4.

Network externalities and other perspectives of research

4.1 Introduction

In Chapter 3 it has been argued that most innovations experience some difficulty in early stages of their life cycle because a limited knowledge about them penalizes sales. The first phase of an innovation diffusion process, usually indicated in literature as the "incubation period", has proven to have a chilling effect on new product growth and the model presented in Chapter 3 was aimed at recognizing that effect, since the standard Bass model does not. Though chilling effects exerted by incubation seem typical of many innovations at their first generation, this phenomenon appears particularly evident in the case of interactive innovations or network goods, like telephony, facsimiles, electricity, Internet, whose benefit and adoption by the single agent depends on the perceived number of others who have already adopted and thus on the creation of a physical network of interacting devices.

The increase of a product's utility for a consumer as the number of other users increases is defined as *network externality* (Rohlfs, 2001). Network externalities may be *direct*, when the utility is directly affected by the number of other users, as in the case of telecommunications, or *indirect*, when the increase of utility occurs through market mediation, so that, for example, the number of users of DVD players influences the number of DVD titles available in rental outlets (see Muller, Peres and Mahajan, 2007). While indirect network externalities require to analyse market mechanisms, the case of direct externalities specifically deals with those interdependences between consumers that tie together their utilities.

Economic literature on network externalities has generally focused on their effect on industry structure, suggesting that network effects provide a competitive advantage for producers with larger market share over later entrants (Katz and Shapiro, 1985; Shapiro and Varian, 1999): as a consequence, this may lead to a greater tendency towards monopolization and influence optimal policy choices of firms, such as the adoption of low pricing strategies to deter the entry of competitors (Fundenberg and Tirole, 2000). Thus, the ability to build network effects has been generally considered as an important factor to facilitate the success of a producer in its market.

Adopting a different perspective, Goldenberg, Libai and Muller (2005) have noticed that the effect of network externalities *in new product adoption* has not been formally examined in economic literature, in this sense paying more attention to the production side of economies. Interestingly, Srinivasan, Lilien and Rangaswamy (2004) have proposed an analysis that contradicts the idea that such externalities just imply a competitive advantage for early market entrants, rather finding that these have a *negative* impact on the survival of pioneers. Indeed, Mahler and Rogers (1999) and Goldenberg, Libai and Muller (2005) have stressed that in early stages of the diffusion of an innovation with strong network externalities, the rate of adoption proceeds extremely slowly and this extended incubation period is often reflected into a long left tail of the diffusion curve. This suggests that pioneer firms that introduce new network goods into markets do not only benefit by the opportunity to create a network for their technologies as first markets entrants, but have to sustain some costs to achieve this position, given that the rate of adoption is initially very low. Thus, network externalities may be both a source of benefits and disadvantages for firms: analysing the *evolution* of the markets for network goods may help to understand both sides of this story. While it is intuitively clear that the collective response of demand plays a crucial role in defining the evolution of these markets, since it is the final choice of consumers that decrees the success of an innovation or not, aggregate adoption processes have been modelled so far without taking into formal consideration the effect of network externalities.

The standard approach to innovation diffusion represented by the Bass model does not incorporate the effect of network externalities, in spite of a clear perception of it, and for this reason Muller, Peres and Mahajan (2007) and Hauser, Tellis and Griffin (2006) have identified in this fact an open question to be addressed by research in innovation diffusion, both in theoretical and empirical terms. Research efforts in this direction may provide a wider range of tools for treating different phenomena in different ways and imply a better understanding of their effect on growth.

This chapter is dedicated to discuss, as a direction of research, the possibility to incorporate network externalities into an innovation diffusion model, extending the structure of the Bass one. As an interesting fact, the perspectives adopted by economic literature that stresses the advantage implied by them and by innovation diffusion theory that, on the contrary, emphasizes their chilling effect on early phases of new product growth, offer a useful intuition on the fact that markets for network goods are not stable over time, rather presenting an evolving structure. As in the case examined in Chapter 3, the variable structure of the market for an innovation may be the rationale for justifying an extended incubation period at the beginning and network-related advantages later, when the product has been accepted by a sufficient number of consumers. This conceptualization may exploit a strong theoretical ground, represented by collective choice literature and in particular by threshold models, whose main concerns will be presented in section 4.2. On the basis of the concepts discussed in section 4.2, section 4.3 will be dedicated to propose a possible formalization of an evolving market for network goods. Section 4.4 summarizes the research path realized so far and indicates some likely directions for future research.

