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Chapter 1

Introduction to Diffusion Theory

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What is the pattern and pace of the spread of new ideas and artifacts (innovations)? How are new process technologies incorporated into the capital stock of an economic sector or the whole economy? How do new products become part of the consumption patterns of a population? These questions are addressed by diffusion research, which evolved as a discipline after World War II.

Diffusion research studies the spread, adoption, and effects of innovations within a social system. The research tradition originates from a variety of disciplines including anthropology, sociology, education research, communication theory, marketing, economics, and geography. The status of diffusion research has been reviewed recently at two conferences: one in Venice in 1986 and the other at IIASA in Laxenburg, Austria, in 1989.[1] Because of the heterogeneity of the originating research disciplines, it is not surprising that diffusion research has not yet evolved into a coherent, interdisciplinary research topic. Instead, one of the most prominent characteristics of diffusion research is the lack of diffusion of the research findings from one discipline to another (Rogers, 1983). Consequently, a single, universally accepted model dealing with the diffusion of innovations does not exist. However, Rogers provides a number of synthesizing generalizations drawing on the findings from various disciplines (Rogers, 1962, 1983; Rogers and Shoemaker, 1971).

1.1 Innovation Diffusion and Adoption Models

According to the definition given by Rogers (1983), *diffusion* is the process by which an *innovation* is *communicated* through certain *communication channels* over *time* among the members of a *social system*.

An *innovation* may be an idea, object, or practice that is perceived as new by an individual or another adopting unit (e.g., an organization or a firm).

Communication, via *communication channels*, refers to how knowledge about an innovation is transferred to the members of a social system. Communication takes time, and is therefore an important aspect of innovation diffusion. In fact, all theoretical and empirical diffusion studies agree that an innovation does not instantly diffuse into a social system. Instead a typical time pattern of diffusion along an S-shaped trajectory seems to be the rule. The S-shaped pattern of diffusion appears to be a basic anthropologic phenomenon, as it is also confirmed by several studies of preindustrial societies (see Rogers, 1983; and Rogers and Shoemaker, 1971).

The typical diffusion pattern stems from the last element of the diffusion process, i.e., from the heterogeneity of the members of a *social system* with respect to their attitudes toward an innovation. Members of a social system have diverse expectations about the potential benefits of an adoption decision. However, at the same time, they are not isolated; they exchange experience (learn) and imitate the behavior of others.

The French sociologist Tarde (1895) was the first to describe the process of social change as an imitative "somnambulistic" mechanism and an S-shaped pattern in this process. It is, however, only the *aggregation* of individual behavior that portrays such a characteristic pattern. Individuals with different expectations, value systems, communication networks, etc., *interact* with each other (sharing information and experience), and the aggregate diffusion pattern is merely an expression of this interaction between the economic agents or members of a social system.

A necessary step for diffusion is therefore the transfer of knowledge and experience about an innovation from its early adopters to the rest of the population. Hägerstrand (1952) was one of the first to recognize the importance of information flows (either via mass media or interpersonal communication) in the diffusion of innovations. Whereas mass media are more effective in communicating the *knowledge* about an innovation, interpersonal contact appears to be more effective in *influencing* the adoption decision of individuals.

Thus, information transmission is the first step in innovation diffusion. The next step concerns how information is used to arrive at a decision. Rogers (1983) developed a four-stage model of the innovation decision process consisting of (1) knowledge, (2) persuasion, (3) decision and implementation, and (4) (re-)confirmation.

In the knowledge stage, individual characteristics of the decision maker (social, economic, communication behavior, innovativeness), his or her previous practices and perceived needs, and the general norms of the social system act as "filter" mechanisms for incoming information. In this context Gatignon and Robertson (1986) propose (from a marketing perspective) the following influencing parameters on information "filtering" and, in consequence, on the persuasion stage:

- Availability of positive information (negative information will have greater impact than positive information).
- Credibility of information ("objective" information or information from persons with high personal or societal influence will have higher credibility).
- Consistency of information (the more consistent, the higher the impact of the information).
- The information source (media or personal influence, the latter being more influential).
- Personal characteristics (information processing style, life stage, and social integration).

In the next stage (the persuasion stage) the actual adoption/rejection decision is made. The obtained knowledge is evaluated in terms of the perceived characteristics of the innovation (relative advantage, compatibility, complexity, "trialability," and observability). These characteristics are treated further on in this section when discussing the determinants of the diffusion speed. In the third stage the decision to reject or to adopt and implement an innovation is made. Finally, the decision is reassessed in that confirmation from other members of the social system is sought, which may lead to the (dis)continuation of the adoption decision.

This is a general model (the stages and influencing variables of which are confirmed by numerous empirical studies) of the *individual* decision-making process. However, the population of potential adopters is not homogeneous with respect to the innovation decision process. Consequently, Rogers (1983) divides the population of adopters according to their adoption date and categorizes them by their standard deviation from the mean adoption date

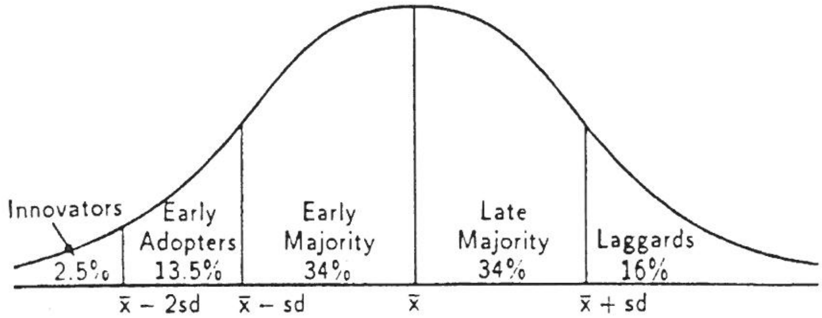

Figure 1.1. Distribution of adopters as a function of mean adoption date $\bar{x}$. Source: Rogers, 1983.

(*Figure 1.1*). He presents extensive empirical evidence to suggest a symmetric bell-shaped curve for the distribution of adopters over time. This curve resembles the first derivative of a logistic function; consequently, the cumulative number of adopters will yield a symmetric S-shaped pattern as, for instance, described by a logistic curve that has been used as a descriptive tool in several diffusion studies.

The symmetric diffusion pattern as postulated by Rogers shows *how* the members of a social system *learn* from the experience and *imitate* the behavior of the innovators (i.e., the first ones to introduce an innovation). The learning aspect is described by Casetti (1969), and in terms of social learning theory by Bandura (1977). The main trait of the argument is that the potential adopters show different degrees of resistance against an innovation as a function of their diversity in expectations, experience, etc. Resistance may be gradually overcome by appropriate stimulus, like the frequent repetition of messages (Casetti, 1969). The learning behavior of individuals is the deeper underlying cause of the symmetry of the diffusion process according to Rogers (1983).

Decision processes for adopting an innovation can be understood as learning processes. At the beginning, when an individual is confronted with a new situation he or she makes many mistakes. These mistakes are gradually reduced (by learning) over time because more information is received and acts as a stimulus. The gain in learning from each trial is proportional to the amount already learned and the amount remaining to be learned before the limit of learning is reached. This is equivalent to the linear transformation of a logistic curve [equation (1.6) in Section 1.2.2]. It should be emphasized that these properties of the learning process were found in real learning situations and are confirmed by laboratory and field experiments (for a bibliography see Rogers and Shoemaker, 1971). Thus each adoption of an innovation in a social system is *equivalent to a learning trial by an individual* (Rogers, 1983). Thus, the symmetric diffusion pattern results from the way messages about an innovation are emitted and processed by social learning.

This completes the overview of diffusion models, primarily based on sociology and behavioral sciences. We now discuss the rate of adoption of an innovation, i.e., the diffusion rate or adoption speed (denoted by Δt in this chapter [2]).

Rogers (1983) identifies five variables that determine the rate of adoption of innovations.

(1) Type of innovation decisions (optional, collective, or authoritative).
(2) Communication channels (external via mass media or internal through interpersonal contact, a categorization based on the work of Hamblin *et al.*, 1973).
(3) Nature of the social system (norms, degree of interconnectness).
(4) Extent of change agent's promotional effort.
(5) The perceived attributes of an innovation.

To date little research has been devoted to determining the relative contribution of each variable. For the diffusion of an innovation *inside* a larger social and economic system (like a country), it is (with the possible exception of the role of change agents) primarily the attributes of an innovation that should determine the diffusion rate. The attributes of an innovation that influence the rate and extent to which it becomes accepted inside a social system are *relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability*.

Relative advantage is the degree to which an innovation is perceived as being beneficial and, in particular, better than the idea-product-organizational form it supersedes. Perceived relative advantage may in reality be a complex vector of costs, performance, personal utility, social prestige, and so on. *Compatibility* is the degree to which an innovation is considered as being consistent with existing values, past experience, and individual needs and expectations. *Complexity* relates to the extent to which an innovation is perceived as being difficult to understand and to use (the learning requirement needed for its adoption). *Trialability* is the degree an innovation may be experimented with before making a final commitment on its adoption, and *observability* is the degree to which the results of an adoption and/or an innovation are visible to other members of the social system. All variables, except complexity, are positively correlated to the adoption rate.

In Section 1.2 diffusion models in economics are discussed in more detail. These models try to explain the pattern and rate of diffusion of new technologies or consumer products primarily based on the (perceived) relative advantage of an innovation, as reflected in conventional economic variables.

1.2 Diffusion Models in Economics

This section presents the oldest and most influential diffusion model in economics. In a seminal contribution, Mansfield (1961) proposed a model explaining the adoption rates of industrial innovations and provided empirical tests of his model for a number of innovations in various sectors.[3]

We continue with an overview of the literature on first generation diffusion models and their empirical findings and then proceed to subsequent extensions of the basic model to include additional explanatory variables. As a result, several second generation models have been proposed, which one might group together as "equilibrium" type of diffusion models. Here, diffusion is seen as a sequence of equilibria determined by changes in the economic attributes of an innovation as well as in the environment. These models are mainly discussed in terms of their relevance to the most recent, and most promising, research direction: the evolutionary type of diffusion models.

Evolutionary models, which describe diffusion as an evolutionary process under conditions of uncertainty, diversity of economic agents, and disequilibrium dynamics, try to model the complex feedback mechanisms at work at the micro level between economic agents, while still being consistent with the overall ordered diffusion pattern at the macro level. Thus, these models integrate the concept of self-organizing systems as, for instance, formulated by Prigogine (1976) into economic theory. This is illustrated by the Dosi-Orsenigo-Silverberg model in Section 1.3.

1.2.1 The Mansfield model

The expression m_{ij} denotes the number of firms in the i-th industry having introduced the j-th innovation at time t and n_{ij}, the total number of firms; the model proposes that the number of firms at time t that will introduce the innovation at time $t+1$, λ_{ij}, is a function of (1) the proportion of firms that have already introduced the innovation, (2) the profitability of the innovation relative to other possible investments, π_{ij}, (3) the size of the investment S_{ij}, and (4) other unspecified variables:

$$\lambda_{ij}(t) = f_i[m_{ij}(t)/n_{ij}, \pi_{ij}, S_{ij}, \ldots] \ . \tag{1.1}$$

The postulated relationship between the number of adopters and the number of firms having already adopted an innovation is a typical learning model where the rate of learning depends on the already accumulated knowledge. The asymptote of this learning process is reached when all potential adopters have adopted the innovation. The structure is similar to the linear transform of the Fisher-Pry model discussed below, where the ratio of adopters to non-adopters, $F/(1-F)$, is a function of time. Consequently, Mansfield derives from equation (1.1) a logistic function to describe the diffusion process. Assuming that $\lambda_{ij}(t)$ can be approximated by a Taylor's expansion, which drops third- and higher-order terms, and assuming that the coefficient of $[m_{ij}(t)/n_{ij}]^2$ in this expansion is zero and that for $t \to -\infty$ the number of adopting firms tends to zero, i.e.,

$$\lim_{t \to -\infty} m_{ij}(t) = 0 \ , \tag{1.2}$$

it follows

$$m_{ij}(t) = n_{ij} \left[1 + e^{-(l_{ij} + \Phi_{ij} t)}\right]^{-1} \tag{1.3}$$

which is the logistic diffusion function (see Appendix). Mansfield's original notation has been retained.

