Technology Diffusion

3

(. . .) diffusion concerns issues that are among the more difficult to analyze adequately. Time is involved. Uncertainty is inherent. Change is the major topic. Imperfect markets abound

Paul Stoneman (2002)

Abstract

This chapter provides a theoretical framework of technology diffusion, which is defined as a dynamic and time-attributed process involving the transfer of information, knowledge and innovations, and standing for a continuous and gradual spread of new ideas throughout large-scale and heterogeneous societies. First, it extensively discusses theoretical technology diffusion concepts and models, explaining the technology diffusion trajectories by the use of S-shaped curves. Second, it presents the fundamental ideas and models standing behind the idea of technological substitution. Third, there is demonstrated a novel approach to identification of the 'technological take-off' and 'critical mass' effects with respect to the dynamics of the technology diffusion process and its prerequisites. Finally, based on theoretical frameworks derived from economic growth theories, it shows conceptualizations of technology convergence and technology convergence clubs.

Keywords

Technology diffusion • S-curve • Technological substitution • Technology convergence • Technology convergence clubs • Critical mass • Technological takeoff

3.1 Technology Diffusion: Theoretical Framework

The term '*diffusion*' originates from the Latin nouns '*diffusio*' and '*diffusionis*', and the verb '*diffundere*'. By definition, it refers to the process of spread, expansion, dissemination, propagation or generalization.

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Diffusion is a dynamic and time-related process, involving the transfer of information, knowledge and innovations. It stands for a continuous and gradual spread of new ideas and concepts, over large-scale and heterogeneous societies (Gray 1973). Therefore, from the socio-economic perspective, the diffusion of innovations, new technologies and new ideas is of seminal importance, as it provokes profound changes in society and economy, impacting shifts in productivity and education, and transforming markets and organizations, among other things.

The concept of diffusion of innovation developed by Everett Rogers (2010), and extensively described in his touchstone book 'Diffusion of innovation'[1], constitutes a starting point for a great variety of discussions on technology diffusion. Rogers (2010) defines technology diffusion as '*the process by which an innovation is communicated through certain channels over time among members of a social system*'. Mansfield (1961, 1968, 1971), following Rogers, emphasizes the unique role of 'two-step' communication in diffusion processes, which enables the exchange of knowledge between 'users' and 'non-users' about the advantages of new technologies.

Gray (1973) calls the process of diffusion the spread of innovations, which depends on the effectiveness of communication channels and social attitudes. Davies (1979) defines technology diffusion in a *strict* economic sense, claiming that the process can be seen as passing from an equilibrium state, determined by the use of 'old' technology, to another equilibrium where the whole society adopts the 'new' technology. This approach suggests that shifting from one technology to another, over a diffusion time path, implies that the process is marked by constantly emerging disequilibria. Nathan Rosenberg (1982) in his seminal book '*Inside the black box: technology and economics*', underlines that diffusion introduces inventions into economy and society, and thus is perceived as being of seminal importance for further development. On the same lines, Mansfield (1986) recognizes diffusion as a process of transfer of innovation which hugely affects national economies. Following Rogers's concept, Mahajan and Peterson (1985) claim that technology diffusion stands for the spread of ideas over time among society members. Paul David (1986) argues that through diffusion channels new technologies randomly reach new users; however, considering the socio-economic environment, the process is less hazardous as agents are driven by the anticipated profitability of new technologies. A broader perspective on the perception of diffusion was proposed by John S. Metcalfe (1997), who considers diffusion as flows of a multitude of technological improvements which—despite the fact that they spread instantaneously—bring crucial changes to technological, social and economic progress. Stoneman (1995) argues that the process of diffusion involves increases in the number of adopters of new technologies, which results in a growing number of users, while Sarkar (1998) states that '*technological diffusion can be*

[1] In his work 'Diffusion of Innovation', E. Rogers presents 508 different case studies explaining the diffusion of different innovations adopted by both companies and individuals in rural areas (see Rogers and Havens 1962).

defined as a mechanism that spreads 'successful' varieties of products and processes through an economic structure and displaces wholly or partly the existing 'inferior' varieties'. Stoneman (2002) also suggests that the process of diffusion of innovation explains the constant expansion of newly emerging technologies which are being gradually adopted and used by individuals and/or companies[2]. Following the logic of Metcalfe, Saviotti (2002) argues that technology diffusion brings a wide array of new products to markets, and thus is perceived by societies as highly desirable. Apart from the contributions mentioned above, there exists a substantial body of literature discussing conceptual issues associated with technology diffusion. Various aspects of technology diffusion are studied in the works of Kindleberger (1995), Bell and Pavitt (1995, 1997), Geroski (1990, 2000), Reinganum (1981a, 1989), Castellacci (2006b, 2007), Helpman (1998), Findlay (1978a, b), Battisti (2008), Stoneman and Battisti (2010), Ireland and Stoneman (1986), Karshenas and Stoneman (1993, 1995), Fagerberg and Verspagen (2002), Kapur (1995, 2001), Gomulka (2006), Kubielas (2009), Antonelli (1986, 1991), Dosi and Nelson (1994), Dosi (1991), Soete and Turner (1984), Comin and Hobijn (2006).