4.2 Critical mass and threshold models of collective behaviour

In a famous work on the effect of network externalities, Economides and Himmelberg (1992) pointed out that network industries typically exhibit a *positive critical mass* (see Economides and Himmelberg, 1992). Mahler and Rogers (1999) have provided a definition of critical mass based on previous ones given by Rogers (2003) and Valente (1995), stating that critical mass is the *minimal number* of adopters of an interactive innovation for the further rate of adoption to be self-sustaining. Economides and Himmelberg (1992) have argued that for many network goods the critical mass is of significant size, so that for these goods small market coverage will be never observed. In addition, they have noticed that the concept of critical mass formalizes the so-called "chicken and egg" dilemma, for which many consumers are not interested in purchasing the good because the installed base is too small, but the installed base is too small because an insufficient number of consumers has adopted the good. Thus, it has been observed that while the rate of adoption of every innovation may present some critical mass effect, this is particularly crucial for network goods (Rogers, 2003).

The importance of the critical mass for network goods is related to their specific nature: while many new products or services provide benefits for the single adopter, independently of the purchase decision of others, in the case of network or interactive products network externalities apply, that is, the utility of a single adopter is strongly dependent on what others decide to do, since these goods need a network to be used. In this sense, critical mass measures the size of an expanding network in terms of the number of users that have adopted a given innovation. One may argue that all interactive goods are characterized by strong network externalities: actually, this also depends on the level of compatibility of the good. A typical example of the fact that not always interactive products experience strong network externalities at the beginning of their diffusion is given by the case of mobile telephones, that diffused quite rapidly given the possibility to be connected to the existing base of all telephone users. Indeed, the diffusion of mobile phones in the USA has been modelled by Krishnan, Bass and Kumar (2000) with a (delayed multivariate) Bass model.

Mahler and Rogers (1999) and Allen (1988) have identified some strategies implemented by the producer for achieving a critical mass. Clearly, a subsidized price or the provision of the product for free may facilitate adoptions. In addition, a simplified adoption procedure may be certainly a stimulating factor: for example, the success of Skype, the Internet telephony software, has been partially attributed to the extremely user-friendly procedure of download and installation of the program.

Nevertheless, most innovations present such a degree of complexity, network effects and investment's riskiness, that the average consumer is initially discouraged to adopt and will eventually decide to adopt when there is sufficient guaranty of investment's safety: in other words, many consumers will wait until a critical mass is reached. However, it is intuitively clear that if all consumers acted like this, a critical mass would never be achieved. Fortunately, diffusion theory states that individuals are characterized by different levels of resistance to innovations, so that some of them will purchase the innovation before reaching the critical mass. The different level of resistance, or receptiveness, to innovations represents a primary source of heterogeneity among the components of a population: for example Rogers (2003) has proposed a distinction of potential consumers based on their personal *threshold* for adoption, providing the well known categorization of innovators, early adopters, early majority, late majority and laggards.

The concept of individual threshold has been widely employed in *collective action* literature and is defined as *the proportion of the group for an individual to engage in a particular behaviour* (Granovetter, 1978). In innovation diffusion context, an individual threshold is a personal evaluation to be compared with the relative number of other individuals that must have adopted an innovation before a given potential adopter will adopt it and the case of network or interactive goods appears particularly suitable for being treated with threshold models.

As suggested by Goldenberg, Libai and Muller (2005), the relationship between network externalities and threshold levels can be explained considering individual's utility function. In particular, the definition of network externalities implies that the size of the network increases the utility of an individual. Thus, the consumer will purchase the product if the number of adopters is larger than a certain level depending on personal evaluations on the relative advantage of the good, prescinding from network effects, as well as reservation price. Personal evaluations of the good and reservation price are individual specific characteristics that define the threshold level of each consumer.