The rate Φ_{ij} is equivalent to the growth or substitution rate b or b_i (i.e., Δt) as used in the Appendix, and describes the "steepness" of the diffusion curve, i.e., a measure of the rate of adoption (or rate of imitation in Mansfield's terminology). The expression l_{ij} is equal to the variable a and a_i (t_0) used in the Appendix and represents a shift parameter determining the positioning of the diffusion curve in time.

The diffusion (imitation) rate in turn depends on the profitability and the size of investments π_{ij} and S_{ij}, in particular,

$$\Phi_{ij} = a_i + b\pi_{ij} + cS_{ij} + z_{ij} \ , \tag{1.4}$$

where z_{ij} is an error term.[4] The model assumes that only the intercept a_i, but not the coefficients b and c, varies among industries. Thus, the diffusion rate is determined by two categories of driving factors: those related to the *industry* (i.e., a_i represents an innovation index measuring the propensity toward innovation in various industries) and those related to the *innovation* (i.e., π_{ij} and S_{ij}). Empirical measures for the first category are, for instance, provided by Blackman *et al.* (1973) for 15 industrial sectors in the USA.

In an empirical test of 12 important innovations in four industries (brewing, coal, steel, and railroads), Mansfield concludes that the logistic curve describes the diffusion pattern of innovations among firms quite well. He observes that the (relative) profitability, in relation to other possible investments, is positively correlated (i.e., the higher the relative profitability of an investment, the faster the rate of adoption) and that the required investment is negatively (i.e., the higher the investment for a particular innovation, the slower the rate of adoption) correlated with the diffusion rate Φ_{ij}. Mansfield finds that the influence of both variables on the diffusion rate was statistically highly significant; the significance of S_{ij}, however, depends on a single observation in the data sample. Also significant interindustry differences (for given π_{ij} and S_{ij}) are found.

For the data sample of 12 innovations in four industries, Mansfield tested four further hypotheses regarding additional influencing variables on the rate of diffusion: the diffusion speed is negatively correlated with the average lifetime of the equipment to be replaced; the diffusion rate is positively correlated with the industry growth rate; the diffusion rate tends to increase over time (due to better communication channels, etc.); and the diffusion rate depends on the time period in the (10-year) business cycle (expansion or contraction phase) when the innovation is introduced. Statistical analysis showed, however, that none of these variables had a significant influence on the diffusion rate of an innovation.

Thus, the model supports the conclusion that the rate of diffusion of a new innovation is, to a large extent, determined by the *proportion of firms already using the new technique*, the *profitability* of introducing it (compared with alternative investments), and the *size of the investment required.* Finally, significant *interindustry* differences in the rate of diffusion were observed.

In subsequent studies (Mansfield, 1968a, 1968b, 1977, and 1984; Mansfield *et al.*, 1971, 1977) the basic model was extended to include:

- Additional industrial sectors, including the chemical industry and the introduction of numerically controlled machines.
- Consideration of product innovations.

- Different measures of the diffusion process (in addition to the number of adopting firms, share of output produced by a new industrial process, share of numerically controlled machines in new installations).
- Analysis of intrafirm diffusion rates in addition to industry diffusion rates.
- Tests of hypotheses associated with additional variables influencing the rate of adoption of industrial innovations.

In his analysis of the intrafirm rate of diffusion, Mansfield (1968a, 1968b) analyzed two aspects of the way in which particular firms respond to a new technique: first, the *time delay*, i.e., the length of time a firm waits before introducing an innovation; second, the *intrafirm* rate of diffusion, i.e., the pattern and driving variables of innovation diffusion *inside* different firms. It is important to consider these two aspects separately, because in the subsequent reception of the Mansfield model they have often been put together and misinterpreted – in particular with regard to the wide acceptance of the positive correlation of firm size to diffusion speed.

The main conclusions from these extensions to the original Mansfield model are the following:

(1) The same kind of model, i.e., logistic type, can be applied to represent diffusion among, as well as within, firms pointing at the unity and similarity between the two processes.
(2) The influence of the profitability and size of investment variables found in the original study are confirmed.
(3) The influence that a firm's size may have on diffusion is more differentiated: whereas the size of a firm appears to influence significantly the amount of *time* a firm waits before introducing an innovation, it "*appears that small firms, once they begin, are at least as quick to substitute new techniques for old ones as their larger rivals*" (Mansfield, 1968a). Company liquidity and possibilities for learning through the experience of other firms already using the innovation appear also to influence the intrafirm rate of diffusion.

Before turning to a discussion of the reception and critique of the original model and the subsequent second generation of diffusion models, it may be useful to summarize the basic conclusions from the model applications. These conclusions, as put forward by Mansfield (1968a, 1968b, 1984) and Mansfield *et al.* (1977), also integrate the empirical findings of other studies supporting the basic model at the phenomenological and economic interpretative level, in particular those of Blackman (1971), Hsia (1973), Nasbeth and Ray (1974), Simon (1975), and Romeo (1977). Mansfield concludes that innovation diffusion is essentially a learning process, characterized by a "bandwagon" or "contagion" effect. There appears to be an economic analogue to classical learning models and psychological laws, in that the extent of learning (diffusion) is a function of accumulated knowledge. Firms learn from the experience of others, who have already adopted an innovation. Furthermore the "reaction time" (time lag for adoption) and the rate of learning (adoption) are dependent on the intensity of the "stimulus," which in economic terms is represented by the profitability of the innovation.

The determinants of the rate of diffusion may therefore be summarized as follows (Mansfield, 1968b):

> Four principal factors seem to govern how rapidly an innovation's level approaches its ultimate, or equilibrium level: (1) the extent of the economic advantage of the innovation over older methods or products, (2) the extent of the uncertainty associated with using the innovation when it first appears, (3) the extent of commitment required to try out the innovation, and (4) the rate of reduction of the initial uncertainty regarding the innovation's performance.

In Mansfield (1984) the following additional determinants were proposed:

(1) Scientific capabilities and skill level of industry (science-based industries with high levels of R&D and consequently higher capabilities to evaluate proposed innovations would have higher rates of adoption).
(2) Industry and market structure, as reflected in the concentration of an industry and the dispersion of the profitability of an innovation among firms.
(3) Experience with the innovation gained outside the industry, thus reducing uncertainty via external learning.

These determinants still constitute the backbone of any satisfactory economic modeling of innovation diffusion. They are taken up again in the rationale underlying the self-organizing model of technology diffusion and structural change discussed in Section 1.3.

1.2.2 Second generation diffusion models

Since the publication of Mansfield's study, the literature dealing with diffusion in the areas of technology, economics, and marketing has grown enormously; it is beyond the framework of this chapter to provide a detailed overview. A good compendium of earlier papers can be found in Linstone and Sahal (1976), and concise overviews of proposed models are presented in Hurter and Rubinstein (1978) and Mahajan and Peterson (1985). This chapter provides an overview of second generation diffusion models. We start with those that can be considered in the tradition of the original model and then discuss subsequent models using four areas of critique of the diffusion-modeling approach in economics.

Several subsequent studies have confirmed the findings about the regularity of the diffusion process, as well as the role of profitability and size of investment on the diffusion rate, in particular, Blackman (1971, 1974), Hsia (1973), Simon (1975), and Romeo (1977). Others, using a different analytical framework to describe the diffusion process (alternative models to the logistic or no formal model at all), have confirmed the empirical findings on the determinants of the diffusion speed postulated by first generation diffusion models, including Metcalfe (1970), Nasbeth and Ray (1974), and Davies (1979, 1980). In an international comparative study reported in Nasbeth and Ray (1974), technological and institutional differences and industry characteristics are said to influence the differences in the adoption rates between countries. An exception is the study by Martino *et al.* (1978), which could not identify any influence of an innovation's profitability on the diffusion speed; however this study is affected by a number of methodological shortcomings, and the negative conclusions should therefore be read with caution.[5]

Finally, several conflicting propositions have been discussed with respect to the relationship of firm size to innovativeness and adoption rates of new technologies. The above-mentioned studies confirm Mansfield's findings, especially if we keep in mind that size appears to influence primarily the amount of time a firm waits before starting to adopt an innovation, but that subsequently the firm may not necessarily be slower than earlier innovators. However, it has been argued that large firms concentrating on domestic markets tend to be technological laggards, such as in the case of the US steel industry (Oster, 1982), and that high-cost firms (i.e., small companies with lower economies of scale) are more likely to adopt a new technology (Reinganum, 1983). This issue is therefore still open for debate. The most likely outcome of such a discussion is that the influence of the firm-size variable can go in either a positive or negative direction depending on the structure of the industry and the market, the existence of different economies of scale, and so on. Still, size apparently matters, not only with respect to explaining differences in the propensity to introduce an innovation and the economics of adoption but also with respect to differences in communication and information networks which can be shown to be instrumental to explain differences in diffusion characteristics especially of small firms (e.g., Kelley and Brooks, 1991). This problem appears thus to be adequately tackled only when market and industry *diversity* in diffusion models is explicitly considered, as done in Section 1.3 or by Tani in Chapter 2.

The following discussion summarizes the critique on second generation diffusion models based on four areas that have been advanced within diffusion studies in economics (see, e.g., Davies, 1979; Rogers, 1983; or Sahal, 1981):

(1) The mathematical properties (especially the symmetry aspect) and the adequate application of a logistic model to describe the diffusion process, and the fact that the model is not derived functionally from an underlying economic rationale or the driving force model explaining the rate of diffusion.
(2) The nature of the adoption process, in particular, the binary nature of diffusion models (regarding both the population of potential adopters and the pool of innovations available) and the static assumption on the size of the potential adopters, i.e., the competitive "niche" for an innovation (be it individuals, firms, and, by extension of the model, market volume).
(3) The process innovation bias of model applications, which has led to the foundation of a second stream of innovation diffusion models (marketing models) for consumer products.
(4) The narrow definition of the group of influencing variables, the ignorance of other factors affecting diffusion, and the model's (implicit) assumption that both the economic (social) and the technological environments in which the innovation is embedded remain unchanged over time. Finally, there are objections against the somewhat atheoretical nature of the definition of the object of diffusion research (i.e., of an innovation).

(1) Mathematical Properties of Diffusion Models

This criticism deals with the use of a logistic model to describe diffusion patterns when it is not derived functionally from an underlying economic theory of diffusion. It is claimed that the model has been taken from a different field of reasoning, i.e., the spread of contagious diseases as applied to the dissemination of information, as well as from (social) learning theory. In addition, the assumptions underlying the behavioral (learning) rationale of the logistic model (resulting in its symmetry around $K/2$) are considered to be too constraining. In particular, the model assumes that the probability to adopt an innovation (or the "infectiousness" of the innovation decision), as reflected in the growth rate parameter of the logistic Δt, stays constant over time.[6] In other words, the logistic model assumes that the interaction between adopters and non-adopters does not change over time. A second corollary of the logistic is that it assumes a homogeneous population, in the sense that potential adopters broadly speaking share the same value system (e.g., profit maximization), and that each potential adopter is susceptible to a new innovation.