The contemporary qualitative and quantitative conceptualization of technology diffusion is deeply rooted in the evolutionary paradigm of Charles Darwin (1968) and his pioneering work on natural growth and the spatial diffusion of species; but it also refers to the theories of natural selection developed by Fisher (1930). Darwin (1968) predicted the unique ability of species to multiply at exponential growth rates, and to compete for survival in the environment in which they live. This concept was then gradually adjusted for multipurpose use in the economic sciences, rigidly assuming that 'species' are various variables (e.g. national income, technology or products) which tend to grow over time. Today, technology diffusion theories are designed to explain the spread of new ideas, innovations and technologies within societies. Thus the process itself is strongly related to time and its speed depends on the unique characteristics of people (Rogers and Shoemaker 1971; Metcalfe 1997). Moreover, technology diffusion theories allow for detecting patterns in the spread of new ideas, discovering regularities that the process depends upon, and identifying factors stimulating or impeding it. Difficulties associated with the elaboration of diffusion trajectories of newly emerging technologies reflect the heterogeneity of the social and economic environment (Rosenberg 1972). People rarely make their decisions interdependently (Geroski 2000), their cognitive capacities are limited, and various reference points are referred to before accepting or rejecting new technology (Dosi 1991). People's behaviour is driven by customs, culture, traditions and moral attitudes (Simon 1972; Silverberg 1994). Moreover, an individual's decision on the adoption of a new technology is made under uncertainty (Keller 2004; Ward and Pede 2013) and through cost-benefit analysis. Risk-averse people will adopt innovations once they notice that a 'new' one brings relatively greater

[2] Agents.

advantages compared to the 'old' one, and consequently the 'old' is replaced by the 'new' and better technology (Hall and Khan 2003). However, it is important to note that diverse personal characteristics determine the diffusion time path, illuminating the strength of the '*domino effect*' which perpetuates the spread of new ideas. Rogers (2010) claims that the diffusion process encompasses four major elements: (1) innovation; (2) communication channels; (3) time; (4) a social system. He defines an innovation as a new idea (i.e. product) which is desirably adopted by market agents, and the process happens over time. As diffusion is time-related, the rate of diffusion[3]—explaining the speed at which individuals in heterogeneous societies adopt new ideas—is recognized as its most prominent feature. The speed of diffusion is, however, heavily conditioned by social system absorptive and learning capabilities, as well as by the propensity and ability to adopt novelties (Cohen and Levinthal 1990; Keller 1996; Castellacci and Natera 2013; Lall 1992). This implies that existing communication channels (means and forms of communication and information dissemination) and social systems (defined as sets of social norms, formal and informal institutions) precondition both diffusion itself and its speed (Rogers 1976).

Despite potential disruptions, discontinuities and permanent uncertainty (Ehrnberg 1995), the phenomenon of rises and falls of new technologies is well described by simple logistic growth models and S-shaped curves that are generated by plotting the technology's behaviour over time, as this unique shape allows for a straightforward explanation of the characteristic phases of the diffusion process. Simply plotting the total number of adopters of new technology *versus* time generates the sigmoid curve, and the special shape of this sigmoid pattern[4] explains the characteristic phases of the diffusion process. It is slow initially, then it accelerates (the '*domino effect*' is revealed), and finally slows down, heading for the stabilization phase as the population approaches full saturation regarding the new technology (Jaber 2011). Rogers (2010) uses a derivative of the sigmoid curve—the bell-shaped curve (Nakicenovic 1991; Van den Bulte and Stremersch 2004)—to show five types of adopters: (1) innovators, (2) early adopters, (3) the early majority, (4) the late majority and (5) laggards. The group of 'innovators' introduces new technologies to societies, while the 'early adopters' are those who acquire novelties quickly and demonstrate little risk-aversion. The 'early majority' group follows the 'early adopters' and, *prior* to decisions made by the 'early majority' decide to adopt the new technologies expecting benefits. The last two groups—the 'late majority' and the 'laggards'—are those who are generally uncomfortable with new technologies and lag behind in their broad adoption[5].

[3] The rate of diffusion is additionally associated with the concept of '*critical mass*' and it reveals 'network effects'—explained in Sect. 3.3.

[4] The unique characteristics and basic mathematics related to sigmoid curves are explained in Sect. 3.2.

