology than others. Hence, one may rank all potential adopters on the basis of their expected returns. Firms with a sufficiently high ranking will adopt right away when an innovation first becomes available. However, over time as sector-wide production and information costs fall, the new technology is refined, and as the existing capital depreciates lower ranked firms will adopt as well (Davies, 1979). Firms are myopic, as they do not anticipate the falling costs.

"Order” models are applicable when there is a fixed critical input into production such as a pool of specially trained labour or a scarce natural resource. In such situations, the order of adoption clearly matters – initially only first movers who want to secure access to the critical input will find it profitable to adopt (Reinganum, 1981). Finally, so-called “stock” models are also premised on the idea that early movers obtain higher returns on the new technology. However, they attribute this phenomenon to the fact that as the stock of firms that have adopted a cost-saving innovation grows, average production costs fall, and eventually output prices fall as well. Thus, initially it will only be profitable for a limited number of firms to adopt (Fudenberg et al., 1985). “Stock effects” reflect the decline in benefits which arise over time as more and more firms adopt the new technology (see Karshenas and Stoneman, 1993, for a survey on rank, stock and order effects on innovation diffusion).[4] This puts forward that the degree of competition is likely to be endogenous to the process of diffusion (Chatterjee et al., 2000; Geroski, 2000). For example, sets of innovations diffusing at about the same time in a

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4 It is important to note that these four types of theoretical models, epidemic, rank, stock and order effect models, are not mutually exclusive. Indeed, the diffusion of any specific technology is likely to be influenced by some combination of the factors emphasized by the models: information and learning, the characteristics of potential adopters, the characteristics of technology, the scarcity of critical inputs and the sensitivity of output prices to technological change.

system are interdependent (Bucklin and Sengupta, 1993; Colombo and Mosconi, 1995; Norton and Bass, 1987)[5].

Bayus et al., (2000) review the existing literature concerned with the phenomenon of interaction, i. e. subsequent appearance and substitutions of innovations. This leads to models that have been developed by population ecologists as they study the interaction among several competing “population species” which offer considerable promises in extending the understanding of product interaction (Tuma and Hannan, 1984). Innovations compete for adopters, a species corresponds to an adopter population of one innovation, which competes against another similar innovation and its adopters in the boundaries of a market and its adopter potential (Hannan and Freeman, 1989). The basis of these models is the observation that changes in a population’s size are considered as a general function of its size at any point in time, i. e. the dynamics of population growth are density dependent.[6]

This model family accounts for the systematic increases and decreases in net birth and death rate observed in natural settings. Suppose a particular population inhabits a particular environmental niche, a market, and increases at the ‘natural rate of increase’. When the population approaches the ‘carrying capacity‘ of the niche, i. e. the maximum population density, which can be supported by the niche and its resources, the death rate rises as a consequence of the scarce resources and competition. The carrying capacity is interpreted as the market potential for the competing innovations (Hannan and Freeman, 1989). An S-shaped curve depicts the (adopter) population in the niche or market. These models account for competition in the diffusion process, but do not give theoretical explanations for the adoption decisions of the modelled populations.

An important contribution to our understanding of the sequence of innovations and competition between them was made by Abernathy and Utterback (1978) and Utterback (1994), who presented a model of the product or technology life cycle. Essentially, this says that for any product or technology there is a finite life span. The model is often presented as an S-shaped curve and the experience of many different sectors showed that there are different phases in the technology life cycle. In the early days, during the fluid phase of a new technology there is enormous potential for innovative application. No one knows quite what to do with it and people may try things, which turn out to be impossible. This phase is characterized by lots of experimenting around the technology and its applications. People take risks because the stakes are low, no one knows quite what the future will hold and the markets for the new applications do not exist yet.

But gradually these experiments begin to converge around what they call a 'dominant design', something that begins to set up the rules of the game – as the transitional phase is entered. This can apply to products or processes; in both cases the key characteristics become stabilized and experimentation moves to eliminating unsuccessful combinations and refining the dominant design. Innovation does not stop at the dominant design, but it moves from taking big steps and radical experimentation to focusing more on improvement and refinement. In the specific phase, as the technology matures still further, this incremental innovation becomes more significant and emphasis shifts to factors like cost, which means efforts within the industries which grow up around these product areas tend to focus increasingly on rationalization, on scale economies and on process innovation to drive out cost and improve productivity. Finally, the stage is set for change as the scope for innovation becomes smaller and smaller whilst already new possibilities are emerging. Eventually a new

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5 See Chatterjee et al. (2000) for a recent survey on diffusion models incorporating competition; see Beath et al. (1995) for a survey on game-theoretical diffusion models.

6 While traditional diffusion models for durables consider only the first adoption (Ratchford et al., 2000), survey models include replacement and multiple adoptions, which is interpreted as innovation interaction over time.

technology emerges which has the potential to challenge all the by now well-established rules and the game is disrupted and repeated.

Extended epidemic, probit or density dependence models are also too simple to provide a really satisfactory account of the process of legitimation or standardization in markets and for the same reason: economic agents often behave strategically as in stock or order effect models, anticipating the effects of increased competition density. As a consequence of their behaviour – and this is not integrated in either one of the introduced models – adopter behaviour itself changes the driving forces of diffusion and therefore the evolution of market structures. Standardization processes also generate externalities which can complicate market processes and either hasten or delay the development of a standard (Blind, 2004) and what is more important, standardization processes involve making choices between alternatives, meaning that some technologies will fail while others succeed. More generally, it seems reasonable to believe that the process of making choices between alternatives ought to have a profound effect on the time path of adoption of the technology, which is ultimately selected. To make any kind of progress on this issue, however, means pushing well beyond the model of density dependence and looking at diffusion models, which encompass both the choice between alternative new technologies and the time path of imitation, which follows that choice.