In response to this perceived "lack of flexibility" several alternative models have been proposed (the mathematical properties are discussed in the Appendix). These include the use of a modified exponential curve following Bass' (1969) distinction between external and internal influence driven diffusion [see Hamblin *et al.* (1973) on the sociological rationale for these models, first proposed by Coleman *et al.* (1966)]; the Floyd curve (1968); the Gompertz curve (e.g., Dixon, 1980); or a cumulative normal or cumulative lognormal pattern (e.g., Davies, 1979).[7] Other models tried to develop more comprehensive formulations with additional parameters to accommodate a whole set of different S-shaped diffusion patterns. Examples of these models include the Sharif-Kabir model (1976a), the NSRL (nonsymmetric responding logistic) model (Easingwood *et al.*, 1981), and the model proposed by Skiadas (1986).

In view of the amount of effort devoted to the development of various asymmetric diffusion models, one has to note that the flexibility of these models (describing a wide range of diffusion patterns) is achieved by paying a high theoretical price. Model developers do not explain *why* a particular diffusion pattern should follow their models or what the economic and behavioral interpretation of the additional model parameters might be. It appears that this line of research has to some extent thrown out the baby (behavioral-economic rationale of diffusion models) with the bathwater (the supposedly too constraining conditions underlying the behavioral rationale of the logistic model).

The only remaining justification for these models appears to be that they can describe *ex post* the diffusion patterns more accurately.[8] Whereas we do not argue that there are diffusion-substitution processes that do not conform to logistic trends, we find it somewhat ironic that in the majority of cases the logistic performed better than the "more flexible" models. For instance, the fit of the logistic turns out to be superior in nine out of ten cases analyzed by Sahal (1981) and in six out of eight cases analyzed by Sharif and Kabir (1976a).

With respect to the frequently postulated asymmetrical diffusion pattern a final point has to be considered. Hardly any innovation is in fact introduced into a vacuum. In fact, in most innovation diffusion-substitution cases more than two technologies (innovations) compete in the market. Therefore it is entirely inadequate to arrive at conclusions with respect to a particular innovation diffusion pattern by looking at it in isolation. An extremely illustrative case is provided by Skiadas (1986) in his comparison of various asymmetric diffusion models of the adoption of the oxygen steel process in different countries. It can be shown that the process of leveling off the diffusion of oxygen steel (i.e., the "retarding" of diffusion, resulting in asymmetry) is simply the result of the oxygen process being replaced by a newer process, namely, the electric arc process (growing itself logistically, see, e.g., Nakićenović, 1987). Therefore, it is completely pointless to argue in favor of a particular model in the absence of a theoretical basis for the functional form of the diffusion process and without a complete analysis of the technological and market environments (i.e., the competitive "niche") the innovation is embedded in.

The last area of criticism in relation to logistic diffusion-substitution models is the fact that the models are not derived functionally from an underlying economic rationale. This critique was certainly valid for first generation models. However, several formulations have been proposed to show that a particular diffusion curve can be deduced functionally from an underlying economic rationale. Davies (1979) deduces a cumulative normal curve (i.e., a symmetric diffusion curves, which he considers equivalent to the logistic curve), based on the plausible assumption of a lognormal distribution of firm size. Russell (1980), considering marketing diffusion models, argues that income distribution is lognormally distributed and that, if the price of a new consumer item falls linearly, the resulting diffusion process will yield a lognormal curve. A similar line of argument is followed by Gottinger (1986), who takes a probabilistic perspective of adoption and derives a logistic diffusion curve from a logistic probability distribution of the utility function vector of the possible entrants. Finally, Tani (1988) derives a Gompertz curve for the diffusion of industrial robots in Japan based on a rank size distribution of firm size and a size-dependent distribution of the potential benefits of adoption. The underlying rational is that the labor reduction effect of robots is higher in large firms than it is in small ones; this is due to different economies of scale. Tani (Chapter 2) illustrates a further refined diffusion model providing an integration from the micro to the macro level. Thus both symmetric (like logistic or lognormal) and asymmetric diffusion curves (like the Gompertz) have been analytically derived from underlying economic rationales. This would justify the use of these models even in cases where data limitations (distribution of firm size, income, etc.) do not allow the inclusion of these additional variables into the diffusion model proper. In this context, however, critical observations on the link from the micro to the macro level have been advanced. In view of the multitude of feedback mechanisms at work during diffusion (e.g., it is likely to expect that the distribution of firms inside an industry will change during – and due to – diffusion) any analytical aggregation formulation will always rely on a number of simplifying *ceteris paribus* assumptions, whereas in reality complex (nonlinear) feedback mechanisms may be at work (cf. Section 1.3) which would render a clear-cut aggregation impossible to derive analytically.

(2) The Nature of the Adoption Process

The binary nature of most diffusion models with respect to the adopting population (by considering just adopters and non-adopters) is certainly an oversimplification of the various stages of the adoption process (awareness, knowledge, etc.) formulated, for instance, by Rogers (1983). However, in an economic context such a model simplification appears justified; as we are mainly interested in the *impact* of the adoption decision and its resulting economic consequences. Within this context another critical point has been raised; diffusion models tend to be pro-innovation biased and do not explain why an innovation is not adopted (see Rogers, 1983). Clearly this is both an empirical problem and a philosophical problem; unsuccessful innovations are usually badly documented, if at all, and to date practically no diffusion researcher has pursued a Popperian falsification approach in analyzing technological change. However, we do not consider it a major deficiency in the approach as long as one is primarily interested in studying the economic *effects* of innovation adoption.

Diffusion models generally assume implicitly only one adoption per adopter (i.e., excluding repeat purchases), and the models do not consider the possibility that an adopter might give up the innovation ("curing") and readopt it at a later stage ("reinfection"). The exclusion of repeat purchases is certainly a drawback for the marketing analysis of the diffusion of consumer durables, where most models (e.g., Bass, 1969) are concerned only with initial purchases. There appear to be only two pragmatic ways out of this situation. The first is to consider stock variables (like items in use or per capita values) rather than flow variables (like sales). Thus, only the increase in stock would be used to measure the diffusion of a new product into the market. The second more difficult, but at the same time more realistic, possibility would be to model initial purchase and replacement demand separately. This is more plausible; the time constant involved in diffusion and the resulting annual sales might be very different from the annual replacement demand, which depends on the size of the age cohorts of the product and its average lifetime, for instance, represented dynamically by a "death curve" [see, e.g., Marchetti (1983) for such a model of the Japanese car market]. A diffusion model incorporating replacement, in addition to expansion investments, is discussed in Section 1.3.

The critique on the binary nature of the population of innovations treated by most diffusion models is to be taken seriously. In fact, most models cannot even be considered to be of a binary nature in dealing *strictu sensu* with the case of diffusion, e.g., in analyzing the number of firms adopting a particular technique or the aggregate number of new equipment installed. Whereas such approaches apparently describe the dynamics of the introduction of new process technology at the macro level (cf. Chapter 12 by Tchijov) there are limitations of such models to capture in more detail what happens inside an industry and its capital stock during the diffusion process. Such models tend to ignore the fact that potential adopters do not introduce the innovation into a vacuum, but instead replace existing techniques, equipment, etc. Therefore the process of technological change should in most cases be considered as a substitution rather than a diffusion phenomenon. This argument was convincingly put forward by Sahal (1981) and Mahajan and Peterson (1985), among others.

The analysis of technological competition and substitution draws from biological analogies. In biology a competitive substitution pattern was first described by Lotka (1924) to describe the evolution of two types of a species inside a population in which selection operates subject to Mendelian inheritance. Volterra (1927, 1931), as discussed in d'Ancona (1939), analyzed the evolution of two species competing for a limited food supply. If one species outnumbers the other (even by very small numbers) at the initial stage of the process, then the system converges to a state where one species completely replaces the other. Thus, initial random fluctuations in the number of a competing species may "lock-in" the competitive pattern, which via a positive feedback mechanism (in economic terms referred to as increasing returns to adoption) becomes self-sustained with one species completely replacing the other. Such a concept has been proposed for the initial selection mechanism of competing technological designs by Arthur (1983).

As the total population in both competitive situations (the two types of a species and the two species inside the population competing for the food supply) remains constant, the evolution of competing species is renormalized in considering only the *relative* share of the competing species in the total population. This relative share evolves according to an S-shaped trajectory with the obvious constraint $K = 1$, i.e., no species can have a higher share in the total population than 100%.

Such a model was first proposed by Fisher and Pry (1971) and Blackman (1971) to analyze technological change. They analyzed diffusion and substitution on the basis of measuring the relative market share of old versus new competing in a market. The basic assumptions of the Fisher-Pry technological substitution model are the following: (1) the substitution process is competitive; (2) once substitution has progressed as far as a few percent (i.e., "lock-in"), it will proceed until a complete takeover occurs; (3) the rate of fractional substitution F_1 is proportional to the possible remaining substitution $1 - F_1$,

$$\frac{F_1}{1 - F_1} = \exp(a + bt) \ , \qquad (1.5)$$

where the share of the two technologies F_1 (for technology 1) and $1 - F_1$ (for technology 2) in the total market is calculated: $F_1 = N_1/(N_1 + N_2)$. The Fisher-Pry model is equal to the logistic model with a linear right-hand side, which is discussed in the Appendix. Of course, the fractional shares may be calculated not only by measuring the number of economic or technological "species" (e.g., number of firms, number of technological objects), but also by measuring production capacities, output, and so. In equation (1.5) a and b are constants and t is the independent variable, usually representing time. *Figure 1.2* shows the fractional logistic substitution curve for the introduction of 17 technological innovations (basic oxygen steel production, synthetic fibers, etc.) studied by Fisher and Pry. The curve on the left shows the linear transform log $[F/(1 - F)]$, i.e., market share of the new innovation divided by the market share of the old technology on a logarithmic scale, highlighting in particular the early and late phases of the substitution process. The same model was applied by Blackman (1971, 1972, 1974), and numerous studies have since confirmed the descriptive power of this simple

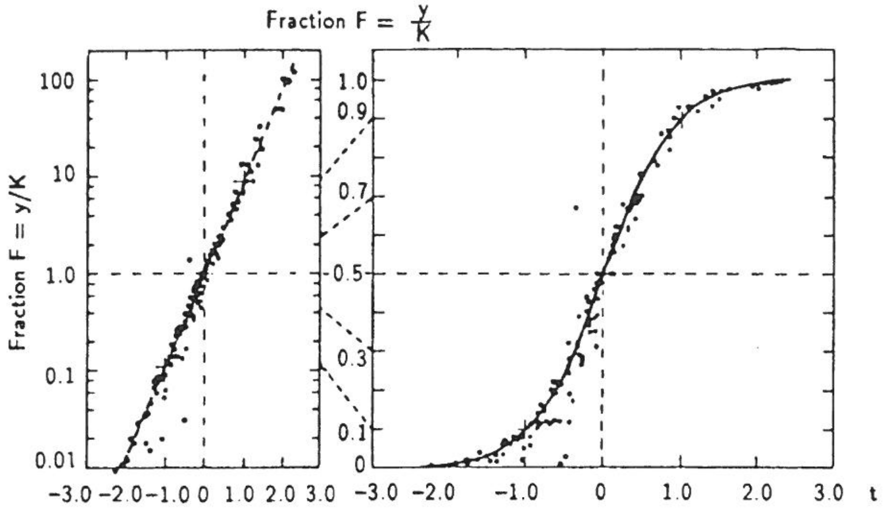

Figure 1.2. Life cycle of the introduction of 17 different technological innovations measuring fractional market shares. Source: adapted from Fisher and Pry, 1971.

substitution model not only in market economies but equally for centrally planned economies (e.g., Astakhov *et al.*, 1989).