[5] Goeffrey Moore, in his book 'Crossing the Chasm' (1991), proposes a modified version of Roger's bell-curve. He emphasizes the role of 'disruptive innovations' that generate the chasm

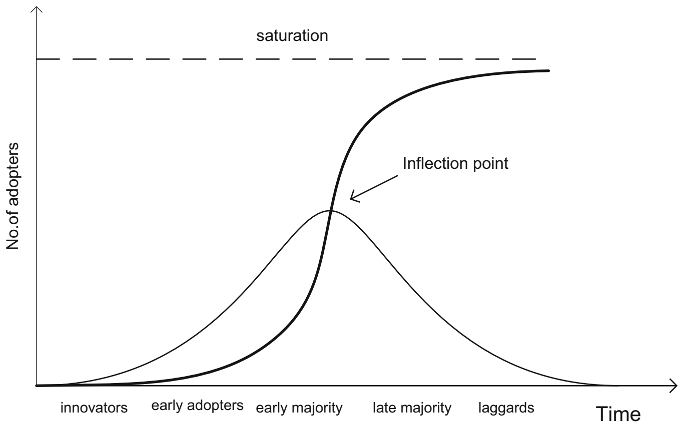

Fig. 3.1 Diffusion and innovation expansion curves. Theoretical specification

Figure 3.1 presents the cumulative sigmoid curve, approximating the new technology diffusion time path, and its derivative—the bell-curve.

The bell curve explains knowledge accumulation (or expansion of innovation) that is generated by the gradual diffusion of new technology through society. The slope of the bell curve decreases systematically as the cumulative number of adopters grows, and its maximum coincides with the inflection point of the S-shaped pattern.

The logic and basic mathematics used to formalize the phenomenon of the diffusion of technologies and the process of shifting from 'old' to 'new' ones is explained by technology diffusion and technological substitution models, discussed in the following Sect. 3.2.

3.2 Technology Diffusion and Technological Substitution

> Models are abstractions and simplifications of reality. Useful models capture the essence of reality in a way that enhances the understanding of phenomena
> Frank M. Bass (2004)

The technology diffusion process is formalized in a wide array of 'technology diffusion models' describing how novel emerging technologies tend to spread through societies. Most of these models are well grounded in mathematics, which allows *ex-post* diffusion trajectories to be approximated; and, relying on rigid assumptions, future development scenarios and forecasts to be draw up.

(gap, discontinuities) between the group of innovators and the early adopters and the group of the early majority, the late majority and the laggards.

3.2.1 Technology Diffusion. Concepts and models

> For people who attempt to forecast the future, there is a continuing need for simple models that describe the course of unfolding events. Each such model should be based upon easily understood assumptions that are not susceptible to unconscious or invisible tampering by the forecaster in his efforts to make the future what he wants it to be. The model should be easy to apply to a wide variety of circumstances, and should be easy to interpret
> Fisher and Pry (1972)

As clarified in Sect. 3.1, the term ‘diffusion’ has multiple meanings. However, despite the diversity, it refers to the process of the physical spread of ideas, products and many other things in the human environment. Time plays a central role in most empirical studies that concern technology diffusion, as regardless of the source of an innovation, its type and the cost of acquiring it, it is always a time-consuming process for innovations to spread through societies and to be fully adopted and used. A great part of the theoretical and empirical literature on technology diffusion is mainly concerned with first the identification of factors that determine (enhance or hinder) the diffusion process, and second tracing causal links between the technology diffusion dynamics and its determinants. Put another way, diffusion models allow projections of how fast the technology will expand, and when (or *if*) the total population will be saturated with the new technology.

As discussed in Karshenas and Stoneman (1993), theories of technology diffusion can be classified into four general categories: epidemic models, rank (probit) models, order models, and stock models. The theoretical specifications falling within each of the four categories exclusively analyze technology diffusion from the demand-side perspective, and refer to stand-alone technologies, assuming that uncertainty does not emerge. In this book, to meet the general goals of our empirical analysis, we concentrate on technology diffusion models originating from ‘epidemic models’, as they well suit the major aims of our research, although the other theories and models are briefly discussed in this section.

Theoretically, technology diffusion process is analogous to the spread of information over society. Thus, the growing ‘*mass*’ of those who get the information depends on intensity and the number of contacts that facilitate further information spread and acquisition. In a broad sense, this assumption yields the adoption of ‘epidemic models’ to explain technology diffusion dynamics and trajectories, while the adjustment of ‘epidemic models’ to the needs of the formal analysis of technology diffusion leads to incorporating the concept of the logistic growth curve,[6] which allows for approximating diffusion trajectories.

Originally, the concept of ‘epidemic models’ was derived from an analogy between the spread of contagious diseases and that of technological innovation (Sarkar 1998; Kumar and Krishnan 2002). The general logic behind the epidemic model is following. Suppose we have an area where a population of hypothetical agents (adopters, users) lives that tends to acquire new technologies as they emerge.

[6] The concepts and mathematics underlying logistic growth are explained in Sect. 3.2.2.