Put in a formal way, defining a random variable H to represent thresholds, adoption will occur if, for h_i ! H,

$$h_i \leq y(t) \qquad (1)$$

where h_i is the individual threshold and $y(t)$ is the proportion of adopters at time *t*.

Although the possibility to compare individual threshold with the size of the network expressed with $y(t)$ may appear reasonable and intuitively correct, specific effort is certainly needed to justify this choice, in particular giving a more rigorous definition of threshold h_i, able to clarify the role of individual features responsible for individuals' heterogeneity, such as reservation price and other personal characteristics.

The important implication of considering individual thresholds, is that adoption process depends on the realization of condition $h_i \leq y(t)$: not all consumers have the same willingness to purchase the good and, in particular, those for which $h_i \geq y(t)$ applies, will not adopt.

The description of an innovation diffusion process with network externalities should take into account this aspect with appropriate modelling choices. As in the model proposed in Chapter 3, where an individual became a potential adopter only if he/she was informed about the existence and the features of an innovation, in the case of diffusion with network externalities an *individual will become a potential adopter only if* $h_i \leq y(t)$. As a consequence, also in the presence of network externalities, the market potential cannot be considered constant, rather having a variable structure that depends on threshold levels.

4.3 A variable market potential as function of thresholds

The market potential in an innovation diffusion process represents the maximum number of realizable adoptions within an innovation life cycle, its value is generally considered determined at the time of introducing the new product and remains constant along the whole diffusion process. However, the introduction of thresholds implies a market potential with a dynamic structure, which is defined with probability

$$P(H \leq y(t)) \tag{2}$$

where $h \in H$.

Considering the total number of individuals that may be potential adopters, K, the market potential will be defined as

$$m(t) = KP(H \leq y(t)) . \tag{3}$$

Notice that if all individuals have a very low threshold, so that condition $h_i \leq y(t)$ is always satisfied, then $P(H \leq y(t)) = 1$ and $m(t) = K$ as occurs in the standard Bass model where the market potential reaches its asymptotic level, here denoted by K, as soon as the product is launched. On the contrary, if $h_i \; ! \; y(t)$, which is a typical situation of very early stages of diffusion, when the size of the network $y(t)$ is still too small, then $P(H \leq y(t)) \ll 1$ and consequently the market potential may take a long time to develop. Alternatively, it may never reach a sufficient size for the adoption process to be self-sustaining.

The specification of $P(H \; ! \; y(t))$ requires an important hypothesis on the distribution of thresholds in the population. As reported by Goldenberg, Libai and Muller (2005) there is not much empirical evidence on threshold distributions, however much literature on threshold modelling has generally assumed that these are normally distributed (see Valente, 1995).

A normality assumption, $H \sim N(\mu, \sigma^2)$ yields

$$m(t) = KP(H \le y(t)) = K\Phi\left(\frac{y(t)-\mu}{\sigma}\right). \tag{4}$$

Interestingly, it may be observed that the dynamic structure of the market potential depends on the adoption process, represented by $y(t)$. In particular, it may reasonably expected that as $y(t)$ increases, the average level of thresholds will decrease, that is, the mean μ will have a decreasing value: this would allow to avoid a quite unrealistic assumption of thresholds' stationarity.

4.3.1 An innovation diffusion model with network externalities

Following the approach developed in Chapter 3, an innovation diffusion model with a dynamic market potential may be described

$$z'(t) = m(t)\left\{(p + q\frac{z(t)}{m(t)})(1 - \frac{z(t)}{m(t)})\right\} + z(t)\frac{m'(t)}{m(t)} \tag{5}$$

and its closed form solution will be

$$z(t) = m(t)\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{6}$$

or

$$y(t) = \frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{6a}$$

where $m(t) = KP(H \le y(t)) = K\Phi\left(\frac{y(t)-\mu}{\sigma}\right)$. Consequently, the final model will take the form

$$z(t) = KP(H \le y(t))\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}. \tag{7}$$

A graphical representation of the model proposed in (7) may help to appreciate the difference with the Bass model.