Innovation adoption choices are subject to expectations about the emergent technological dominant design and the outcomes of the described changes in the competition during the diffusion process. Arthur (1989) models this initial choice in the following way (Geroski, 2000). Suppose that two variants of a new technology, A and B, simultaneously appear on the market and threaten to displace an existing technology. No one really knows for sure whether A is better than B or B is better than A, and least of all whether either A or B is better than the existing technology. If, for some reason, early adopters are willing to experiment with the new technology and prefer A to B, then early trials with the new technology are likely to generate more information about A than B. Arthur (1989) models the technology choice as a process of drawing choices from an urn, a polya urn process. If A turns out to be better than the existing technology, then it will gradually become more commonly used. These early adoption decisions are risky investment decisions, but as more and more information becomes available about A in particular, later adopters will be less willing to invest in making a serious choice between A and B: after all, if A seems to work better than the existing technology, why invest in B and take the risk that it will be worse than A or even worse than the existing technology? It follows that something like a bandwagon develops, with later adopters making the same choice as early adopters without having gone through the same investment in learning by experience. This process is referred to as an information cascade. Early investments may give pioneering firms long-lasting advantages, due to the bandwagon effect. An information cascade is a situation in which it is optimal for an individual, having observed the actions of those ahead of him, to follow the behaviour of the preceding individual without regard to his own information and this is used to explain 'herd' behaviour. Overall, one might identify three phases in a diffusion process driven by information cascade: the initial choice between A and B, the lock-in to A, then the bandwagon induced by imitation. In case A and B emerge in different countries, this effect may result in lead markets (Beise, 2004).

In the case of the existence of network externalities, these effects can even be strengthened as the model by Farrell and Saloner (1985; 1986) shows. After some point in the diffusion process, A is more attractive than B because A has a large installed base, which B does not have. Moreover, as the market for the new technology saturates, the possibility of creating a similar sized installed base for B in the future will be smaller than it once was, since there are fewer potential adopters left and they are even less likely to choose B than A. For both of these reasons, the incentive to adopt B falls as the diffusion of A proceeds. This effect will be stronger, the more important network externalities are and the more marginal the technical difference between A and B is. In fact, network externalities can have two effects on diffusion, i. e. two Nash equilibriums, when modelled as a game (Farrell and Saloner, 1985; 1986): a lock-in effect, just discussed, and a risk creating effect which can delay diffusion. When network externalities exist, early users risk making the “wrong” choice and become stranded with a technology, which has failed to generate the network externalities, it is potentially capable of. This may make early adopters reluctant to move first, lacking a ‘herd of reference’, and may delay the adoption bandwagon. This phenomenon is called “excess inertia” in the standards literature. Its consequence is an initial convexity in the diffusion pattern plotted over time.

As Farrell and Saloner (op. cit.) introduce adopter heterogeneity and bounded rationality behaviour about the choices of potential adopters to the original model, the adopters can be segmented into three categories: players who do not switch, those whose who will switch unilaterally and those who will jump on the bandwagon created by others’ previous adoption. Again, an equilibrium exists in which there is excess inertia, if all players are happy to jump on the bandwagon, but neither is prepared to make the first move and create it. So market failure may still arise.

The identified driving forces determining the diffusion process so far were the communication of the innovation (epidemic models), the adopter heterogeneity (rank effects models), expectations (stock and order effects models) and network and decision externalities (network and information cascade models). Agent-based diffusion models are the richest models of innovative demand; they incorporate all of the introduced driving forces. IMAGES (2001), a research project of the EU on innovation diffusion, reviewed these models, which offer the possibility to go beyond the computation of correlation between the adoption time and various network measures: they allow the process of adoption to be reproduced dynamically. One has to differentiate between the *agents* and their *environment*, and to consider that the time is discrete (divided in time steps), at each time step an agent may get some *inputs* from the other agents of the system and from its environment. An agent may have internal variables, which characterize its *internal state* at each time step. The internal variables can be modified by current and past inputs. They are the main source of folk psychology interpretation. For instance, these variables may be interpreted as beliefs, desires, intentions etc. At each time step, an internal procedure may trigger an *action* chosen among a set of possible actions. This choice is made according to a *choice of action function*. There is a wide variety of possibilities, from direct rules to elaborated optimization, with the development of complex representations of the possible consequences of the actions in time. When the choice is directly made, without any anticipation of its consequences, the agent is often called reactive. At the other extreme, some agents may try to anticipate the reaction of other agents, by imagining their own internal states (by game theoretical calculi). In general, the agents follow the bounded rationality principles. Therefore, they do not have a complete knowledge about the possible consequences of their actions. This rises trade-off between exploration (to act only to increase knowledge when the consequences are not well known) and exploitation (to choose the best action among those for which the consequences are well known) or the consideration of the satisficing hypotheses (Simon, 1957; 1992). In this context, communication can be seen as a particular action. The environment may change at each time step, because of its own dynamics or because of the action of agents on it. This modelling approach to innovation diffusion is named evolutionary as driving forces of the modelled decision processes change endogenously giving birth to disequilibrium of the process (Dosi, 1991; Nelson et al., 2004).

Deffuant et al. (2000) in the IMAGES project develop a model of innovation diffusion for a given case study. Their model of the decision process mixing rational anticipation and social influences is proposed to study the dynamics of the adoption of an agri-environmental innovation by farmers in some region in Scotland. The decisions of the farmers are based on uncertain anticipations related to different criteria (revenue, independence, nature). These anticipations can be the result of a rational evaluation or a feeling or impression gathered from interactions with other farmers and institutional actors. The model simulates emissions and receptions of messages about these anticipations. Different states of the decision are defined, taking into account the anticipations and the motivations of the farmers. The model is linked to different sources of data: interviews with farmers and institutional actors and data on the population of farms. The different parameters are fitted with the data of participation in meetings and adoption and show excellent results in terms of fit and forecasting ability.