Moreover, the number of these potential adopters is constant over time. Initially, the groups of ‘users’ and ‘non-users’ coexist, but the ‘non-users’ imitate those who already use new technologies and are gradually ‘*contaminated*’. Hence, the ‘*contamination effect*’ arises (Gray 1973) as agents are involved in personal contacts, which perpetuate the process of further diffusion. It is assumed that the probability of ‘*contamination*’ is time invariant and ‘non-users’ convert into ‘users’ once the two get in touch; thus, the ‘adopters’ (‘users’) influence social systems in such a way that the total number of ‘adopters’ increases. In systems where innovation spreads, information and interpersonal contacts are perceived as significant driving forces of diffusion processes, which inevitably leads to a growing number of ‘users’ (Stoneman 2002). The concept of epidemics, adjusted to the needs of technology diffusion analysis, can be formalized as follows. Suppose that N denotes the total number of potential users of a new technology, and $n(t)$ stands for the actual number of those who have already adopted the new technology at time t. We assume that new adopters arrive as they get information on newly emerging technologies, and the process of transmitting information is not disrupted by any external factor. φ represents the probability of getting ‘*contaminated*’ and acquiring new technology, so that the total number of users at a certain point in time t is expressed as (Stoneman 2002):

$$\frac{dn(t)}{dt} = \frac{\tau \cdot n(t)}{N(N - n(t))}, \tag{3.1}$$

where $\tau = \varphi \cdot \vartheta$, and ϑ stands for the probability that the contact between a ‘user’ and ‘non-user’ will be effective and lead to the adoption of the new technology. If Eq. (3.1) is a class of first-order differential equations, its solution can be formally written as:

$$n(t) = \frac{N}{(1 + \exp\{-\beta - \alpha t\})}. \tag{3.2}$$

In Eq. (3.2), τ from Eq. (3.1), is replaced by α. Equation (3.2) is the classical formula for a logistic curve with imposed growth limits (N), where β denotes the initial year of diffusion, and α is the rate (speed) of diffusion.

Starting from the late 1950s, many contributions in the field of technology diffusion studies were made. Extensive empirical analyses of technological diffusion both within and between countries were conducted (see, e.g., the works of Griliches 1957; Mansfield 1961, 1968), which resulted in the elaboration of diffusion models that provided theoretical frameworks for more sophisticated formal analysis of technology diffusion. The oldest and probably the most influential model of technology diffusion, strictly basing itself on the concept of ‘epidemics’, was proposed by Edwin Mansfield (1961). His pioneering works gave a solid background for future studies of technology diffusion and its economic consequences (Metcalfe 2004). In his works, Mansfield, strongly incorporates evolutionary ideas (Darwin 1968; Fisher 1930) into technology diffusion theories, which *inter alia*, induced a broad adoption of logistic curves into the analysis of the dynamics of innovation spread. The idea of incorporating logistic laws of evolution (Darwin 1968; Fisher 1930) into formalized concepts of technology diffusion was provoked by the analogies observed between the evolutionary paths of natural and social systems. The dynamics of evolving populations is significantly driven by a competitive selection process (Dosi and Nelson 1994; Silverberg and Verspagen 1995; Metcalfe 2004) that is often reported in economic processes. Social systems or market structures tend to evolve along time paths, and logistic laws can successfully approximate the dynamics of the evolutionary process. In the literature, Mansfield's prime technology diffusion model is classified as an evolutionary disequilibrium model (Srivastava and Rao 1990). It relies on four fundamental assumptions (Mahajan and Peterson 1985; Sarkar 1998): (1) adopters are rational; (2) adopters do not necessarily head for profit maximization that would be potentially obtained from new technology acquisition; (3) technology diffusion is self-perpetuating, and thus endogenous; and (4) the technology diffusion process might not be continuous and is disequilibrating in its nature. Even if it is assumed that the equilibrium is represented by N (in Eq. (3.2)), the level of use of the technology at time t $\left(\rightarrow n(t)\right)$ is always below N. Diffusion trajectories can, however, be explained as processes of constant adjustment of the level of $n(t)$, which is approaching N. To capture the process of new technology spread, Mansfield suggests adopting a logistic growth equation to explain the phenomenon. Additionally, he introduces the '*word of mouth*' effect (Geroski 2000; Lee et al. 2010) to the formal model. This emerges once potential adopters of the new technology tend to communicate among themselves, which transmits knowledge of the advantages of new technologies[7]. Put another way, Mansfield's model assumes that the technology diffusion process is pre-determined by previous users, as they are the main source of information about new technologies.

Equation (3.3), below, summarizes Mansfield's technology diffusion concept. Assume that each 'user' of a new technology freely contacts a 'non-user', which leads to the adoption of the new technology by the latter, and the probability of an 'effective' contact is denoted as ϑ. If the total number of 'users' increases by Δt, and $\Delta t \rightarrow 0$, the time path for technology diffusion yields:

$$n(t) = N/(1 + \vartheta \exp[-\mu t])^{-1}, \tag{3.3}$$

or alternatively:

$$n(t) = \frac{N}{(1 + \vartheta \exp[-\mu t])}, \tag{3.4}$$

where $n(t)$ is the number of 'users' at time t, and N the potential number of total 'users'. Following Geroski (2000), for Eqs. (3.3 and 3.4) we assume that $\mu \equiv \vartheta N$ and

[7] '*Word of mouth*' models are also labelled '*contact*' or '*disease*' models.