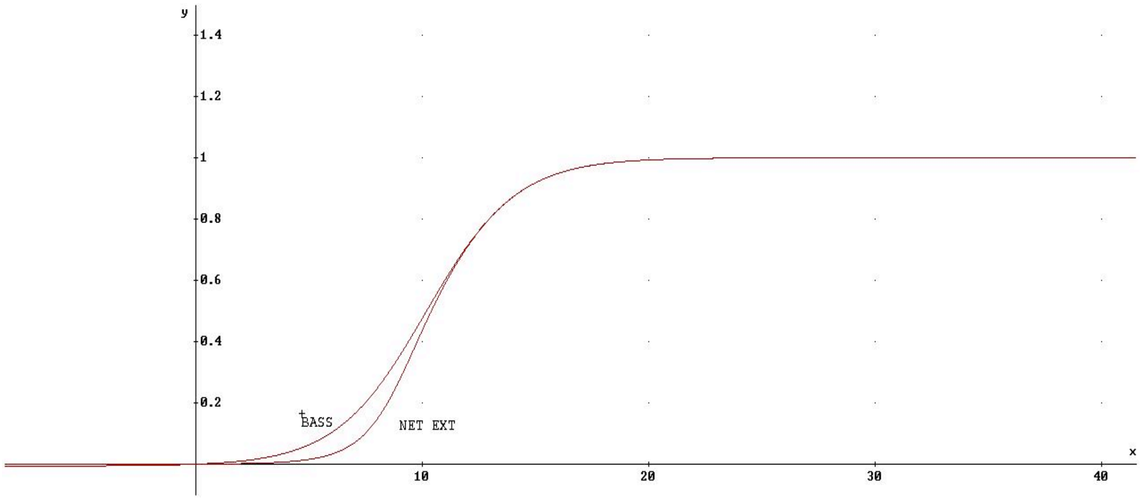

Figure 1. Standard Bass model versus Bass model with network externalities: cumulative adoptions.

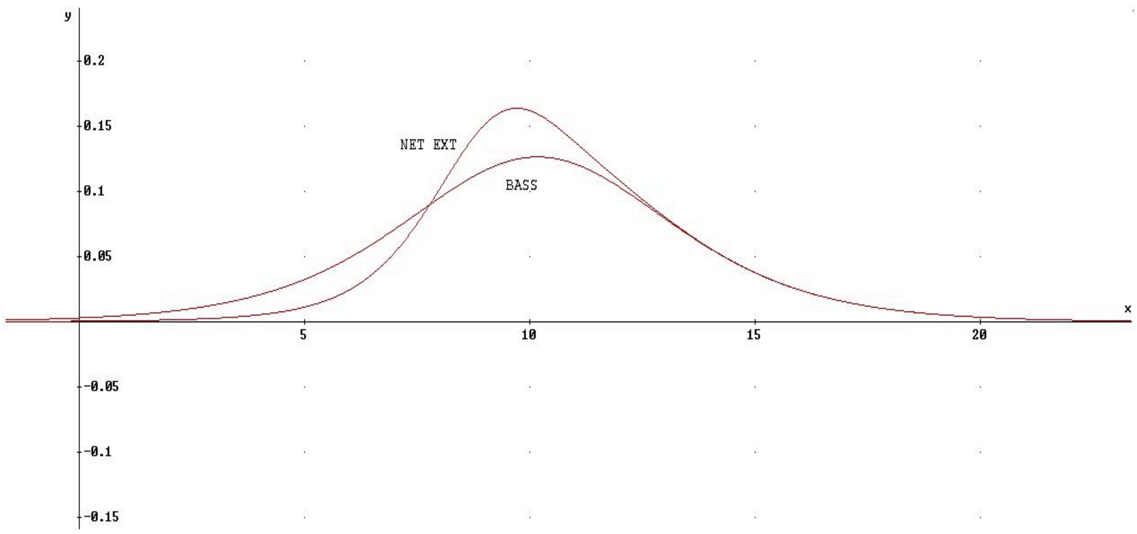

Figure 2. Standard Bass model versus Bass model with network externalities: instantaneous adoptions.