Tesfatsion (2002) gives an outlook about new fields of research in the modelling approach. It should be noted that the agent-based modelling approach is most promising for innovation diffusion on the demand side, but, on the other hand, it is demanding time and effort for its implementation. The agent-based modelling approach identified the influence of networks and its topology on the process of innovation diffusion into this system. Certain well-connected decision makers have a crucial influence on the spread of an innovation into their network. They are called opinion leaders or promoters of an innovation (Hauschildt and Gemünden, 1998; Rogers, 1995) and are especially important in the situation a bridge between different diffusion systems has to be established, such as inter-firm and intra-firm diffusion (Karshenas and Stoneman, 1995).

The distinction between inter-firm and intra-firm diffusion has been interpreted as a diffusion process into several systems and therefore has a parallel in a context of diffusion into multiple markets, as the diffusion *across* markets is somewhat different from the diffusion process *within* a particular market. Dekimpe et al. (2000) label these two processes as the breadth and depth of diffusion and survey modelling techniques of global diffusion. In this context, Lundvall et al. (2002) survey the economic concept of “national systems of innovation”, a descriptive approach to model knowledge flows and competence building on national level.

On an industry-level, there is another approach to supply-side innovation diffusion analysis that is termed evolutionary: neo-schumpeterian models of industrial dynamics. Nelson and Winter (1982) were the first to introduce innovation genesis and its diffusion into their supply-side model. Further, they repudiate completely informed, rational, homogeneous adopters and instead postulate limited information, firm heterogeneity and bounded rationality. In essence, firms’ decision process is modelled, i. e. how they adopt innovations without knowing whether they are profitable or are not (Nelson et al., 2004). The profitable technologies provide a surplus that may be invested to generate further use; non-profitable technologies and firms leave the market. Over time, the best practice technologies will become dominant as the process of selection maps out a diffusion path. Kwasnicki (2001) makes a comparative analysis of this family of neo-schumpeterian models in the tradition of Nelson and Winter from a technical point of view giving a strict classification. These models focus on the innovation adoption processes of firms and resulting changes in the market structure, i. e. on industrial dynamics.

3 Categorization of innovation diffusion models

All introduced models are being categorized in this section in order to bring out the difference in focus and the resulting explanatory potential. Thus the section comprises the underlying explanations of the introduced models. But first the uses of diffusion models are discussed.

Use of diffusion models

Innovation diffusion models have traditionally been used in the context of sales forecasting. However, this is not their only purpose, perhaps their most effective use is for descriptive and normative purposes (Mahajan et al., 1990; 2000). Since diffusion models provide an analytical approach to describe the spread of diffusion phenomena, they can be used in an explanatory mode to test specific diffusion-based hypotheses. Furthermore, since the diffusion models are designed to capture the life cycle of an innovation, for normative purposes they can clarify how the diffusion of an innovation could be influenced.

Model classification structure

A classification of diffusion research, respectively diffusion models, will be introduced by means of some underlying dichotomies in the analytical hypotheses and stylized facts which they assume (cf. Dosi, 1991). This is needed to group models into families according to common hypotheses and for matching models to the case study by proving or disproving models hypotheses with real world observations in order to introduce some systematic into the modelling of innovation diffusion. This systematic categorization of diffusion models provides a base for further research and the selection of diffusion model for ex-ante evaluations in specific business environments.

Diffusion models differ substantially in their explanation of the diffusion process. Based on Dosi (1991), ten hypotheses and stylized facts which underlie diffusion models are listed:[7]

(1) Heterogeneity vs. uniformity of potential adopters of innovations: Are all agents the same? Do they have similar incentives to adopt an innovation? Or, conversely, do they differ in some structural characteristics, or in their capabilities of efficiently acquiring new products and processes of production, or in their technological expectations?

(2) Perfect vs. imperfect information: Can the adopting agents be assumed to have adequate information – at least for interpretative purposes – about the nature and future developments of any one technology? Or, rather, should we suppose that an essential determinant of innovation diffusion concerns information diffusion about the existence and attributes of a particular innovation?

(3) Non-increasing vs. increasing returns in new technological developments: Under what circumstances can we expect the use and/ or the production of innovation to exhibit constant or decreasing returns? Conversely, are there factors, which may yield size-related economies of scale, various sorts of learning processes, and, generally, dynamic increasing returns?

(4) Importance of history for the patterns of diffusion: learning history, path dependency, and long-term dynamics. Clearly this point refers to the two preceding ones. The higher the uncertainty about the technical and economic characteristics of innovation, the greater the importance learning history of individual agents is likely to be with respect to their adoption decisions. But does this also affect the general patterns of diffusion, or can one assume that the final ”attractor” or stationary state of a diffusion process will still be independent of individual vicissitudes? Most is going to depend on the existence of dynamic increasing returns (3) and on the feedback processes between the number of adopters of the technology, on the one hand, and the changing incentives to further adopt it, on the other. Whenever these circumstances occur, one is clearly in the domain of path-dependent, non-ergodic[8] processes. In all these cases, history counts, not only for individual patterns of behaviour, but also in terms of the general long-term dynamics of the system.

(5) Interaction between supply and demand of innovations: When can one reasonably assume that the innovation to be adopted is supplied once-and-for-all, and conversely, when is it correct to assume a continuous process of improvement in its technical characteristics – which also make adoption easier and enlarges the set of potential

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[7] Grupp (1998) states three hypothesis dichotomies: (1) adopter rationality vs. bounded rationality, (2) exogenous vs. endogenous technology genesis and (3) equilibrium vs. disequilibrium modelling. Lissoni and Metcalfe (1994) categorize only into equilibrium and disequilibrium models. Other reviews of diffusion models do not provide a classification system, they only introduce the different modelling approaches subsequently (Geroski, 2000; Mahajan et al., 2000) or focus only on a specific model family, such as evolutionary models (Kwasnicki, 2001).