$\vartheta \equiv (N - n(0))/(n(0))$, where $n(0)$ stands for the number of 'users' in the initial year of technology diffusion. Mansfield's model of technology diffusion explains the process as long as it is purely imitative. Thus, it explains the diffusion exclusively by the internal influence (Turk and Trkman 2012) of earlier adopters who, due to the '*word of mouth*' effect, transmit information to later adopters. However, if we relax the assumption of strictly endogenous determinants of technology diffusion among 'non-users', and incorporate exogenous (external) factors which influence the diffusion process (Lee et al. 2010), Eq. (3.3) can be expressed in an adjusted form. Frank Bass (1969, 1974, 1980, 2004; Bass and Parsons 1969) in the late 1960s developed an extended version of the Mansfield model by incorporating a new 'innovator perspective'. The Bass model relies on the assumption that technology diffusion is determined not only by 'imitators' but also by 'innovators' (those who intend to try new technologies), who *massively* influence the decisions made by their peers (Satoh 2001). The Bass specification is also recognized as a 'mixed-information-source' model, as it assumes that 'users' of new technology differentiate their decision 'to adopt or not' according to information obtained from various sources. In the Bass diffusion model, it is assumed that the speed (rate) of diffusion is shaped by imitation and innovation determinants. If this is true, then, following the logic of the Bass model, we can propose that the final outcome of new technology diffusion can be easily decomposed into an 'innovation effect' and an 'imitation effect'. The basic linear specification of the Bass formula (1969) is as follows:

$$S(t) = p + \frac{q}{\kappa}(N(t)), \tag{3.5}$$

where $S(t)$ specifies the likelihood of adoption of the new technology by a 'non-user' at time t, p is the imitation coefficient, q is the innovation coefficient, and $N(t)$ is the cumulative adoption of the new technology (product) at time t. By differentiating Eq. (3.5), we obtain (Satoh 2001):

$$\frac{dN(t)}{dt} = \left(p + \frac{q}{\kappa}N(t)\right) \times (\kappa - N(t)). \tag{3.6}$$

In Eq. (3.6), p and q are parameters, $N(t)$ explains the same as in Eq. (3.5), while κ is the total potential number of users of the new technology (product). Imposing that $F(t)$ is the fraction of potential 'users' who have adopted the new technology at time t, so that $F(t) = {}^{N(t)}\!/_{\kappa'}$, we rewrite Eq. (3.6) as:

$$\frac{dF(t)}{dt} = (p + qF(t)) \times (1 - F(t)). \tag{3.7}$$

The time path for new technology diffusion following the Bass specification is:

$$N(t) = \kappa\left(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\right), \tag{3.8}$$

with notation analogous to that in Eqs. (3.5–3.7). Estimation of Eq. (3.8) returns predictions on the growth in the number of users of the new technology (product). The inflection point in the diffusion time path is at:

$$N(t^*) = \kappa\left(\frac{1}{2} - \frac{p}{2q}\right), \tag{3.9}$$

if $t^* = -\frac{1}{p+q} ln \frac{p}{q}$, and under the condition that $N(t = t_0 = 0) = 0$.

Today, the Bass model is broadly applied in marketing, mainly in predictions of the dynamics of purchases of new products by consumers, or in forecasting potential scenarios for future market exploitation.

Undoubtedly, the theoretical approaches to technology diffusion analysis have certain shortcomings and limitations. 'Epidemic models' have been widely criticized for their oversimplifying assumptions and weak theoretical background. The approach is 'blind' to societal, demographic, cultural, educational and institutional prerequisites which condition the rate of adoption of a product and its effective use. Additionally, in systems in which the spread of technologies is supposed to be highly homogenous, agents acquire perfect information on new technologies through interpersonal contacts, and the process of diffusion stops only in the case that all the members of society use the new technology. Moreover, as is stressed by Karshenas and Stoneman (1993), the 'epidemic model' assumes that agents' decisions on acquiring—or not—new technology are free of risk. However, omitting risk can be misleading, especially when predicting the development of future technologies, and risk should definitely not be ignored in the long-term perspective. Applying an *explicit* or *implicit* 'epidemic' analogy to the theoretical concepts explaining the technology diffusion process, to a point, was criticized by the next two prominent authors, Paul David (1969) and Stephen Davies (1979), who made significant contributions to the theory of technology diffusion. Davies (1979) points out that 'blind' acceptance of the assumption that the diffusion process is well approximated by logistic growth equations leads to another unrealistic assumption—of a constant diffusion rate. If we relax the assumption of a time-invariant diffusion rate, the logistic pattern is not generated. In addition, many authors claim (see Griliches 1957; Mansfield 1968; Romeo 1977; Davies 1979; Metcalfe 1987; Karshenas and Stoneman 1995; Stoneman 2001; Stoneman and Battisti 2005) that these models fully and correctly explain the process of the systematic adoption of new technologies by societies.