Figure 1 and 2 allow a direct comparison between a standard Bass model and the extended version with the dynamic market potential, in order to incorporate network externalities effects. The model's parameters have been set to the following values: $p = 0.003$, $q = 0.5$, $K = 1$, $\mu = 0.2$, $\sigma = 0.2$.

It may be easily observed that the exteded model with network externalities would offer a better representation of the long left tail of diffusion than that provided by a standard Bass model. In this sense, this extension seems more suitable for modelling situations affected by network externalities, like diffusions of interactive innovations. Also notice that for a constant market potential $m(t) = m$, we obtain the structure of the standard Bass model.

This chapter has presented as a perspective of future research the case of innovation diffusion with network externalities. Given that network externalities imply a considerable chilling effect on early phases of new product growth, as demonstrated by the long left tail of the diffusion curve, it has been argued that the model should be based on a rationale similar to that developed in Chapter 3, considering the structure of a variable market potential. Specifically, it has been considered that network externalities may affect the structure of the market potential, whose size is not given, but depends on the willingness to adopt of individuals with different degrees of resistance to new products, whose utility is determined by the presence of a network of users (i.e. interactive innovations). The proposed model grounds on the well known literature on threshold models of collective behaviour and presents a possible insight on how to separate the effect of network externalities from other diffusion related phenomena, like word-of-mouth, a topic of research also indicated by Muller, Peres and Mahajan (2007).

4.4 Discussion and further directions of research

Since new products and technologies directly affect many aspects of the life of persons, communities, countries and economies, the diffusion of innovations appears a very important field of research. Many scholars have dedicated their inquiries to several aspects of diffusion, whose current understanding benefits of the contribution offered by various disciplines, namely marketing, economics, natural sciences, mathematics and statistics, social sciences and geography. The field of marketing has become particularly strong since the 1970s after the formalization of the most famous models of innovation diffusion, Fourt and Woodlock (1960), Mansfield (1962), Bass (1969), whose general purpose is forecasting the development of a product life cycle already in progress, identifying the main drivers of it, like institutional communication, word-of-mouth, learning, individuals' characteristics, and its most crucial phases, such as, take off, point of maximum growth and market saturation. Innovation diffusion models can be used both in a predictive way and for *post hoc* explanations of facts, helping to understand the evolution of a particular market, its response to various factors, like marketing strategies, incentive mechanisms, change in prices, policy measures. A timely investigation on the evolving structure of markets for innovations seems particularly crucial from an economic and managerial perspective, especially considering the shortening of innovation life cycles, the increasing level of competition between firms and products, the rise of successive generations of product, that require to manage commitments and resources.