[8] A system is called ergodic, if the long-term observation of a single motion leads to the same frequency of measured values as the observation of many motions with different starting points, in short: “All for one, one for all".

users? How important are changes in supply conditions, first of all prices, for the changing pace of innovation diffusion?

(6) Diffusion in demand vs. diffusion in supply: The way diffusion processes are often represented typically concerns a new good, e.g. a new type of production machinery, whose manufacturer is keen on selling to as many customers as possible. However, another side of the diffusion process concerns, as mentioned, the diffusion of the manufacturing capacity of this new good among the producers themselves. The theoretical representation of this kind of diffusion in production clearly relates to the conditions of imitation of an innovation and thus to the theoretical analysis of technological appropriability, possibly entry- and mobility-barriers, “tacitness” versus “universality” of technical knowledge. Ultimately, it is an area where diffusion analysis joins with the economics of innovation and the economics of industrial dynamics.

(7) The forces driving diffusion: Are these forces mainly exogenous to the context in which the diffusion of a particular innovation takes place, such as general changes in relative prices and macro demand growth? Or rather do they mainly relate to factors that are endogenous to the supplying and adoption industries, such as learning in the manufacturing of the innovation, learning by using, network effects and resulting externalities?

(8) Behaviour and choice of individuals or individual organizations: At one extreme, one may represent decision processes about adoption/ rejection of new technologies as a standard optimization exercise, whereby the agents explicitly form expectations about the returns on the new technologies, confront the entire payoff matrix reachable through their actions, and choose by maximizing some objective function. Following an economist’s convention, call this “rational” or “optimizing” behaviour. At the other extreme, a few authors attribute much less “rationality” to individual choice processes, according to a methodological option grounded in the empirical observation and in some theoretical reasons for the impossibility of literally maximizing behaviours in environments that are sufficiently complex and non-stationary. Thus in this other approach, behaviour is likely to be rather “routinized”, influenced by specific “visions” and norms. Call this “institutionalized behaviour”.

(9) Equilibrium versus disequilibrium dynamics of diffusion: Dosi (1990) uses the convention that diffusion dynamics is an “equilibrium one” whenever micro diffusion decisions are postulated to be *reciprocally consistent* and “rational” micro-behaviour all turns out to be fulfilled in their objectives. Conversely, “disequilibrium” diffusion processes are all those dynamics wherein (a) the “attractors” of the process change themselves as a result of the action of the agents – such as when there are system-level increasing returns to technology adoption – or (b) the diffusion process is explicitly represented in terms of the trial-and-error efforts of the agents, which exhibit “disequilibrium behaviour” and deliver “disequilibrium signals” to other agents.

(10) Forecasting ability of the model: Does the model have the ability to forecast the diffusion of the analyzed innovation? Or has it been conceptualized for normative use only? This issue is of importance, as forecasting is demanded for the thorough analysis of the given case study.

These ten dichotomies of hypotheses and stylized facts are applied to classify the models in order to find out which model integrates which hypotheses according to their specification concerning each of the ten dichotomies of modelling hypotheses introduced, see table 1. Additionally the models’ quantitative data requirements are stated.

Logit diffusion analyses: Mansfield (1961)

As the early diffusion studies are empirical analyses, no hypotheses are assumed before conducting the analyses, as these first diffusion scholars laid the foundations for innovation diffusion research and the later formalization. Data required to conduct the two-step diffusion study according to Mansfield (1961) are (1) adoption data series aggregated on the relevant system-level and (2) independent variables of the innovation, the diffusion system, and some adopter characteristics which can be correlated to adoption timing, i. e. data on individual adoptions.

Epidemic models: Bass (1969)

The Bass model has been introduced in communication section. It is an epidemic model, which assumes that homogeneous potential adopters do not know of an innovation, but will directly adopt when information about the innovation reaches them, they are infected by the innovation, i. e. imperfect information and bounded rationality prevail. The history of adoption affects the future adoption over imitation effects; the equilibrium of the innovation's market potential is reached after complete diffusion. Returns of adoption do not increase; no interaction between supply and demand is modelled. Epidemic models possess excellent forecasting capacities as they were originally designed for this purpose (Bass, 1969). Epidemic models require only an adoption data series aggregated on the relevant system-level. Any data either quantitative or qualitative on communication efforts and behaviour may be used to discuss the models' parameters.

Probit models or rank effect models: Davies (1979)

Probit or rank effect models assume that perfectly informed adopters with heterogeneous preferences only adopt an innovation if it meets their personal utility-cost threshold at a certain time (Davies, 1979). Adopters are rational, but myopic, i. e. they adopt instantaneously as their utility threshold is reached. Changing preferences or a changing innovation quality setting the market potential, which is an interaction between supply and demand, fuels the subsequent adoption over time. The exogenously given model parameter price, adopter preferences, and technology quality are myopically processed by the adopters, keeping the model in equilibrium at all times. There is no forecasting capability reported. The data requirements are the (1) exogenously given parameters of the model, the (2) preference structure among adopters towards the innovation and its price-performance-rate, as well as (3) changes in either one of them.

Hazard-rate modelling with Bayesian learning: Chatterjee and Eliashberg (1990)

As opposed to the assumed rational behaviour pattern of adopters in probit models, hazard rate models are based on the probability of a population member performing a certain behaviour. These probabilities are influenced by the characteristics of the adopter, but also by characteristics of the innovation and environment at the same time. Hazard-rate diffusion models therefore integrate the logit, the probit and the epidemic modelling approach and deserve an intensive introduction.