However, despite obvious limitations of the theoretical approaches to technology diffusion, their contribution to diffusion analysis is pervasive and unquestionable. As claimed and proved in multiple empirical studies, this approach, despite its drawbacks, approximates time diffusion paths and the dynamics of the process relatively well. Systems, despite being attributed to various features, tend to develop in a similar way. S-shaped curves (logistics growth patterns), which are what are 'generated' from the Mansfield and Bass models, allow for broad intuitive interpretations, describing and forecasting the growth of various technologies (products) (Bass 2004). As growth trajectories have generally similar features, classical S-time path analysis creates the possibility of 'guessing by analogy' (Bass 2004) with the growth histories of past technologies. 'Epidemic models' are simple, clearly describe and explain the diffusion trajectories of new technologies, and allow the prediction with little uncertainty of future development paths.

The next paragraphs briefly discuses alternative approaches to the conceptualization of technology diffusion: probit (rank), stock and order models. The probit (or rank) approach, mostly developed and explained by Paul A. David (1969) and Stephen Davies (1979), is based on two major assumptions: the behaviour of agents (individuals or firms) is rational; and they head toward utility maximization. This specification contains elements of rational choice theory (e.g. Rawls 1999; Foley 2009). In the probit approach, it is assumed that technology diffusion is attributed to unique features of agents (in the case of companies, these can be the size, geographical location and production profile of firms), risk aversion to new technologies, or just the opposite—risk acceptance, the relative prices of alternative technologies to be potentially acquired, and the variety of substitutes for the technology (product) in question. In other words, the rank approach relies on a supposition that technologies spread in heterogeneous societies, and potential users of new technology condition their decisions on cost/benefit analysis (Davies 1979; Stoneman 2002). If the cost of technology acquisition at time t is defined as $C(t)$, while the benefits[8] generated from effective use of it are $B(t)$, then an individual decides to buy the technology only if $B(t) > C(t)$ is satisfied. The model, however, although more sophisticated than simple 'epidemic' models, includes multiple latent factors (e.g. consumer expectations) that determine agents' final decisions on new technology acquisition, and which heavily disrupt quantitative specification. The rank models of technology diffusion fall into the equilibrium model category. The equilibrium, referring to the actual numbers of users of a particular technology, can be established along the diffusion path for each period of time. Once, due to some external (exogenous) factors, the number of users changes, so the equilibrium is disrupted and the system heads toward another equilibrium state.

The stock[9] models include three main approaches to technology diffusion: those of Reinganum (1981b) and Schumpeter (1984) and a last stream which is based on an evolutionary approach. Both Reinganum (1981b) and Schumpeter's (1984) specifications may be classified as equilibrium class models. Both concepts are

[8] The benefits from the adoption of new technology are mainly associated with introducing 'process innovation' that underlies company performance. This can be conditioned, *inter alia*, by prospective profitability, expected risk, organizational structure and other factors which may impact outcomes for a company.

[9] The models, are labelled 'stock', as diffusion in time (t + 1) depends on the stock (number) of given technology users in period 't'.

deeply rooted in neoclassical theories. Thus, the technology diffusion path is characterized by a sequence of equilibria in each time period. The consecutive equilibria are generated as agents, driven by infinite rationality and having access to full information, make decisions on new technology acquisition. The Reinganum approach assumes that firms tend to buy new technology when they expect a reduction in cost, so that the cost generated by the 'old technology' $C_{old}(t)$, is greater than $C_{new}(t)$ in a given time period. If $C_{old}(t) > C_{new}(t)$, then positive externalities, accounted as increases in profits, are expected. The Schumpeterian approach is similar in its logic to Reinganum's. However, the Schumpeterian concept (Soete and Turner 1984; Aghion et al. 2013) of technology diffusion is conceptually placed in a broader macroeconomic perspective, and it accounts for spillovers as new technologies expand and are gradually acquired by new users. Finally, the evolutionary approach offers a similar explanation of the technology diffusion process to the two just discussed. However, the main difference between the Reinganum and Schumpeterian explanations of technology diffusion and the approach argued by the evolutionary school lies in the basic assumptions that the models rely on. Evolutionary concepts reject assumptions on perfect information and perfect market competition, as is the case in the Reinganum and Schumpeterian models, and they relax the assumption on profit maximization and the infinite rationality of agents. To a point, evolutionary models are similar to those based on 'epidemic' concepts, as they claim that technology diffusion is *not* a self-equilibrating process. In evolutionary models, the process of technology diffusion is also defined as self-perpetuating, and the individual features of agents are assumed to be endogenous. If companies (individuals) get profits from newly acquired technologies, i.e. if $B(t) > C(t)$, then new users arrive and the diffusion proceeds. Generally, models developed under evolutionary economics are recognized as being more open-ended and more real-world-oriented, providing a more suitable insight into the nature and dynamics of the process. Following Allen (1988a, b), Sarkar (1998) argues that '*(…) diffusion (…) of innovations and technological changes has been considered in neoclassical economics, abstracted from history, culture, social structure (…).* (…) *such abstraction may have rendered equilibrium models simpler, (…) but having very low economic plausibility of [their] assumptions, thereby making it difficult to test these models rigorously for falsification*'.