Chapter 1 has been dedicated to analyse and discuss several aspects of the most famous and employed diffusion model, the Bass one, which constitutes a fundamental reference of a huge body of literature principally, but not exclusively, produced in marketing research since its publication in Management Science. The formal structure of the model has been presented, highlighting the conceptual hypotheses underlying its use in the context of new product growth, its main mathematical properties and some of its characterizing assumptions, like the constant level of the market potential, that permit to deal with a simplified yet powerful model. Some aspects on the statistical implementation of the Bass model have been presented in a dedicated section, also pointing out some typical estimation problems, like the tendency to underestimate the size of the market potential. Two examples of the concrete use of the Bass model in real diffusion processes have been presented: the first one refers to the diffusion of a new pharmaceutical drug in Italy, the second one to the diffusion of solar energy technologies in Japan, thus evidencing that the model represents a valid tool of analysis and technological forecasting in a broad set of industrial sectors. Indeed, the applicability of the Bass model has been proven to range over durable goods, services, entertainment products, technologies, agricultural products, medical innovations, Internet services. Probably the most valuable extension of the Bass model is represented by the Generalized Bass model, GBM (Bass, Krishnan and Jain, 1994) that allows to take into account marketing mix variables like advertising and price strategies and test their impact on diffusion, by multiplying a time dependent intervention function $x(t)$ to the standard structure of the BM. Though conceived to represent the effect of advertising and price changes on growth, the GBM is suitable to describe patterns of growth affected by various kinds of exogenous interventions, like marketing variables other than price and advertising and non-marketing factors influencing diffusion, such as environmental upheavals and policy measures. In this sense, it represents a relevant instrument of analysis and market diagnostics, particularly for cross-country studies, where social, political and cultural differences among countries are determining factors to explain different responses to innovation and related diffusion processes may strongly depart from the bell shaped form, described by the Bass model. The GBM yields a crucial result: the introduction of exogenous variables to alter diffusion is able to modify the temporal structure of it, anticipating or delaying adoptions, and not the diffusion parameters, market potential in particular, whose size is formally independent of it. The GBM proves to be essential in modelling and accounting for the effect of external dynamics on the diffusion process: however, it is also important to detect and understand those dynamics that are internal to the diffusion process and may affect it even in a more serious way. Indeed, the need to extend in several directions the basic structure of the Bass model, in order to take into account variables and factors that clearly have an impact on diffusion has been indicated as a primary issue of research in the most important reviews on this theme: consumers' heterogeneity, interdependences between individuals that tie their utilities and influence final adoption decisions, like social interactions and network externalities, spatial proximity and the rise of networks within diffusion are some of the relevant aspects that should deserve more investigation, according to these. In this sense, encouraging perspectives seem to be produced by the study of diffusion related phenomena with the Complex Systems Theory, in particular with Agent-Based models, like Cellular Automata models and Network models.

Chapter 2 deals with the analysis of Cellular Automata models, CA, that are widely used in many scientific disciplines for studying the emergence of a collective behaviour with a bottom-up perspective, that is, from the characterization of individual agents, acting with just local information. The advantage provided by this class of models is the possibility to test how a collective structure may change as individual conditions do and therefore to provide a representation of how single choices, once aggregated, may produce results not obvious *a priori*. In this sense, Cellular Automata models represent a very interesting opportunity to research on diffusion, offering a new way to study individual characteristics that surely affect diffusion, but that are hardly understandable just from an aggregate point of view. While CA are generally implemented through computer simulations, some uncertainties on the reliability of these instruments, have suggested to follow a different path, trying to study a formal connection between these models and aggregate ones. This has led to find the interesting result that the aggregate structure of the Bass model can be reconstructed from an individual rule of behaviour specified in a CA, through a *mean field approximation*, thus avoiding computer simulations. This achievement has opened the possibility to design new aggregate models, incorporating assumptions and elements of an agent's behaviour, with a bottom-up perspective. The first development of this procedure presented in Chapter 2 is an aggregate model for innovation diffusion, that extends the Bass model in taking into account both inward and outward flows of adopters: this model seems particularly useful for those situations where disadoption cannot be neglected, as in the case of services, where customers' retention is a crucial concern for firms providing them. Some difficulties in the statistical implementation of this model have been observed, both for lack of data that simultaneously account for adoptions and disadoptions and for some instabilities in parameter estimation, so that much research on these aspects should be certainly due. In addition, the first specification of the model considers disadoptions as individuals' independent decisions: however, also describing this choice as the result of an imitative process would deserve a focused attention.

In general, the interesting feature of the CA approach with respect to the aggregate one is the possibility to deal with single agents, whose interactions and sources of information are essentially local. The local nature of agents' interactions suggests that the CA approach may be useful for studying spatial diffusion. The purpose of spatial diffusion is to model how products diffuse over *space*, and though its theory is not so well developed especially in the marketing field, it appears an important theme of investigation. Recent reviews on innovation diffusion models (see for example Muller, Peres and Mahajan, 2007) have pointed out that it is still an open question whether additional information conveyed by spatial aspects of diffusion can help a better prediction of its course and thus a methodological framework, including definitions, measures and tools needs to first be constructed. Moreover, it would be certainly interesting to verify and formalize the intuition that spatial proximity may stimulate the formation of clusters or networks of adopters and therefore facilitate diffusion, or on the contrary, if spatial constraints can create a sort of resistance to it.