The main drawback of the Fisher-Pry model is that it deals with only two competitors, whereas in reality more than two technologies may compete in the market. An extension of the Fisher-Pry model to a multiple substitution model was first proposed by Marchetti and Nakićenović (1979).[9] In this model each technology undergoes three distinct phases as measured in the market share F_i – logistic growth, non-logistic saturation, and finally logistic decline. The growth and decline phases of technologies are described in the model in the same way as the Fisher-Pry model, however, two additional assumptions are made: (1) when more than two technologies compete in a market, one technology is in its (non-logistic) saturation phase, defined as residual after the logistic growth-decline trajectories of the other technologies are calculated; and (2) the technology that enters the saturation phase (which is due to the increase of newer competitors) is the oldest of the growing technologies. Thus the market share of growing-declining technologies is

$$y_i(t) = \log \frac{F_i}{1 - F_i} = a_i + b_i t \tag{1.6}$$

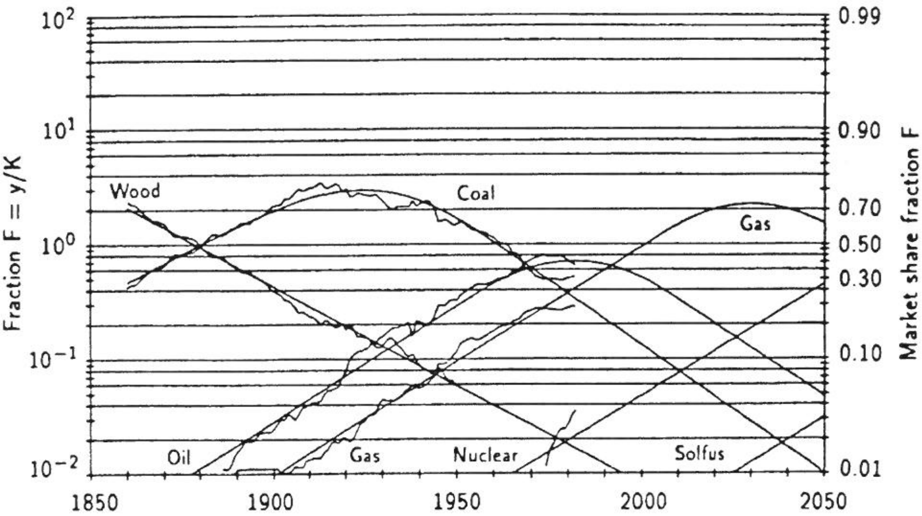

Figure 1.3. World primary energy substitution. Source: Nakićenović, 1984; after Marchetti and Nakićenović, 1979.

and the market share of the saturating technology is then given by

$$F_j = 1 - \sum_{i \neq j} F_i \ . \tag{1.7}$$

The saturation phase is represented by a parabolic transition function between the linear growth and decline phases in the log $[F/(1-F)]$ transformation of the logistic-substitution curves (see *Figure 1.3*). The model is thus nearly complete; growth and decline as well as entry into the saturation phase (defined by the growth of the $j+1$ technology) are determined. The point where the non-logistic transition trajectory ends and the logistic decline phase for technology F_j begins remains to be defined. This is done by using the properties of the non-logistic transition function. This function has negative curvature, passes through a maximum (peak of market share of the technology F_j), and then starts to diminish again.

The end of the saturation phase and beginning of the logistic decline phase is then defined as the point where the curvature of $y_i(t)$ relative to its slope reaches its minimum value:

$$y_j''(t)/y_j''(t) = \text{minimum} \ . \tag{1.8}$$

Note that y'' and $y\prime$ are both negative in the region of the minimum. When this minimum condition is satisfied at time point t_{j+1}, then technology

$j+1$ may in turn enter the saturation phase. The logistic decline trajectory of technology j is determined by

$$b_j = y_j''(t_{j+1}) \tag{1.9}$$

$$a_j = y_j(t_{j+1}) - b_j t_{j+1} \ . \tag{1.10}$$

This mechanism is continued for the successive technologies until the penultimate technology $n-1$ enters its saturation phase, leaving the market ultimately to the winner – which in the model is assumed to be the most recently introduced technology.

Figure 1.3 illustrates this multiple substitution case by analyzing the share of different primary energy forms in the world energy balance (Nakićenović, 1984). The parameters of the model defining the slopes and the position of the various estimated substitution curves in *Figure 1.3* are determined using an ordinary least squares regression algorithm from historical data. Because the share of nuclear energy has hardly penetrated the market, its slope is assumed to be similar to the introduction of fossil fuels – coal, oil, and natural gas. It thus represents a scenario. The technology referred to as *solfus* (*sol*ar or *fus*ion technology) is introduced to analyze the system's response to a new technology.

The development of (relative) market share models resolves most problems dealing with changing market sizes. However, it leaves one question unanswered: What is the impact of the diffusion of an innovation on market growth? The answer is discussed below in considering Metcalfe's (1983) model. In this model diffusion is regarded as an adjustment process between two equilibria (technology and market volume) and the increase in market volume is determined by the shift in the demand-supply curves as a result of changing prices that are due to the introduction of an innovation. With respect to the critique on the constant geographical size of the market niche for diffusion assumed in most models, we mention that temporal diffusion models may also be coupled with the spatial spread of innovations (for instance, illustrated by Mahajan and Peterson, 1979).

(3) Process Innovation Bias

The critique on the process innovation bias of diffusion models has led to a second stream of innovation diffusion models (marketing models) for consumer products.[10] The formal descriptive characteristics of these models is very similar to the S-shaped models of technological innovation diffusion and substitution, including a large variety of models developed to represent asymmetric S-shaped diffusion patterns [for an overview see Mahajan and Peterson (1985), Mahajan and Wind (1986), and Mahajan *et al.*, (1990)]. However, marketing diffusion models differ somewhat in their underlying behavioral rationale and in the driving forces of the diffusion process. In addition to the relative advantage and costs of a new consumer product, marketing models also emphasize other factors relating to the potential adopter's perception of an innovation and its attributes such as product complexity, its compatibility with existing consumer experience, and its trialability.

Of particular importance for marketing is the two-dimensional approach underlying the behavioral assumptions of marketing models. This approach was first proposed by Bass (1969), who developed a diffusion model of the initial purchase (excluding replacement purchases) of "new" generic classes of consumer products. Bass proposes that the diffusion of a new consumer product is dependent on two factors: the coefficient of innovation and the coefficient of imitation. The innovation coefficient relates to the number of initial innovators buying a product, whereas the coefficient of imitation refers to the rest of the population assumed to be imitating the behavior of the innovators and learning from their experience. Usually innovators are characterized by high levels of income and education and influence the decision-making processes of the rest of the population. Related to this two-dimensional behavioral foundation of the model is the distinction between external and internal influence diffusion models in marketing. This distinction relates to the communication channels through which information about a product is communicated (see Hamblin *et al.*, 1973).

External influence refers to information spreading vertically to potential adopters through mass media, advertising, etc., whereas internal influence refers to horizontal communication channels, i.e., interpersonal communication. It is generally argued (e.g., Gatignon and Robertson, 1986) that products that involve low consumer learning (are of low social relevance and are characterized by high marketing/advertising efforts) diffuse via external influence communication, yielding a modified exponential diffusion pattern as first proposed by Coleman *et al.* (1966). More complex and socially visible products, which require experimentation as well as observation of the experience of early adopters, frequently entail some economic or social repercussions if they are not adopted. These products diffuse primarily through interpersonal communication channels with a resulting S-shaped diffusion pattern, usually represented by a logistic curve. The model proposed by Bass (1969, 1980), which can be considered a "classic" marketing model, combines both external and internal communication mechanisms. Bass claims that the internal mechanism (i.e., interpersonal communication, as reflected in the coefficient of imitation) exerts much greater influence on the successful diffusion of a new product than the external mechanism.

Thus the rationale underlying technological diffusion and substitution models has also provided the basis for marketing models analyzing the diffusion of new consumer products. Whereas the relative role of influencing factors in diffusion and substitution models may be different from those in process innovation models, the formal analytical descriptions are very similar in both fields and similar conclusions can be made about the regularity and driving forces of the innovation diffusion process. Still, it is somehow surprising that these two streams of diffusion research have never really converged or even interacted with each other. The relationship between marketing and technological substitution models has hardly been explored; this fact has been emphasized by marketing researchers (see, e.g., Bass, 1986).

(4) The Narrow Definition of Influencing Variables and Their Static Nature

This section considers the critique on the narrow definition of influencing variables included in diffusion models, as well as their static nature (e.g., the profitability of an innovation is assumed to stay constant over the diffusion process). It has been argued that changes in the environment in which an innovation is embedded, for example, a changing competitive structure, is ignored by the models.

Probably the most extreme line of argument in this direction was followed by Gold *et al.* (1970). They claim that innovation diffusion is affected by such a large diversity of variables that it is almost pointless to build general models of innovation diffusion. However, this appears to be an unnecessarily pessimistic view. Our main interest is in the general factors influencing diffusion against which special or random influences can be assessed further. The criticism of a narrow definition of influencing variables was certainly valid for first generation diffusion models; for instance, the models would not hold if the (relative) profitability of an innovation would be close to one. However, several additional influencing variables have since been studied both in the technological literature (e.g., Sharif and Haq, 1979, who in addition to profitability and investment size, analyze factors like product quality, marketing, and price ratios) and in the marketing literature (e.g., Gatignon and Robertson, 1986). Ayres (1969) proposed an industry classification scheme, in which the driving variables of diffusion might be regrouped into (a) performance maximization, (b) sales maximization, and (c) cost minimization. Thus, the models have been considerably extended in the direction of a multidimensionality of influencing factors. Monocausality appears thus to be no longer a valid objection to the formulation and application of diffusion models in both technological change and marketing.

Related to the missing multidimensionality of influencing factors is another critique on diffusion models: the static nature of the influencing variables considered. In reality these variables change continuously over time and interact with each other: e.g., technological performance will increase, prices will go down, uncertainty in applications will be reduced. This possible interaction has been neglected by a number of researches arguing that the profitability of adoption (and thus the diffusion rate Δt) should decrease over time, resulting in an asymmetrical diffusion trajectory. However, it is rather the *expected* profitability, i.e., the vector of profitability and uncertainty about the future, that determines the diffusion rate. As profitability is reduced in due course in the diffusion process, uncertainty is reduced as well, so the resulting *vector* may also stay constant over time. In addition, there have been objections to the *ex post* nature of the measurement of the driving variables, like profitability or comparative advantage. Thus, the power of these variables to explain the behavior of individual consumers or firms would appear to be limited; the decisions to adopt are rather the result of an *ex ante* (subjective) assessment of the comparative advantage of an innovation under conditions of uncertainty. This is contrary to the "objective" nature of the *ex post* assessed variables, assuming no radical uncertainty and quasi-perfect information, usually taken for granted in traditional economic theory (for a critique of assumptions in classical, equilibrium economics see the papers contained in Dosi *et al.*, 1988).