The Chatterjee and Eliashberg model is based on Bayesian learning in combination with hazard-rate modelling. Heterogeneous, imperfectly informed potential adopters learn through exogenous information flows and imitation about the innovation, then form rational expectations about the utility yield by the innovation and adopt their preference if the risk-aversion threshold is surpassed. Finally, all uncertainty about the innovation is exterminated and equilibrium adoption is reached. This type of modelling requires a lot of data: adopter preferences, adopter communication behaviour, innovation quality, and communication flow must be quantified in order to use them. The data requirements are (1) data on the adopter character (innovation perception, information responsiveness, and preference structure), (2) information about exogenous influence factors, and the (3) aggregate sales data.

Table 1: Categorization of models of innovation diffusion according to ten underlying hypotheses and stylized facts based on Dosi (1991) and data requirements.

DIFFUSION MODELS					
Author Year	Mansfield 1963	Bass 1969	Davies 1979	Reinganum 1983	Chatterjee & Eliashberg 1990
Model family	Empirical diffusion analysis	Market Level Diffusion / Epidemic Models + Variations	Rank effects / Probit model	Stock and Order effect model - gametheoretic model	Restricted Parameter Individual Diffusion Models
MODEL CLASSIFICATION BY HYPOTHESES					
1. Heterogeneity vs. uniformity	-	Homogeneous adopters	Heterogeneous adopters – preference drivers adoption	Homogeneous adopters	Heterogeneous adopters
2. Perfect vs. Imperfect Information	-	Imperfect information as information is the driving force to adoption	Perfect information	Perfect information	Imperfect information
3. Non-increasing vs. increasing returns in new technological development	-	Non-increasing returns	Non-increasing returns	Decreasing returns drive adoption	Non-increasing returns
4. Importance of history for the patterns of diffusion	-	History counts: previous adoption effects the next over imitation	Change in technology qualityor preference structure	Negative historical stock and order effects	Change in technology quality or preference structure
5. Interaction between supply and demand of innovations	-	No interaction	Product utility yielded or demand preferences change over time	Stock and order effects	Product utility yielded or demand preferences change over time
6. Diffusion in demand vs. diffusion in supply	both	Diffusion in demand	Diffusion demand/supply	Diffusion in supply	Diffusion in demand
7. The forces driving diffusion: exogenous vs. endogenous	-	Exogenous: communication efforts and behaviour	Exogenous – price, preference, technology quality	Endogenous – stock and order effects and expectations	Endogenous: learning; exogenous: information flows, preferences risk aversion
8. Behaviour and choice of individuals: rational vs. routinized	-	Routinized	-	Rational	-
9. Equilibrium vs. disequilibrium dynamics of diffusion	-	Equilibrium: market potential for innovation is pre-set	Equilibrium	Equilibrium	Equilibrium
10. Explicit forecasting ability	No explicit forecasting ability	Excellent forecasting abilities	No explicit forecasting ability	No forecasting ability	No explicit forecasting ability
RESUMEE	Empirical resume of independent variables	Adopter characteristics driving adoptions	Adopter characteristics driving adoptions	Expections and adoption strategies with ex-ante identity	Adoption process among simple rational agents
DATA REQUIREMENTS	Market-level diffusion data series and time series of independent variables	Market level adoption data	Distribution of consumer characteristics or evolution of innovation characteristics	Adopter calcul, expectations, resource distribution relevant to innovation adoption	Adopter character (innovation perception, information responsiveness, and preference structure) + aggregate sakes data

Table 1 (continued)

DIFFUSION MODELS					
Author Year	Hannan & Tuma 1984	Arthur 1989	Farrell & Saloner 1985	Deffuant et at. 2000	Nelson & Winter 1982
Model family	Population Ecology / Density Dependency: Legitimation & Competition	Path-dependency / Information Cascade Models	Increasing retrun diffusion model	Agend-based computational economics AGE-diffusion models	Neo-schumpeterian models of Industrial dynamics
MODEL CLASSIFICATION BY HYPOTHESES					
11. Heterogeneity vs. uniformity	Heterogeneous adopters: two or more populations competing	Homogeneous adopters	Homogeneous adopters	Homogeneous adopters	Heterogeneous adopters
12. Perfect vs. Imperfect Information	-	Imperfect information	Perfect information	Imperfect information	Imperfect information
13. Non-increasing vs. increasing returns in new technological development	-	Increasing returns	Increasing returns	Increasing returns by network effects and learning	-
14. Importance of history for the patterns of diffusion	Historical evolution of niche population	Learning as uncertainly reduction, investment risk is avoided	Network externalities formed by historical decisions	Learning as uncertainly reduction in networks	Imitation of widespread techniques/technological regimes
15. Interaction between supply and demand of innovations	-	None	None	Promoter of inventions	R&D policies based on sales respectively profits
16. Diffusion in demand vs. diffusion in supply	-	Diffusion in demand	Diffusion demand	Diffusion in demand	Diffusion in supply
17. The forces driving diffusion: exogenous vs. endogenous	Endogenous: density of market	Endogenous: learning and its costs	Endogenous – network externalities	Endogenous and exogenous	Endogenous: Environmental selection
18. Behaviour and choice of individuals: rational vs. routinized	-	-	Ration	Routinized	Routinized
19. Equilibrium vs. disequilibrium dynamics of diffusion	-	Disequilibrium	Disequilibrium	Disequilibrium	Disequilibrium
20. Explicit forecasting ability	No explicit forecasting ability	No forecasting ability	No forecasting ability	Data-constrained forecasting ability	No forecasting ability
RESUMEE	Market dynamics and population-density in niche	Stochastic competition in early markets	Adoption in networks with rational agents	Agent modelling close to reality	Selection processes and market dynamics
DATA REQUIREMENTS	Market-level adoption data of competing innovations	Adopter rationale, learning behaviour and learning costs	Network effects, adopter rationale	Indepth panel data of adopters over time, communication, institutional analysis etc.	Selection processes, R&D allocation calcul, market dynamics

Density-dependent models: Hannan and Tuma (1984)

The two-population density dependent model by is hard to fit into the hypotheses framework (Tuma and Hannan, 1984). The two populations are clearly distinct, but within they are homogenous. Adoption returns and information flows are not specified, dynamics are based on only on the population density. No explanations about the behaviour of adopters is given, no supply-demand interaction are modelled. The interaction between competing adopter populations needs to be quantified, independent variables such as adopter preferences, communication, and innovation quality are not originally integrated, but it is possible. The model only requires aggregate adoption data series of the competitive innovations.