In the late 1980s, 'order' models were developed (see, e.g., Fudenberg and Tirole 1985). Also classified as equilibrium models, these rely on the same assumptions under which the stock models operate. However, the 'order' approaches emphasize that the order of adoption of new technologies matters for the diffusion process. Order models relax the assumption that each agent (user) gets equal profit from new technology acquisition, and assume that a user that adopts a new technology first (first in order) enjoys higher profits compared to those who acquire new technologies later on. Hence, along the diffusion path $B(t_i) > B\left(t_{(i+1)}\right)$, where $B(t)$ explains the profits gained by a user of a new technology.

3.2.2 Approximating Technology Diffusion Trajectories

A deep insight into the dynamics of technology diffusion was provided in the influential works of, *inter alia*, Mansfield (1968), Griliches (1957), and Nelson (1982), who analyzed the phenomenon adopting the evolutionary dynamics concept. This resulted in the introduction to economic studies of the logistics law, which is broadly applied in natural science to describe the path dependence of biological growth (Verhulst 1838; Pearl and Reed 1922). According to the logistic law of growth, systems tend to grow exponentially. In 1838, inspired by the Malthusian growth model, the Belgian mathematician Pierre-Francois Verhulst (1838)[10] formalized logistic growth and introduced the logistic function. In a generic sense, the function that Verhulst proposed is a logistic equation, also known as a simple sigmoid asymptotic function, and it produces an S-shaped curve once empirical data on diffusion (growth) is plotted over time. The growth curve can be divided into two specific parts by the inflection point: first (before the inflection point), it is a downward powers function; second (after the inflection point), it is a logarithmic function. The ubiquitous family of S-shaped curves (also recognized as: S-curves, logistic curves, S-shaped patterns, S-shaped paths, S-shaped trajectories, S-shaped time paths, Gompertz[11] curve, Foster's curve, sigmoid curves) allow for the visualization of the logistic growth process and its intuitive interpretation (Modis 2007). Mathematically, the logistic growth function originates from the exponential growth model, and if written as an ordinary differential equation is as follows (Meyer et al. 1999):

$$\frac{dY_x(t)}{dt} = \alpha Y_x(t). \tag{3.10}$$

If $Y(t)$ denotes the level of variable x, (t) is time, and α is a constant growth rate, then Eq. (3.10) explains the time path of $Y(t)$. If we introduce e[12] to Eq. (3.10), it can be reformulated as:

$$Y_x(t) = \beta e^{\alpha t}, \tag{3.11}$$

or alternatively:

$$Y_x(t) = \alpha \exp \beta t, \tag{3.12}$$

with notation analogous to Eq. (3.10) and β representing the initial value of x at $t = 0$.

[10] The logistic equation is also recognized as the Verhulst-Pearl equation, as Pearl and Reed (1922), in the early 1920s already adopted similar formulas in the biological sciences.

[11] Referring to Benjamin Gompertz (1825) and his 'law of mortality', which is a mathematical specification to model time-series (Gompertz model, Gompertz growth).

[12] Base of naatural logarithms.

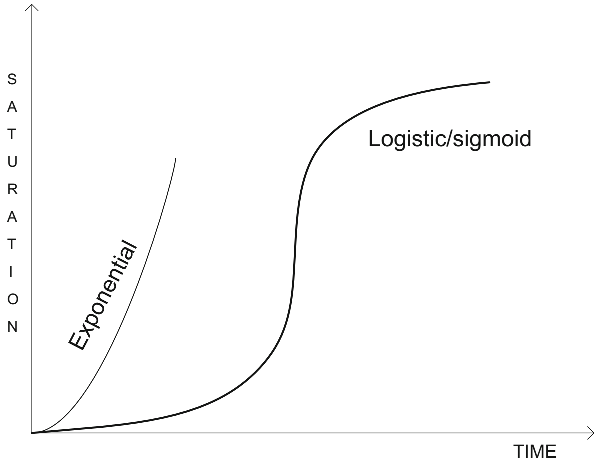

Fig. 3.2 Exponential versus logistic (sigmoid) curve specification. Theoretical specification

By convention, the simple growth model is pre-defined as exponential. Thus, if left to itself x will grow infinitely in geometric progression. But, indiscriminate extrapolation of $Y_x(t)$ generated by an exponential growth model would lead to unrealistic predictions, as due to various constraints, systems do not grow infinitely (Stone 1980; Kingsland 1982; Meyer 1994; Coontz 2013). Therefore, it is reasonable to impose growth boundaries to the original model. To solve the problem of 'infinite growth', the 'resistance' parameter (Meyer et al. 1999; Banks 1994; Cramer 2003; Kwasnicki 2013) was added to Eq. (3.10). This modification introduces an upper 'limit' to the exponential growth model, which instead gives the original exponential growth curve a sigmoid shape (Fig. 3.2).