The dynamic nature of the driving forces influencing innovation diffusion not only applies to the innovation itself (e.g., through changing performance-price relationships, i.e., the well-established learning-curve effect) but has to be extended to the whole environment in which an innovation is embedded. Even an old technology when challenged by competition may improve its technical-economic performance. This phenomenon has been termed the "sailing ship effect" (Ward, 1967; Rosenberg, 1976), referring to the considerable improvements in the technology of sail ships (clippers) when challenged by the introduction of steamships. This effect certainly cannot be denied;

however, some doubts exist about its impact on the diffusion of new technologies. Montroll (1978) determined a time shift (of t_0) in the diffusion curve of steamships of 11 years is due to this effect which, in view of the time constants of steamship diffusion (75 years to diffuse from 10% to 90% market share in the USA), is certainly not dramatic. Similarly, by inspecting the empirical substitution curves (see Nakićenović, 1987) one can observe a certain distortive influence of this effect. However, it does not seem to affect significantly the diffusion rate proper.

Although both old and new technologies are affected by changing performances, prices, and profitabilities over time, it appears that the most important element influencing diffusion is the perceived *relative* performance-price relationship between the old and the new technology. To go one step further, one might argue that it is not so much the perceived relative relationship at the time of adoption, but rather the subjectively assessed difference between the *ultimate* performance-price relationships of competing technologies, i.e., including the subjective assessment of likely future improvements along the learning curve.

Another criticism deals with the fact that diffusion models tend to ignore the *interaction* between the various influencing variables. In particular, the interaction between the supply and demand aspects of innovation diffusion has been noticed. This aspect is highlighted and incorporated into a diffusion model by Metcalfe (1983) and Cameron and Metcalfe (1987). Metcalfe is a prominent proponent of the "equilibrium" diffusion modeling approach [for similar arguments and models see, e.g., Peterka (1977) and Silvennoinen and Väänänen (1987)]. Here, diffusion is seen as a transition between equilibria levels, defined by changing economic attributes (e.g., costs, prices) and a changing environment (e.g., differences in the market structure). Diffusion is not so much interpreted as a learning phenomenon, but as a result of the interaction of changes in the innovation and adoption environment, i.e., the interaction between suppliers and customers of an innovation, e.g., via licensing, price strategies, and so on.

Figure 1.4 illustrates the most important relationships in the model proposed by Metcalfe. The term equilibrium is used in this model in two ways: first, supply diffusion and demand diffusion (i.e., the dynamics of demand growth and capacity expansion) are treated separately, in that each has a different equilibrium asymptote, but are kept in balance (equilibrium) via price adjustment; second, innovation diffusion is seen as the transition from one level to another. During this transition, relative prices, production costs, and the relative profitability of using and producing both the old

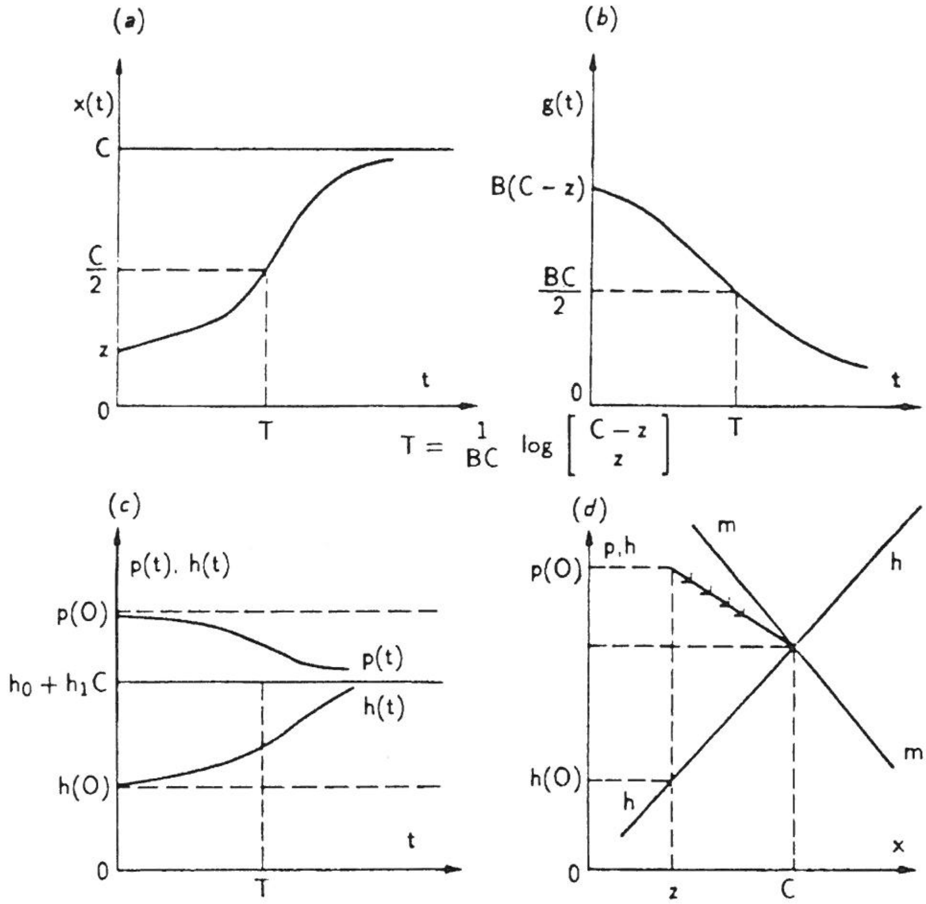

Figure 1.4. Innovation diffusion within an equilibrium framework. Innovation seen as impulse on the economy creating growth potential (from z to C), filled by the innovation. Source: Metcalfe, 1983.

technology and the new technology vary endogenously, with their variations being in turn driven by the substitution process. Without going into detail about the structure and mathematics of the model we summarize its main conclusions.

The substitution trajectory is determined by the long-run market share, the pre- and post-innovation market ratio, and the (supply-demand) balanced output growth of the innovation, as well as the initial conditions that exist between the old and the new product or process. Yet, despite this complexity the substitution curve is reduced to a simple logistic [*Figure 1.4*(*a*)].

The innovation acts as an impulse in the economy creating a potential for growth, which is filled by the innovation. Adjustment to the new equilibrium level is achieved via the continuously retarding *combined* growth rate $g(t)$ [*Figure 1.4*(*b*)]. However, the price and costs of the new innovation change continuously over time producing a profitability squeeze, as shown in *Figure 1.4*(*c*). Finally, *Figure 1.4*(*d*) shows the equilibrium demand and supply curves. The price-output trajectory of the new innovation, i.e., arrowed line in *Figure 1.4*(*d*), does not lie on either the equilibrium demand or the supply curves until the final equilibrium (end of diffusion) is reached. This points to the transient (nonequilibrium type) nature of the diffusion process.

Recent models such as those based on the principles of self-organization are presented in Section 1.3. These models represent to some extent the end point of a long line of increasing complexity in the economic modeling of causal relationships underlying the diffusion process, a line of research initiated by the Mansfield model. Innovation diffusion models are becoming increasingly complex, yet they are still consistent with the empirical regularities of diffusion identified and described by behavioral diffusion models. Thus empirical regularities, as identified by diffusion researchers, are consistent with the causalities of diffusion models formulated in behavioral sciences *and* economics. Structured evolutionary paths at the aggregate level emerge from *diversity* in behavior, technological characteristics, and economics at either the microeconomic level or the individual level.

A valid point of critique on diffusion models has always been that the models tend to simplify the complex dynamics and transformations of both the market environment and technological characteristics of innovations during the diffusion process. In other words, it is during its diffusion throughout the economy that a technology acquires its industrial and economic properties, transforms itself, and widens the initial market in which it was adopted. On the basis of these dynamic properties of the diffusion process, some authors have been hasty in inferring the theoretical impossibility of formal representation, since the object of diffusion is not the same at the beginning, in the middle, and at the end of the process. It appears, however, that the interest of a formal representation resides precisely in the possibility of periodizing the diffusion process, with the aid of criteria which can take into account the principal transformations of the technology under consideration. This, however, requires a framework to define the technologies that are diffusing or competing in a particular market.

In a best-case situation, such a definition is based on expert knowledge; whereas in a worst case, the definition of technologies remains rather arbitrary, based on the disaggregation level available in industry statistics. In any case the definition of the object of diffusion research is generally derived *ex post*, following research interests or application-oriented priorities rather than a comprehensive methodological analysis of the whole technological "space" in which technologies evolve. Such a situation appears unsatisfactory both from the atheoretical nature of the approach and from the perspective of identifying possible technological routes which might emerge in the future or which have been "locked-out" from diffusion in the past. Grübler and Foray (1990) have proposed morphological analysis as a methodological framework for the definition of technologies diffusing or competing. As such, it opens the possibility of ultimately developing a taxonomy and classifying technologies and their diffusion processes, which appear necessary for the advancement of the theoretical foundations and practical usefulness of diffusion studies.

1.3 A Self-organizing Model of Technology Diffusion and Structural Change

This section based on Dosi *et al.* (1986) and Silverberg *et al.* (1988) presents the underlying rationale and structure of a model in which the evolution of a particular system (i.e., the structural change induced by the diffusion of an innovation) is regulated by changing technological and behavioral *diversity*, *learning*, and *selection* mechanisms. These, together with their interrelated feedbacks, generate continuous adjustment processes to a changing techno-economic environment and result in ordered evolutionary paths at the macro (industry) level. The model proposed by Dosi *et al.* (1986) and Silverberg *et al.* (1988) appears particularly appealing as it reconciles both a set of economic driving variables and their interactions (and thus most of the hypotheses generated by first and second generation diffusion models discussed in Section 1.2) at the micro level (i.e., the level of the firm), while still being consistent with the ordered evolutionary paths at the macro-industry level, suggested by behavioral diffusion theory and empirical observations.

1.3.1 Characteristics of technology and industry environments

Technology in a broad sense (i.e., including both process and production innovations) is characterized by varying degrees of *appropriability* (e.g., existence of patents and access to information), *a priori uncertainty* about its future technical and economic characteristics and prospects, *cumulativeness* in the patterns of innovation and capabilities to innovate (i.e., an analog to "learning by doing" as formulated by Arrow, 1962), and *tacitness* of knowledge and expertise on which development and successful adoption of an innovation is contingent. Adoption decisions are characterized by particular *search and learning processes*, drawing on specific knowledge bases, containing both freely available information and internal and external skills.

A fundamental characteristic of any industrial environment undergoing technological change is the *diversity* of the economic, technological, and behavioral environment in which a particular innovation is embedded. Diversity in the economic environment implies that at any given point in time the economic population (be it firms or consumers) is in fact heterogeneous. Firms have different technological capabilities to innovate (for instance, the different R&D expenditures and capabilities among companies), show different degrees of success in the development and adoption of innovations, and finally have different cost structures. Economic structure is the result of differences in economic performance, rates of innovation and adoption of innovations, search procedures, production techniques, combination of factor inputs, and products. The diversity between firms influences the rate and nature of the diffusion process in the following way: if the average *level* of technological capabilities in an industry is high, diffusion will proceed fast; if the *variance* of the distribution of capabilities between firms is high, diffusion proceeds *ceteris paribus* through competition rather than through learning or imitation.

Diversity between economic agents implies that any economic system undergoing change through innovation and diffusion is in a disequilibrium situation in the neoclassical sense. "Better" and "worse" firms coexist. Their technological base is different (even to the extent of a redundancy of the technologies present in the market); they differ in their skill levels, cost structure, and so on. Decisions are affected by uncertainty about the technical and economic outcomes of the introduction of an innovation, because of interactions and interdependencies of firms with respect to prices, technological and market competition, and so on. In fact, the outcome of a decision of any particular firm depends on the actions of other firms. Thus, it is difficult to reduce the behavioral diversity to a simple maximizing behavior (and implied quasi-perfect information) underlying traditional equilibrium-type diffusion models.