Stock and order effect models with game-theoretical, strategic interaction: Reinganum (1981)

Stock and order effect models assume perfectly informed homogeneous adopters anticipating the decreasing returns of innovation adoption as more individuals use it (Karshenas and Stoneman, 1993; Reinganum, 1981). These decreasing returns are the result of stock and order effects over time, which result from interaction of demand and supply. Equilibrium is based on the pre-emptive, rational adopter behaviour. No forecasting capacities are reported. Data requirements are (1) adopter utility calculi and corresponding expectations, (2) resource distribution relevant to innovation adoption.

Information-cascade models: Arthur (1989)

This sub-section is dedicated to present self-induced and self-aggravating driving forces of the diffusion process and its consequences. The information-cascade model by Arthur (1989) specifies the innovation diffusion phenomenon based on prevailing imperfect information and learning effects through innovation adoption among homogeneous adopters. Initial stochastic choice between two innovations eventually creates a lock-in situation into one of them, as learning occurs through adoption. As lock-in and bandwagon are endogenously created, the model is in disequilibrium. Initial adoption behaviour is rational, but model disequilibrium dynamics bound it. The model has only normative, but no forecasting ability because of its stochastic initial phase, nor has it other empirical applications.

Increasing return diffusion model: Farrell and Saloner (1985)

To highlight the issue of network externalities, consider the model by Farrell and Saloner (1985, 1986). There are two technologies, old and new, and two homogeneous users who have to choose simultaneously whether or not to switch from the old to the new. The Farrell and Saloner model of innovation diffusion incorporates network externalities causing increasing returns of adoption. Two homogenous adopters choose simultaneously to adopt or reject an innovation, the users' utility distributions depend on network externalities, which leads to two Nash equilibriums, both adopt or both reject. This model is purely normative, it has no empirical, i. e. descriptive or forecasting capacities.

Agent-based diffusion modelling: Deffuant et al. (2000)

The IMAGES agent-based diffusion model incorporates a decision process mixing rational anticipation and social influences, based on uncertain, bounded rational anticipations related to different criteria, which are heterogeneously distributed (Deffuant et al., 2000). Endogenous information flows through adopter networks and subsequent learning drive the diffusion. Agent-based modelling is the most complex and most elaborate diffusion model to date. The model is linked to different sources of data and provides good forecasts. However, as these models require adaptation to and data about the diffusion setting, e. g. decision modelling of agents, preferences, network structures, information channels and flows.

Neo-schumpeterian models: Nelson and Winter (1982)

The evolutionary theory claims that only under particular circumstances can "rational equilibriums" be postulated to be the "attractor" or end-states of empirically more plausible "disequilibrium" trial-and-error processes, and related, actual end-states may well depend on non-average (bounded rational) behaviour, so that an explicit account of the distributions of specific choice rules and of the specific mechanisms of competitive selection are theoretically required (routines as in Nelson and Winter, 1982). Evolutionary models put their emphasis on diversity (adopter heterogeneity), learning (imperfect information), and environmental selection (endogenous diffusion driver) as the main ordering factor, which ex post but not necessarily ex ante produce recognizable regularities in the diffusion process (Dosi, 1991). Selection processes, R&D allocation calculi and complex market dynamics need to be identified to use the model.

4 Conclusion

"[...] the general importance of innovation diffusion: it does, after all concern the processes by which the economy generates and accommodates 'the new', and thus directly touches all those questions on coordination and change that have puzzled economists since the beginning of economics as a discipline." (Dosi, 1991, p. 192).

As the diffusion of innovations still is not completely understood, however the following empirical generalizations on the patterns of diffusion of innovations have been put forward (Grübler, 1996). No innovation spreads instantaneously. Instead, a typical S-shaped temporal pattern seems to be the rule. This basic pattern appears to be consistent for successful innovations, although the regularity and timing of diffusion processes vary greatly. Diffusion is a spatial as well as a temporal phenomenon. Originating from innovation centres, a particular idea, practice, or artefact spreads out to its hinterland by means of hierarchy of sub-innovation centres and into the periphery, defined spatially, functionally or socially. The periphery, while starting adoption later, profits from the learning and the experience gained in the core area and generally has faster adoption rates. As the development time is shorter, however, the absolute adoption intensity is lower than in innovation core areas (spatial or functional). Although diffusion is essentially a process of imitation and homogenization, it clusters and lumps. The densities of the application of an innovation remain discontinuous in time and heterogeneous in space among the population of potential adopters and across different social backgrounds.

Theories and models explaining these empirical findings on innovation diffusion have been introduced by this paper in a rigorously structured analytical framework. This framework provides an intelligible introduction into diffusion categories and can provide the structure to analyze ex-ante a given case study of innovation diffusion into a social system over time. The categorization of innovation diffusion models provides a ordered overview about quantitative modelling approaches, which can be used to match econometric diffusion models to an ongoing case study according to proven model hypotheses and data availability. A structured survey of models can help to focus further diffusion research as its structure helps to easily put new research into a context.