The fact that diffusion is tied to the formation of networks of consumers constitutes the central topic of Chapter 3. In this chapter it has been proposed a model, that tries to map simultaneously an innovation diffusion process and the evolution of a network of consumers, that create connections in order to share information about the innovation and give rise to a common knowledge about it. In fact, while innovation diffusion is generally defined as a theory of communication, typical models do not consider stages of knowledge and awareness before adoption, although these are clearly a precondition for adoptions to occur. Communication mechanisms in the form of marketing efforts and word-of-mouth seem to have a crucial role in stimulating awareness, so that their impact should be isolated and understood for the consequences it has on adoptions.

The model assumes that communication dynamics exert their effect in generating the market potential for an innovation, since an individual becomes a potential adopter after being informed about it. A central assumption of the Bass model, that of the constant size of the market potential is therefore discussed, rather proposing a dynamic market potential that depends on the creation of a collective knowledge about the innovation. Grounding on existing literature on this, such collective knowledge has been represented as an evolving network, in which connections between consumers rise and die in order to share information and create a mutual understanding. The network has been designed using a particular class of Cellular Automata models, Network Automata models, in order to represent how a single connection between agents can be formed or destructed. Its aggregate evolutionary structure has been obtained through a *mean field approximation* and finally incorporated into an innovation diffusion model, in which information and innovation diffusion are separate but co-evolving processes. The model allows to infer the influence that communication has had on adoptions and is therefore suitable for all those diffusion processes in which consumers' knowledge is a particularly crucial variable. Two case studies have been proposed in order to test the performance of the model as well as to show its improvement with respect to the Bass model in predictive terms.

Given the first results obtained, future research should certainly test the model with other case studies and other data series, trying to give more evidence of its possible usefulness for managerial aspects. Moreover, the model appears to provide a reasonable insight on the intriguing paradox characterizing successive generations of product: it has been demonstrated that adoption parameters across generations remain essentially stable and at the same time that the speed of product life cycles accelerates over time.

This apparently contradictory aspect could be explained arguing that successive generations do not differ for adoption parameters, but for communication parameters. In other words, the acceleration over time of life cycles depends on how fast the market potential has been generated: while the first generation of an innovation is the most critical one, for which the development of a market potential as function of knowledge is particularly crucial and cannot be considered instantaneous, this task is surely easier for successive generations, because consumers' already know the product and are ready to accept it, so that the market potential is generated quite fast.

Another perspective of research has been presented in the first part of this Chapter, representing an evolution of Chapter 3. While in Chapter 3 the market potential for an innovation has been designed as function of a communication process, in Chapter 4 it has been made depend on individual thresholds. Individual thresholds are an important factor for describing the decision to adopt innovations characterized by strong network externalities (telephones, fax machines, emails, Internet), whose utility depends on the creation and expansion of a physical network of interacting devices. Assuming a variable structure of the market potential helps to explain the incubation period typical of diffusion processes affected by network externalities. Moreover, it may help to understand why economic theory has generally considered network externalities as a competitive advantage for firms: this appears true if the product has had success, that is, if it has reached the critical mass. From that stage network externalities may become beneficial, but until then the firm has to bear the costs associated to an extremely slow adoption process (e.g. the incubation period for fax machines lasted about 20 years in the USA).

Network externalities provide an excellent example of the need to look at both sides of economies to understand their evolution and a stimulating opportunity for combining theories and concepts of different disciplines, such as economics and marketing. Further research in this direction is therefore aimed at providing a deeper understanding of the effect of network externalities on new product growth, through likely improvements of the preliminary model proposed in this chapter, empirical applications with appropriate data sets in order to verify if incorporating this phenomenon may produce more reliable forecasts, better characterizations of individual thresholds accounting for economic factors that may influence the benefits and costs associated to the decision to adopt.