The basic task of a self-organizing model consists thus in representing the feedback loops between the structure of an industry, the behavior of firms, and finally the evolution of the industry in general. The coupled dynamics in the areas of technology, economic structure, and diverse behavior interact to produce ordered evolutionary paths at the industry level, and in total at the level of the whole economy. The changing nature of the system in turn feeds back on technological capabilities, incentives, constraints, and behavior of economic agents.

1.3.2 Model description

This section presents an overview of a model proposed by Dosi, Orsenigo, and Silverberg (1986). Further discussions of the underlying economic rationale of some of the model assumptions and equations are contained in Silverberg (1984, 1987). Dosi *et al.* (1986, p. 9) state:

> Innovation/imitation/diffusion [are] represented as the process through which endogenously generated fluctuations of a system become "autocatalytic" and, under certain conditions, progressively change the morphology [the structure] of the system itself. Diffusion of new products and production technologies is the outcome of evolutionary processes whereby the interactions between agents (the carriers of capabilities, technologies and behavior) induce changing incentives, selection mechanisms and learning processes. Innovation and diffusion processes are thus governed by (different combinations of) selection and learning mechanisms. Selection tends to increase the economic dominance of the firms which carry the innovation and penalize others, while learning spreads innovative/imitative capabilities throughout the (changing) set of potential adopters.

The balance and composition of these two different modes of diffusion contain technological, structural, and behavioral components. More specifically, diffusion depends on (Dosi *et al.*, 1986, pp. 8–9):

(a) the characteristics of each technology (sources of basic knowledge, degrees of appropriability and tacitness of innovation, complexity of research, production and products, existence and role of various forms of economies of scale, cumulativeness of technological learning, etc.),

(b) the degrees and forms of diversity between economic agents (including their levels of technological capabilities and variety of search procedures and behavioral rules), and
(c) the endogenous evolution of incentives, constraints and selection mechanisms (including the evolution of relative profitabilities of different technologies, firm sizes, cash flows and market shares).

The assumed industry situation for which the model has been developed is characterized by a supplier-dominated industry, which in turn purchases its investment goods from outside suppliers where no availability constraints are assumed. The market is characterized by strong price competition, although for the sake of simplicity no difference in product quality is assumed. Only one existing technology and one new technology are considered.

The diffusion of a new technology is represented by its incorporation into the capital stock of a firm, constrained by cash flow – i.e., there is no negative cash flow and self-financing is assumed to make the feedback from profitability and investment (diffusion) more straightforward (but at the same time also less realistic). In addition, the scrapping of old capital stock is included in the model. Demand and supply are represented and linked by the variable orders, delivery delays (in case orders exceed productive capacity in the time interval), capacity utilization, and shipments. Obviously production is constrained by maximum capacity, and average and marginal costs are a decreasing function of the production level up to full capacity utilization. Total demand is assumed to be exogenous: growing at an exponential rate, and demand (orders) for a particular firm is a function of competitiveness (price).[11] The change in the market shares of a company over time is due to disparities in its relative competitiveness. The competitiveness of a firm is defined in relative terms, i.e., the difference between its competitiveness and the average competitiveness for the industry.

Initially, the model consists of a system of equations in which a single best-practice technology is available to all agents. It is assumed that the investment process (implicit in the payback method of the model) ensures that productivity gains from technological advances (incremental innovations) are continually incorporated into the capital stock, even under different payback criteria used by different firms. Thus, the investment policy as represented in the model assures the diffusion of technical progress within the capital stock installed.

However, one has to go further. First, one must consider more than one (old) best-practice technology, although it too evolves in the direction of productivity improvements, and take into account the introduction of a new technology that may, however, not be freely available to everybody.[12] Second, one must consider that although an innovation may initially have a lower productivity level than the best existing technology, it has a larger ultimate improvement potential. A new innovation might consist of improvements in the existing technology in its economic and technical performance and capabilities. It could also constitute a "quantum leap" opening up entirely new performance dimensions, new markets, etc., which might not be apparent at the initial stage of introduction.

Firms making investment decisions have to (subjectively) weigh the improvement potentials of the old versus the new technology, i.e., the remaining improvement potentials of their respective learning curves. However, the exact rate of and ultimate potential for improvements are unknown. In addition, improvements in the technology not only are of a technical or economic nature, but also involve changing levels of expertise (scientific/engineering, qualification of work force, etc.) available both internally and externally to the firm. Different strategies are therefore pursued by individual firms with respect to developing their knowledge base: either by in-house development or by waiting for the competitor to act and thus avoiding (initially high) development and learning costs. These different strategies imply that an innovation might not be introduced at all if no one takes the initiative to develop it. On the other hand, there is also the possibility that a firm might acquire a new technology free or at a moderate cost after it has been developed, improved, and demonstrated as technically and economically feasible by a competitor. In fact, it can be shown by simulation runs that if the subjective assessment criteria (represented by an anticipation bonus related to the future improvements of the technology) for a firm adopting an innovation and being the net "winner" are fixed uniformly for all firms in a subsequent simulation run, the innovation is not adopted at all. No firm is ready to incur the costs of developing the technology and bringing it to the commercialization stage.

Therefore the notion of a single "optimum time" for adoption has to be questioned due to the uncertainty and diversity of expectations about the future "trajectories" of existing and new technologies, and the actions and outcomes of the different agents thereof. Dosi *et al.* (1986) consider this diversity of expectations as not only unavoidable in any assessment for investment purposes, but almost a prerequisite for the adoption of an innovation. They claim that this diversity is socially superior, despite the fact that it forces firms to profit or incur losses unevenly in the process of innovation adoption.

To model the dynamics of different technological trajectories several assumptions are made. Two changing technological trajectories represented by maximum productivities are available. It is assumed that the new technology is superior to the old one. The actual productivity realized by a firm is the result of the changing inherent productivity value of the technology and the changing specific skill levels of the firm. In the model firms are assumed to know only the *product* of the inherent technology efficiency and their respective efficiency in adoption and exploitation. They may (in fact *must*) make subjective assessments about the rate at which the new technology will achieve further productivity improvements as well as the internal rate of application efficiency (learning by doing). The latter can be improved by internal learning and/or by obtaining skills from outside (e.g., hiring engineers and workers from competing firms). For reasons of simplicity the model assumes that the old technology is mature, i.e., its efficiency of application cannot be improved. Modeling the evolution of the efficiency parameter of the new technology is quite simple as it is nothing more than the well-established learning-curve effect, where the rate of improvement (in use) is a function (power law) of the cumulative output (experience) associated with the technology.

The choice of a new technology will thus depend on a firm's assessment of its future learning-curve potential. Investment decisions are awarded on the basis of an anticipation "bonus" with respect to its future prospects. The current realizable productivity of a technology is multiplied by this bonus and then compared with the best practice productivity of the old technology. The new technology will be adopted when its adjusted productivity is higher than the old one and the new technology is either cheaper per unit of capacity at the time of comparison or more expensive, but the investment difference can be compensated for by reducing production costs within the desired payback period.

Despite some simplifying assumptions, the model contains a clear economic rationale for the interaction and feedback mechanisms between economic agents. The complex structure of this model illustrates that many more mechanisms affect the diffusion of innovations at the micro level than have been captured even in the most detailed diffusion models proposed in economics to date. It would be difficult indeed to infer the relative strategies, fate, and performance of economic agents at the micro level from a relatively small number of postulated driving variables, notwithstanding the descriptive power of these simpler models at the macro level.

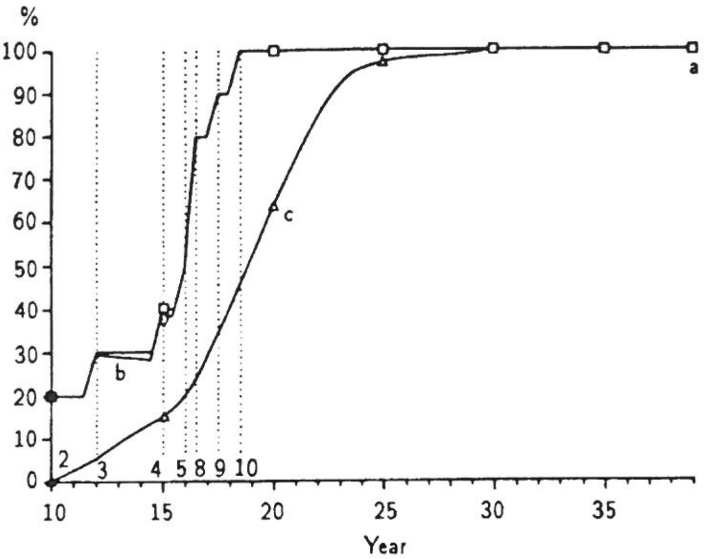

Figure 1.5. Diffusion curves of incorporating an innovation in the capital stock of an industry: (a) share of adopting firms in total number of firms, (b) market share of adopters, (c) percent capacity installed with new technology. Source: Dosi *et al.*, 1986, and Silverberg *et al.*, 1988.

Figures 1.5, 1.6, and *1.7* document some model simulation runs and illustrate the way in which structured, evolutionary paths at the macro level evolve out of uncertainty, interdependence, and competition at the micro level. The feedback mechanisms link the "whole" and the "parts" to demonstrate their mutual coevolution through a self-organizing mechanism. The characteristic diffusion pattern, formulated by traditional macro-level diffusion models and observed empirically, emerges as the outcome of the joint dynamics of technological and economic interactions at the micro level.

Figures 1.5 to *1.7* show the results of a simulation run in which the pre-innovation equilibrium is disturbed by the availability and consequent diffusion of a new technology.[13] The different strategies followed by different firms produce a complex set of phenomena and outcomes at the micro level, while resulting in an ordered path at the macro level.

Figure 1.5 shows the aggregate macro-level behavior of the system represented by three classical measures of diffusion: percentage of adopting firms (curve a), percentage of the market share held by those firms who adopted the new technology (curve b) [14], and percentage of installed capacity, i.e.,

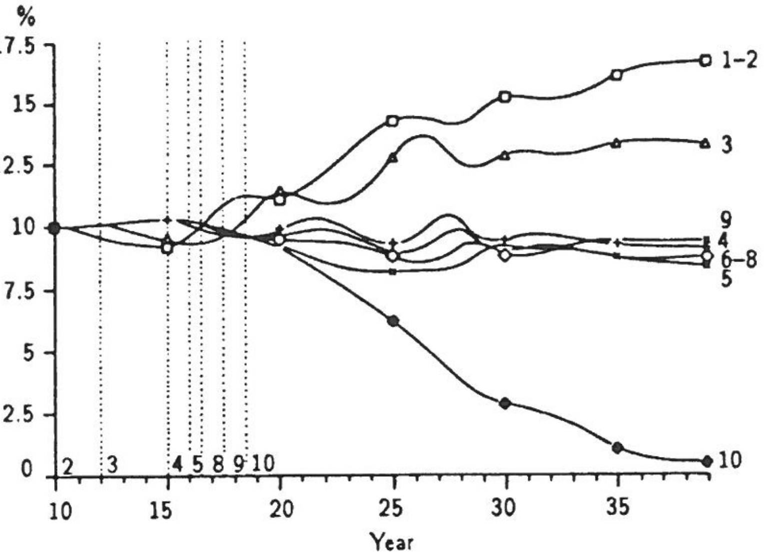

Figure 1.6. Market share of individual firms as a result of changes in competitiveness through adoption (or lagged or non-adoption) of an innovation by individual firms. Source: Dosi *et al.*, 1986, and Silverberg *et al.*, 1988.