Concretely, innovation diffusion models proliferated enormously in the last decades because data-based analysis and projection provide a sound basis for descriptive, normative and forecasting analyses of diffusion settings. However, data availability often restricts the use of rich and elaborate models. Only models parsimonious in parameters, like the relatively simple Bass model (Bass, 1969), are often applied in the diffusion literature, but these simple models generally have strong theoretical drawbacks (Parker, 1994). For these reasons, this paper provides a methodology for an efficient, theory-based analysis and the basis for the selection of theoretical, quantitative models. Special focus has to be put on the further development of flexible empirical analyses such as agent-based modelling or hazard-rate models. These modelling types will become ever more interesting as the data about consumer behaviour become increasingly available.

Based on the systematic approach to survey diffusion models, the outlook into future research as stated by the modellers are repeated: Why do adopters integrate innovations into their behavioural regularities, what are their motivations? How do adopters use innovations in their daily practice to fulfil their motivations?

References Cited

Abernathy, W., J. Utterback, 1978, Patterns of industrial innovation: Technology Review, v. 80, p. 41-47.

Arthur, B., 1989, Competing Technologies, Increasing Returns, and Lock-In by Historical Events: Economic Journal, v. 99, p. 116-131.

Bass, F., 1969, A New Product Growth Model for Consumer Durable: Management Science, v. 15, p. 215-227.

Bass, F., D. Jain, T. Krishnan, 2000, Modeling the Marketing-Mix Influence in New-Product Diffusion, in V. Mahajan, E. Muller, and Y. Wind (eds), New-product diffusion models: Boston, Kluwer, p. 99-122.

Bass, F., T. Krishnan, D. Jain, 1994, Why the Bass model fits without decision variables: Marketing Science, p. 203-223.

Bayus, B., N. Kim, A. Shocker, 2000, Growth Models for Multiproduct Interactions: Current Status and New Directions, in V. Mahajan, E. Muller, and Y. Wind (eds), New-Product Diffusion Models: Boston, Kluwer, p. 141-163.

Beath, J., Y. Katsoulacos, D. Ulph, 1995, Game-Theoretic Approaches to the Modelling of Technological Change, in P. Stoneman (ed), Handbook of the Economics of Innovation and Technological Change: Oxford, Basil Blackwell.

Beise, M., 2004, Lead markets: country-specific drivers of the global diffusion of innovations: Research Policy, v. 33, p. 997-1018.

Blind, K., 2004, The Economics of Standards, Cheltenham, Edward Elgar.

Booz, Allen, Hamilton, 1982, New products management for the 1980s, New York, Booz, Allen and Hamilton.

Bucklin, L., S. Sengupta, 1993, The Co-Diffusion of Complementary Innovations: Supermarket Scanners and UPC Symbols: Journal of Product Innovation Management, v. 10, p. 148-160.

Chatterjee,.R., J. Eliashberg, 1990, The Innovation diffusion Process in a Heterogeneous Population: A Micromodeling Approach: Management Science, v. 36, p. 1057-1074.

Chatterjee, R., J. Eliashberg, V. Rao, 2000, Dynamic Models Incorporating Competition, in V. Mahajan, E. Muller, and Y. Wind (eds), New-product diffusion models: Boston, Kluwer, p. 165-205.

Christensen, C., 1997, The Innovator's Dilemma, Harvard, Harvard Business School Press.

Colombo,.M., R. Mosconi, 1995, A Survival Model for the Study of the Diffusion fo Multiple Technologies: Giornale degli Economista e Annali di Economia, v. 54, p. 353-390.

Davies, S., 1979, The Diffusion of Process Innovations, Cambrigde, Cambrigde University Press.

Deffuant, G., S. Skerratt, F. Amblard, N. Ferrand, E. Chattoe, N. Gilbert, G. Weisbuch. AGENT BASED SIMULATION OF DECISION PROCESS MIXING RATIONAL REASONING AND INFLUENCES FROM SOCIO-INFORMATIONAL NETWORKS: CASE STUDIES OF AGRI-ENVIRONMENTAL MEASURES ADOPTION BY FARMERS. 2000, Cologne. Ref Type: Conference Proceeding

Dekimpe, M., P. Parker, M. Sarvary, 2000, Multimarket and Global Diffusion, in V. Mahajan, E. Muller, and Y. Wind (eds), New-Product Diffusion Models: Boston, Kluwer, p. 49-73.

Deroïan, F., 2002, Formation of social networks and diffusion of innovations: Research Policy, v. 31, p. 835-846.

Dholakia, N., R. Krish, Diffusion and Adoption of Multi-Application Technologies, 34, 1990, University of Rhode Island. Ref Type: Thesis/Dissertation

Dosi, G., 1991, The Research on Innovation Diffusion: An Assessment, in Nakicenovic and A. Grübler (eds), Diffusion of Technologies and Social Behavior: Berlin, Springer, p. 179-208.

Easingwood, C., V. Mahajan, E. Muller, 1981, A Nonsymmetric Responding Logistic Model for Forecasting Technological Substitution: Technological Forecasting and Social Change, v. 20, p. 199-231.

Easingwood, C., V. Mahajan, E. Muller, 1983, A Non-Uniform Influence Innovation Diffusion Model of New Product Acceptance: Marketing Science, v. 2, p. 273-296.

Farrell, J., G. Saloner, 1985, Standardization, compatibility, and innovation: RAND Journal of Economics, v. 16, p. 70-83.

Farrell, J., G. Saloner, 1986, Installed base and compatibility: American Economic Review, v. 76, p. 940-955.

Fudenberg, D., D. Levine, J. Tirole, 1985, Infinite-Horizon Models of Bargaining with One-Sided Incomplete Information, in A. Roth (ed), Game-Theoretic Models of Bargaining: Cambridge University Press.

Geroski, P., 2000, Models of Technology Diffusion: Research Policy, v. 29, p. 603-625.