A first concern is clearly related to the empirical testing of the model with appropriate data sets, in order to verify its suitability for analyzing diffusion contexts affected by network externalities. Exploratory tests seem encouraging in this sense: for example, a preliminary application of the model to the cumulative downloads data of Skype, the Internet telephony service launched in 2004, yields quite promising results to be further developed and improved. It is necessary to notice that for achieving the purpose, further assumptions on the structure of the market potential as function of thresholds seem particularly crucial. In fact, since individual thresholds are compared with the proportion of adoptions, $y(t)$, it seems reasonable that, as adoptions increase, the average value of thresholds will decrease. This aspect may be modelled through a time-dependent value of the mean μ.

Another noteworthy aspect for modelling network externalities is clearly the achievement of the critical mass, that is the minimal number of adopters of an interactive innovation for the further rate of adoption to be self-sustaining. Revealing when such critical mass has been reached is certainly a crucial aspect for managerial purposes: however, it is important to observe that it is almost impossible to tell *ex ante* if and when the critical mass will be reached, since the success of an innovation is never guaranteed. As a consequence, the proposed model can be applied to data series in which the incubation phase has been already overcome and the success of the innovation is testified in data. In this sense, the model does not have a predictive value in foreseeing the achievement of the critical mass (a process that may last several years as in the case of fax machines), but allows the recognize the applying effect of network externalities and how long it has lasted. Similarly to the case studied in Chapter 3, failing to reveal a chilling effect on new product growth, may introduce evident bias in parameter estimation, specifically in the estimation of the market potential, and therefore limit in important ways the usefulness of an innovation diffusion model in strategic and predictive terms.

The concept of a dynamic market potential in innovation diffusion models may open various opportunities of further research: not taking the market potential as a given measure indeed stimulates a broad reflection on the aspects and elements that may facilitate an adoption process. This thesis has especially focused on the level of knowledge, which is necessary for understanding and appreciating the value of a new product. In this sense, innovative products endowed with an evident relative advantage and a low degree of complexity may be easily adopted by final users. However, high tech products often present such complex features that are hardly understandable by the average consumer: it follows the need of specific communication efforts and informative campaigns in order to aid people awareness.

Network externalities represent another determining factor: though in this chapter it has been argued that these imply a penalization on new product diffusion, network externalities are also a considerable source of advantage, once the innovation has reached a critical mass of adopters. In literature (see, for instance, Unruh, 2000) it has been pointed out that network externalities arising from systemic relations among technologies, infrastructures, interdependent industries and users, may imply a powerful lock-in condition. In fact, the growth of interconnected networks and subsystems generally requires a high level of coordination, which is achieved through the establishment of codified standards and conventions (some examples include 110 and 220 V current, the hypertext markup language, HTML, etc.). The introduction of standards presents the notable advantage of reducing uncertainties on the one hand, but tends to create (strong) barriers to the emergence of innovative solutions, whose features do not meet the requirements of the *dominant design*. The concept of *dominant design* has been conceived in the evolutionary economics reasoning (see Nelson, 1995) to theorize the fact that in the early stages of a technology's history there usually are a number of competing variants in order to meet some expected consumer demand and the competition among these, generating a period of uncertainty, ends when one of the variants captures a significant market share and becomes the dominant solution. Dominant design models have been applied to numerous industries, showing that actually a superior technological variant does not necessarily become the dominant one, because other mechanisms, such as network externalities, may interfere and determine the winner. The concept of dominant design would suggest that the features of an innovation are a very critical aspect for the generation of a market potential, and therefore for the diffusion process. In addition, it offers a useful insight to see that in early stages of a diffusion process, the market potential for an innovation is highly unstable because of the presence of other technological solutions, "competing for the same resource". Specific efforts in research may be therefore focused on modelling the market potential of an innovation as function of other factors, not accounted in this thesis, and, in parallel, on modelling multivariate diffusion processes, able to reveal dynamics of competition and substitution between technologies.

Consequently, the innovation diffusion approach, enlarged with more flexible structures that consider variable structures of market potentials, competition and substitution dynamics, various sources of consumers' heterogeneity may offer an important, customer-oriented integration to the theory of technological evolution, which has generally maintained a supply-side view. In this sense Hauser, Tellis and Griffin (2006) have argued that a consumer-oriented perspective would complement rather than replace theories of technology supply and development.