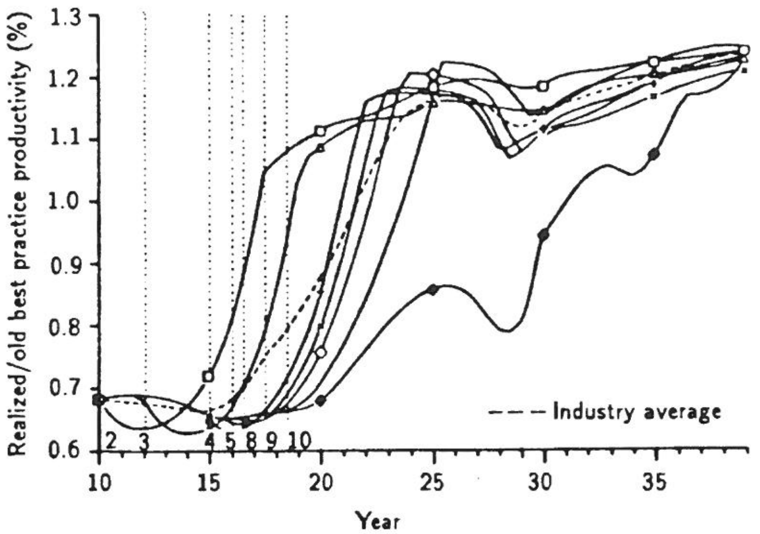

Figure 1.7. Realized average productivity of capital stock of different firms as well as industry average (dashed line) as a result of innovation adoptions. Source: Dosi *et al.*, 1986, and Silverberg *et al.*, 1988.

the result of inter- and intrafirm diffusion as well as of the changes in the relative sizes of firms (curve c). Dotted lines indicate the adoption dates of particular firms. All three measures display the classic S-shaped diffusion pattern.

Figures 1.6 and *1.7* illustrate the microeconomic "drama" going on underneath the smooth macro-level surface. The relative success of the different firms in terms of their market share (*Figure 1.6*) and in their productivity of the capital stock (*Figure 1.7*) is very different.

In terms of market share, early adopters of technology 2 do not perform as well as later adopters. This particular simulation outcome is (among other factors) the result of the assumed appropriability of technology 2, as reflected in the rate of internal learning. If the respective coefficient is set higher, the appropriability of technology 2 is accelerated; the adopters become net benefiters. Particularly noteworthy is the market share of the "laggard" in adopting the technology 2: it is completely driven out of the market. This demonstrates the *"pitfalls of missing the boat by not providing for an anticipation bonus in the productivity assessment of a new technology"* [Dosi *et al.* (1986, p. 33)]. The results show that the relative payoffs of different adoption strategies depend partly on factors beyond the control of an individual firm, such as the adoption decisions of other firms, appropriability conditions of a technology, etc. This illustrates the disequilibrium nature of the diffusion process, i.e., there is no individual optimal strategy independent of the strategies of one's competitors.

Figure 1.7 shows the productivity of the capital stock for each firm, as well as the industry average (dashed line in *Figure 1.7*). It shows, in particular, how successful adopters realize above-average productivity levels, which contribute to their market share gains, whereas late adopters stay consistently below this average. This is a result of the differentials in the internal efficiency (skill) levels of firms. Whereas the innovation pioneers build up their skill levels, later adopters benefit from this experience via external learning and eventually overtake the earliest adopters in skill level and realized productivity. It should, however, be remembered that productivity is only one variable influencing competitiveness and thus market shares. The dynamics of the delivery delay incorporated into the model contribute equally to the changes in the market shares and the price margins realized.

Of course the outcome of the simulation run presented is the result of the particular technological, market, and behavioral variables assumed. The main purpose here is not to discuss the simulation result in terms of how well it represents reality, or in terms of "robustness" of innovation policies responding to the diversity in, and uncertainty about, the behavior of economic agents and the interdependencies of their strategies. Instead, the model demonstrates only the dynamic behavior of such an evolutionary self-organizing system. The main lesson to be learned is that the dynamic interaction between the macro and micro levels in such a system leads to the emergence of spatial and temporal patterns, which are *driven*, rather than dissipated, by micro-level diversity. This becomes especially important when interpreting the empirical long-term regularities of diffusion and technological substitution (see, e.g., Ausubel, 1989; Grübler, 1990, Nakićenović, 1986). From this perspective, regularity in the evolutionary paths at the macro level is not a contradiction but rather a *consequence* of the diversity of technological expectations, designs, dynamic appropriability, and behavior of economic agents.

1.4 Conclusion

The characteristic S-shaped diffusion pattern, and the resulting rates of diffusion, is a macro aggregate of an underlying complexity of adoption causes. Diffusion phenomena are probably best conceptualized as proceeding through various stages of a "diffusion life cycle," in each of which the process is characterized by different market niches, different determinants of diffusion, and different relationships to other diffusion processes, of both a competitive nature and an interdependent nature. Diffusion processes should therefore be analyzed based on multivariate (i.e., considering an innovation diffusion case not in isolation) and multiattribute (i.e., using a number of measures to describe diffusion trajectories and develop comprehensive vectors of driving variables) types of approach.

This multistage view of diffusion also raises the issue of whether the term "diffusion" is at all appropriate to capture the essence of most processes of technological or social/institutional change. Hardly any innovation in fact diffuses into a vacuum. All along its growth trajectory an innovation interacts with existing techniques, depends on the development of a mediating framework for its effective absorption into the socioeconomic system, and changes its technological, economic, and social characteristics. From such a multistage perspective diffusion is probably best described as an "evolution resulting from a sequence of replacements" (Montroll, 1978), i.e., as a succession of substitutions along various specific (expanding) market niches.

These processes must be analyzed comprehensively. It appears that much of the uncertainty of the appropriate mathematical model(s) of diffusion, in particular, the issue of symmetrical versus asymmetrical diffusion models, may be the result of looking at an innovation from a unary (i.e., an innovation grows in a vacuum) or a binary (an innovation's market share, *vis-à-vis* the remainder of competing technologies, is analyzed) perspective.

Diffusion and substitution phenomena can be observed all along a spatial and temporal hierarchy. They range from very short-term processes, such as the rapid spread (and disappearance) of fashion gadgets, to extremely long-term and pervasive transformations in the technological and social fabric as reflected in the growth of infrastructures, new forms of social and institutional organizations, etc. Whereas shorter-term diffusion processes operate within a more or less equilibrium configuration, very long-term and pervasive diffusion processes are of an evolutionary, nonequilibrium type because they profoundly transform the boundary conditions of the system within which they operate.

At this point also a caveat on the too frequent overoptimism of the rapid diffusion of new technologies appears appropriate. The historiography of technological change clearly demonstrates that the diffusion of an innovation of some economic or social pervasiveness is a long process: diffusion time constants (Δts) range in the order of decades and even centuries. Even in the case of the diffusion of process innovations, diffusion time constants are considerable. Ray (1989), for instance, reports that "the time period to reach or to approach saturation is long – about three decades or even more – in a completing discussion of a pioneering international comparative technological diffusion study" (Nasbeth and Ray, 1974). Thus decades are required for the diffusion of innovations of any economic significance and even longer time periods are involved in the pervasive transformation of economic activities by whole clusters of technological and organizational innovations.

If the diffusion of CIM technologies indeed represents an "industrial revolution," an isolated view of specific technologies or application areas alone could be misleading. Instead, one would have to analyze comprehensively what is happening in the industry as a whole, e.g., the important interlinkages to other technologies like the need for more storage and logistics, the dependence on increased technological performance and improved skill levels of the work force (i.e., of the application efficiency of a new technology), among others.

Although well established in geography, the importance of the spatial aspects of diffusion appears to have found only limited attention in economics and the technological and marketing diffusion research disciplines. For instance, spatial diffusion research has identified the importance of innovation centers as well as the spatial heterogeneity in the ultimate diffusion (adoption) levels between innovation centers and their periphery [see, e.g., Hägerstrand (1967); for an overview of spatial diffusion, see, e.g., Morrill *et al.* (1988)]. These findings are frequently ignored in diffusion studies of technological change or marketing and in normative approaches to diffusion, i.e., when inferring from the diffusion levels achieved by early starters as market potential for followers. Thus, taking the spatial dimension of diffusion processes into consideration could yield useful additional insights into the differences in diffusion levels and diffusion rates because there is little reason to expect similar diffusion rates and penetrations levels across different economic and geographical spaces.

Multiple interaction, sequence of successive replacements, importance of specific market niches in introduction and phase out of technologies, and a constantly changing environment of relative technological performance, costs, and prices all appear to be inherent characteristics of diffusion and substitution processes. From such a perspective diffusion can hardly be reduced to single, determining variables but emerges from a complex vector of influencing factors. The importance of any individual driving variable such as relative costs or prices is different not only in the various phases of the diffusion life cycle of an innovation (e.g., relative costs appear to be of minor importance compared with technological performance in the initial diffusion phase) but also between successive technological generations. The diversity and complexity, along with the ordered evolutionary structural change patterns at the macro level, suggest that the diffusion of large pervasive systems, which can span several decades in time, occurs in a constantly changing adoption environment. As such it portrays the features of dynamic self-organizational systems rather than operating in a classical equilibrium-type framework.

Notes

[1] Arcangeli *et al.*, (forthcoming). Selected papers from the IIASA diffusion conference are to appear in a special issue of *Technological Forecasting and Social Change* (Vol. 39, No. 1–2, 1991, forthcoming). A more exhaustive selection of papers is combined in N. Nakićenović and A Grübler (eds.), *Diffusion of Technologies and Social Behavior*, Springer-Verlag, Berlin, Heidelberg, New York, 1991 (forthcoming).

[2] That is, the time interval required to go from 10% to 90% adoption level of the population of potential adopters, or from 10% to 90% market share. For symmetrical diffusion curves like the logistic Δt corresponds also to the time interval to go from 1% to 50% adoption level (see Appendix).

[3] The first model of this type was actually proposed by Griliches (1957), who analyzed the diffusion of the use of hybrid corn seeds in various states in the USA. The approach followed is very similar to that of Mansfield's in terms of both using a logistic curve to describe the diffusion patterns and linking the (empirically) estimated diffusion rate to the profitability of adopting the innovation. Because Griliches's study deals only with the diffusion of a single innovation and lacks a strong technological component, we prefer to discuss the Mansfield model within the present context.

[4] The expression π_{ij} is defined as the average pay-out period required by the firms divided by the average pay-out period for the innovation. For relatively long-lived investments, the reciprocal of the pay-out period is an approximation of the rate of return, i.e., π_{ij} is approximately equal to the average rate of return derived (*ex post*) from the innovation divided by the average rate of return firms required (*ex ante*) to justify investments. S_{ij} is defined as the percentage of the average initial investment in the innovation as a percentage of the average total assets of firms.

[5] The shortcomings relate to (1) the procedure in determining the independent variables considered in the model; (2) a large number of apparent mistakes in the data-gathering process from original references; (3) a restrictive definition of the appropriate market in which the innovations compete; and (4) the inappropriate use of a simple (binary) diffusion model of the Fisher-Pry type for innovations which compete simultaneously on the market (i.e., in multiple substitution cases).