Griliches, Z., 1957, Hybrid Corn: An Exploration in the Economics of Technological Change: Econometrica, v. 25, p. 501-522.

Grübler, A., 1996, On the Patterns of Diffusion of Innovation: Daedalus, Journal of the American Academy of Arts and Sciences, v. 125, p. 19-42.

Grupp, H., S. Maital, 2001, Managing New Product Development and Innovation, Northampton, MA, USA, Edward Elgar.

Grupp, H., 1998, Foundations of the Economics of Innovation; Theory, Measurement and Practice, Northhampton, Edward Elgar.

Haldar, S., R. V., 1998, A micro-analytic threshold model for the timing of first purchases of durable goods: Appl.Econom., v. 30, p. 959-974.

Hannan, M., J. Freeman, 1989, Organizational Ecology, Cambrigde, Harvard University Press.

Hauschildt, J., H. Gemünden, 1998, Promotoren – Champions der Innovation, Wiesbaden, Gabler.

Hauschildt, J., 1997b, Innovationsmanagement, München, Vahlen.

Hauschildt, J., 1997a, Innovationsmanagement, München, Vahlen.

Henderson, R., K. Clark, 1990, Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms: Administrative Science Quarterly, v. 35.

Horsky, D, L. Simon, 1983, Advertising and the Diffusion of New Products: Marketing Science, v. 1, p. 1-18.

IMAGES. Improving Agri-environmental Policies: a Simulation Approach to the Cognitive Properties of Farmers and Institutions. FAIR3 CT 2092. 2001. Brussels, Commission of the European Communities, Agriculture and Fisheries (FAIR). 2-10-2001. Ref Type: Report

Karshenas, M., P. Stoneman, 1993, Rank, stock, order and epidemic effects in the diffusion of new process technologie: RAND Journal of Economics, v. 24, p. 503-528.

Karshenas, M., P. Stoneman, 1995, Technological Diffusion, in P. Stoneman (ed), Handbook of the Economics of Innovation and Technological Change: Oxford, Basil Blackwell.

Katz, M., C. Shapiro, 1994, Systems Competition and Network Effects: Journal of Economic Perspectives, v. 8, p. 93-115.

Kwasnicki, W., Comparative analysis of selected neo-schumpeterian models of industrial dynamics. DRUID, 2001, Aalborg, Denmark, DRUID. Ref Type: Conference Proceeding

Lancaster, K., 1971, Consumer Demand: A New Approach, New York, Columbia University Press.

Lissoni, F., J. Metcalfe, 1994, Diffusion of Innovation Ancient and Modern: A Review of the Main Themes, in M. Dodgson and R. Rothwell (eds), The Handbook of Industrial Innovation: Cheltenham, UK, Edward Elgar, p. 106-131.

Lundvall, B.-A., B. Johnson, E. S. Andersen, B. Dalum, 2002, National systems of production, innovation and competence building: Research Policy, v. 31, p. 213-231.

Mahajan, V., E. Muller, F. Bass, 1990, New-Product Diffusion models in marketing: A Review and Directions for Research: Journal of Marketing, v. 54, p. 1-26.

Mahajan, V., E. Mulller, Y. Wind, 2000, New-product diffusion models, Norwell, MA, USA, Kluwer.

Mansfield, E., 1963, The speed of response of firms to new technologies: Quarterly Journal of Economics, v. 77, p. 290-311.

Moore, G., 1991, Crossing the chasm, New York City, Harper Business.

Nelson, R., S. G. Winter, 1982, An evolutionary theory of economic change, Cambridge, Belknap Press.

Nelson, R., A. Peterhansl, B. Sampat, 2004, Why and how innovations get adopted: a tale of four models: Industrial and Corporate Change, v. 13 (5), p. 679-699.

Norton, J., F. Bass, 1987, A Diffusion theory Model of Adoption and Substitution of Successive Generations of High-Technology Products: Managment Science, v. 33, p. 1069-1086.

OECD, 1992, Oslo Manual, Paris, OECD.

Parker, P., 1993, Choosing Among Diffusion Models: Some Empirical Evidence: Marketing Letters, v. 4, p. 81-94.

Parker, P., 1994, Aggregate diffusion forecasting models in marketing: A critical review: International.Journal of Forecasting, v. 10, p. 353-380.

Ratchford, B., S. Balasubramanian, W. Kamakura, 2000, Diffusion Models with Replacement and Multiple Purchases, in V. Mahajan, E. Muller, and Y. Wind (eds), New-product diffusion models: Boston, Kluwer, p. 123-140.

Reinganum, J. F., 1981, On the diffusion of new technology: a game theoretic approach: Review of Economic Studies, v. 48, p. 395-405.

Roberts, J., J. Lattin, 2000, Disaggregate-Level Diffusion Models, in Y. Wind, V. Mahajan, and E. Muller (eds), New-product diffusion models, Boston, Kluver, p. 207-236.

Robinson, B., C. Lakhani, 1975, Dynamic Price Models for New Product Planning: Management Science, v. 21, p. 1113-1122.

Rogers,.E., 1995, Diffusion of Innovations, New York, The Free Press.

Simon,.H., 1957, Model of Man, Wiley.

Simon, H., 1992, Economics, Bounded Rationality and the Cognitive Revolution, Aldershot, Edward Elgar.

Tesfatsion, L. Agent-Based Computational Economics, 1, 2002, Amnes, Iowa, Iowa State University.
Ref Type: Report

Tuma, N., M. Hannan, 1984, Social Dynamics: Models and Methods, New York, Academic Press.

Utterback, J., 1994, Mastering the Dynamics of Innovation, Boston, Harvard Business School Press.

Valente, T., 1995, Network models of the diffusion of innovations, Cresskill, NJ, Hampton Press.

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