[6] There is a certain semantic difficulty in the argument. Of course the *growth rates* (i.e., the first derivative of the logistic function) vary over time in the form of a symmetric bell-shaped curve with a maximum at $K/2$, resulting in the particular shape of the diffusion process over time: slow growth at the beginning, followed by very fast growth (the bandwagon effect), and finally leveling off toward the saturation level. The argument about the constant value of the diffusion rate (Δt, b, or Φ) merely refers to a perceived "lack of flexibility" (Mahajan and Peterson, 1985) of the logistic to represent data exhibiting a certain skewness (see also Davies, 1979; Sahal, 1981).

[7] Davies reasons that a cumulative normal pattern (a symmetric S-shaped curve) describes adequately the diffusion of innovations characterized by relatively large capital outlays and complex technology, whereas the (positively) skewed cumulative lognormal curve is assumed for relatively inexpensive, uncomplicated processes (often of a supplementary nature).

[8] *Ex ante* use of these models does not appear reasonable in view of the absence of a theoretical rationale underlying the model application.

[9] See also Marchetti (1975), Peterka (1977), Marchetti *et al.* (1978), and Peterka and Fleck (1978). For the algorithmic and computer implementation of the model see Nakićenović (1979). In this context we note also a simple three-way substitution model proposed by Sharif and Kabir (1976b).

[10] This bias is represented by the fact that models generally deal with important (contrary to small incremental), investment intensive process innovations, the diffusion of which is not impeded by patents. The dominant role profitability plays as a causal driving force of the diffusion process relates only to process innovations, for which it represents the paramount adoption criteria used by firms.

[11] This model simplification appears problematic in view of the link between diffusion and market expansion, argued by Metcalfe (1983), and discussed above.

[12] The model deals just with the rather special case of a one-to-one competition between two process innovations producing the same type and quality of output, i.e., a fully standardized commodity. Quality differentiation, multiple competition, and/or the possibility that a (radical) innovation opens completely new product lines or markets are not considered.

[13] The (new) technology, 2, is potentially 100% more productive. Both technologies evolve at a rate of 4% per year as do nominal wages (production costs). The initially higher price of technology 2 decreases at a rate of 1% per year. All firms start with identical conditions (model parameters) except for their "anticipation" bonus used to estimate the improvement potential of technology 2. This bonus ranges from 3.3 (i.e., the firm that introduces technology 2 first, evaluates its potential productivity a factor 3.3 higher than its present productivity) to 1 (i.e., the firm does not consider technology 2 to have any future productivity gain potential).

[14] In this particular example the adopters aggregate together and have not gained significant market shares over the nonadopters. See, however, *Figure 1.6* for the drastic differences in the market shares of the individual adopting firms.

Appendix

Mathematical Characteristics of Diffusion and Substitution Models

Diffusion models can be grouped into two broad classes: growth models with *a priori* unknown asymptote K; and technological substitution models, based on measures of relative market shares with known asymptote ($K = 100\%$). All the functions discussed contain (at least) three parameters, which have the following interpretation:

(i) As t tends to infinity, $y = f(t)$ approaches an upper bound that represents the level at which the growth process saturates,

$$\lim_{t \to \infty} f(t) = K \quad , \tag{1A.1}$$

where K is positive and finite. Furthermore we consider only curves with

$$\lim_{t \to \infty} f(t) = 0 \ .[1]$$

(ii) There exists a time t_0, at which the curve has a point of inflection,

$$\frac{d^2 f}{dt^2}(t_0) = 0 \ , \tag{1A.2}$$

where the growth rate reaches its maximum. A growth curve is called symmetric if it is point-symmetric around t_0, i.e., $f(t_0) - f(t_0 - t) = f(t_0 + t) - f(t_0)$. A necessary condition for symmetry is

$$y_0 := f(t_0) = \frac{K}{2}. \tag{1A.3}$$

(iii) A third parameter, denoted by Δt, gives the length of the time interval needed to grow from 10% of K to 90% of K. More precisely, let t_p be defined by

$$f(t_p) = \frac{p}{100}K, 0 < p < 100 \ , \tag{1A.4}$$

then Δt is given by

$$\Delta t = t_{90} - t_{10} \ . \tag{1A.5}$$

As a first example of an S-shaped curve we consider the logistic function.

(1) Three parameter logistic: This curve is given by

$$y = f(t) = \frac{K}{1 + e^{-b(t-t_0)}} \ . \tag{1A.6}$$

The curve is symmetric around t_0.[2] A simple calculation shows that the parameter Δt is related to the growth rate b by

$$\Delta t = \frac{1}{b}\log 81 = \frac{1}{b}4.39444915\ldots \ . \tag{1A.7}$$

It was first proposed by Verhulst (1838) as a model for human population growth and then rediscovered by Pearl (1925) for the description of biological growth processes. Often the logistic function is rewritten with a linear right-hand side:

$$\log \frac{y}{K - y} = b(t - t_0). \tag{1A.8}$$

Here the interaction between the growth achieved (available resource used, growth potential realized), y, and the growth remaining to be achieved (resources remaining to be used, remaining growth potential), $K - y$, when plotted on a logarithmic scale yields a linear function. When plotted this linear function highlights, in particular, the early and late phases of the growth process.

(2) Positively skewed S-curves: A growth curve displaying asymmetry was proposed by Floyd (1968) within the context of technological forecasting for the description of the evolution of technical performance or "figures of merit," with very rapid initial takeoff, i.e., an asymmetrical growth pattern:

$$F(K,y) = \log \frac{y}{K-y} + \frac{y}{K-y} = bt + c \ . \tag{1A.9}$$

Here the inflection point, y_0, is given by

$$y_0 = f(t_0) = \frac{K}{3} \tag{1A.10}$$

instead of $K/2$ for the logistic. The parameter Δt is given by:

$$\Delta t = \frac{1}{b}\left(\log 81 + \frac{80}{9}\right) = \frac{1}{b} 12.28333803\dots \ . \tag{1A.11}$$

(3) Gompertz function: This nonsymmetric growth function was first proposed by Gompertz (1825) for the description of human population growth. It is given by:

$$y = f(t) = K \exp[-e^{-b(t-t_0)}]. \tag{1A.12}$$

The value at the point of inflection is given by

$$y_0 = f(t_0) = \frac{K}{e} \quad \text{where} \quad \frac{1}{e} = 0.36787944\dots \ , \tag{1A.13}$$

e ... denotes the basis of the natural logarithm, and the parameter b is related to Δt via

$$\Delta t = \frac{1}{b} \log \frac{\log 10}{\log(10/9)} = \frac{1}{b} 3.08439977\dots \ , \tag{1A.14}$$

The Gompertz function can be rewritten with a linear right-hand side:

$$F(K,y) := -\log\log \frac{K}{y} = b(t - t_0), \tag{1A.15}$$

for instance, if a linear regression algorithm is used to estimate t_0 and b.[3]

(4) Modified exponential: This function, which is not a genuine S-shaped curve but has been proposed several times in the diffusion literature (e.g., Coleman *et al.*, 1966), is defined by

$$y = f(t) = K[1 - e^{-b(t-t_0)}]. \tag{1A.16}$$

For this function the parameter t_0 does not indicate the point of inflection. The curve exhibits constantly decreasing gradients; it has no inflection point; and $f(t) < 0$ for $t < t_0$. The parameter b is related to Δt by

$$\Delta t = \frac{1}{b}\log 9 = \frac{1}{b}2.197224577\ldots\ , \tag{1A.17}$$

and the "linear form" of the function is given by

$$F(K,y) = \log\frac{K}{K-y} = b(t-t_0). \tag{1A.18}$$

(5) Substitution models: Any of the above-described diffusion curves may be used for describing technological substitution processes setting $K = 1$. Simple logistic and multivariate logistic substitution models have been discussed already in the chapter.

Sharif-Kabir Model

The only additional (binary) substitution model is the substitution model proposed by Sharif and Kabir (1976a). This is a so-called flexible substitution model, in that an additional parameter is introduced to accommodate a whole range of substitution patterns from the symmetric logistic to various degrees of positively skewed (asymmetric) ones. The model, originally proposed as a substitution model (with $K = 1$), becomes a growth model when the parameter K is allowed to take positive values other than one. Using the notation ($K = 1$), this model is given by

$$\log\frac{F_1}{1-F_1} + \gamma\frac{F_1}{1-F_1} = bt + c, 0 \le \gamma \le 1\ . \tag{1A.19}$$

This model contains two special cases: for $\gamma = 0$ it reduces to the Fisher-Pry model and for $\gamma = 1$ it corresponds to the Floyd model presented in equation (1A.9) above (with $K = 1$). For $\gamma \neq 0$ it is a nonsymmetric function; the value at the inflection point, y_0, is given by

$$y_0 = f(t_0) = \frac{2}{3+\sqrt{1+8\gamma}}, 0 \le \gamma \le 1 \tag{1A.20}$$

showing that y_0 drops from 1/2 to 1/3 when γ increases from 0 to 1. Introducing the parameter t_0, equation (1A.19) can be rewritten in the following way:

$$\log\frac{F_1}{1-F_1} + \gamma\frac{F_1}{1-F_1} = b(t-t_0) + \log\frac{2}{1+\sqrt{1+8\gamma}} + \frac{2\gamma}{1+\sqrt{1+8\gamma}}\ . \tag{1A.21}$$

The parameter Δt now depends on γ and is given by

$$\Delta t = \frac{1}{b}\left(\log 81 + \frac{80}{9}\gamma\right) = \frac{1}{b}(4.39444915\ldots + \gamma 8.88888888\ldots)\ . \tag{1A.22}$$

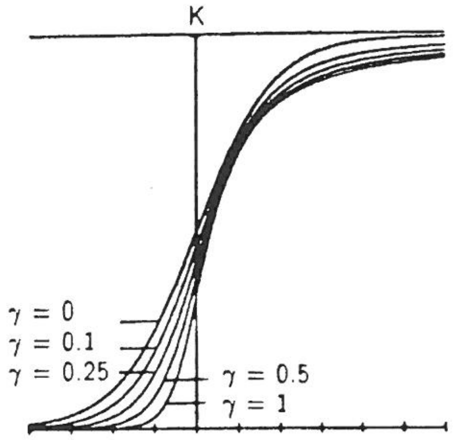

Figure 1A.1. Sharif-Kabir substitution functions for $\gamma = 0$ (logistic curve), $\gamma = 0.10$, $\gamma = 0.25$, $\gamma = 0.50$, and $\gamma = 1$ (Floyd curve). Source: Posch *et al.*, 1988.

Figure 1A.1 shows some substitution curves resulting from the Sharif-Kabir model for different values of the parameter γ.

This particular model offers considerable flexibility to describe a whole range of binary substitution processes, when the empirical data cannot support the symmetry assumption underlying the logistic Fisher-Pry model. However, before a conclusion with respect to a deviation of a particular data set from the functional form of a substitution model can be reached, a careful analysis has to be carried out on whether the process under investigation is indeed a binary substitution process. In a most cases asymmetric substitution patterns are an indication that additional technologies compete in the market. In such cases the substitution process can only adequately be described by a multiple substitution model such as the Marchetti-Nakićenović model discussed in Section 1.2.2.

For a computer program implementing these diffusion-substitution models, see, Posch *et al.* (1988). For statistical uncertainty in parameter estimation, see Debecker and Modis (1986).

Notes

[1] Of course a growth process may "takeoff" also at initial levels > 0. In such a case the original level is subtracted from the data and reintroduced thereafter in the model in the form of a constant intercept.

[2] Other symmetric growth curves like the cumulative normal derived from probability theory (see, e.g., Davies, 1979) are not discussed here because they are only gradually different from the logistic function.

[3] Because of the twofold exponential factor, nonlinear least square fit algorithms do not easily converge, therefore linear regression of the transformed data based on equation (1A.15) is preferred.

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