Formally, the modified version of Eq. (3.10) is the logistic differential function, defined as:

$$\frac{dY(t)}{dt} = \alpha Y(t)\left(1 - \frac{Y(t)}{\kappa}\right), \tag{3.13}$$

where the parameter κ denotes the imposed upper asymptote that arbitrarily limits the growth of Y. As already mentioned, adding the slowing-down parameter to exponential growth generates an S-shaped trajectory[13] (see Fig. 3.3).

The three-parameter[14] logistic differential equation, Eq. (3.13), can be re-written as a logistic growth function, taking non-negative values throughout its path:

[13] Following Meyer et al. (1999), we define $\left(1 - \frac{Y(t)}{\kappa}\right)$ as a 'slowing term' ('negative feedback'), which is close to 1 as $Y(t) \ll \kappa$, but if $Y(t) \to \kappa$ then $\left(1 - \frac{Y(t)}{\kappa}\right) \to 0$.

[14] For estimates of the asymmetric responses 5-parameter logistic functions (5PL) are applied. A standard 5PL is as follows (Gottschalk and Dunn 2005): $y = f(x; p) = d + \frac{(a-d)}{\left[1+\left[\frac{x}{c}\right]^b\right]^g}$, where

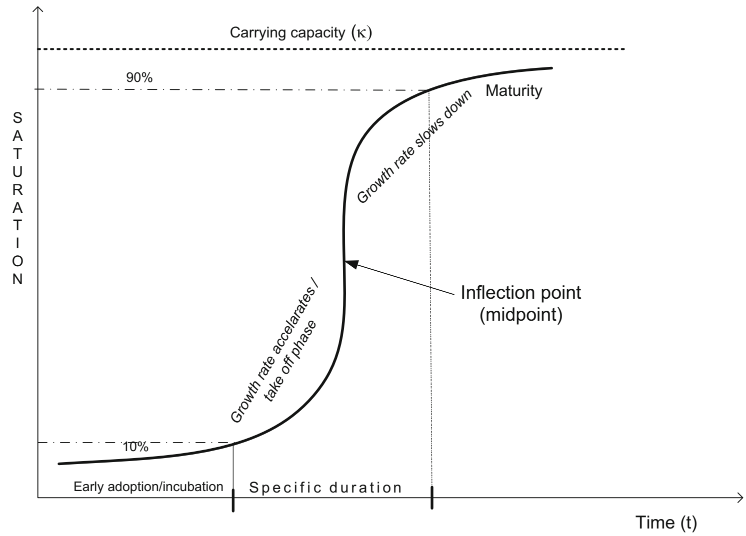

Fig. 3.3 S-shaped time path. Theoretical specification. Note: the logistic function follows the S-path if plotted on an absolute and linear scale. Once the Fisher-Pry (The Fisher-Pry (Fisher and Pry 1972) transform yields: $\equiv {}^{N}(t)/_{\kappa'}$. Thus ${}^{F}/_{(1-F)} = e^{\alpha t+\beta}$.) transform is applied, the logistic curve can be plotted linearly.

$$N_x(t) = \frac{\kappa}{1 + e^{-\alpha t - \beta}}, \tag{3.14}$$

or, alternatively:

$$N_x(t) = \frac{\kappa}{1 + \exp(-\alpha(t - \beta))}, \tag{3.15}$$

where $N_x(t)$ stands for the value of variable x in time period t. The parameters in Eqs. (3.14 and 3.15)[15] explain the following:

- κ—upper asymptote, which determines the limit of growth ($N(t) \to \kappa$), also labelled ‘carrying capacity’ or ‘saturation’;

$p = (a, b, c, d, g)$, $c > 0$ and $g > 0$. If we restrict $g = 1$, a 4-parameter logistic function is generated.

[15] The parameters in Eqs. (3.14 and 3.15) can be estimated by applying ordinary least squares (OLS), maximum likelihood (MLE), algebraic estimation (AE), or nonlinear least squares (NLS). As Satoh and Yamada (2002) suggests, NLS returns the relatively best predictions, as the estimates of standard errors (of κ, β, α) are more valid than those returned from estimation using other methods. Adoption of NLS allows avoiding time-interval biases, which are revealed in the case of OLS estimates (Srinivasan and Mason 1986). However, the main disadvantage of the NLS procedure is that estimates of the parameters may be sensitive to the initial values in the time-series adopted.

- α—growth rate, which determines the speed of diffusion;
- β—midpoint, which determines the exact time (T_m) when the logistic pattern reaches 0.5κ.

The growth rate α additionally determines the 'steepness'[16] of the S-shaped curve. However to facilitate interpretation[17], it is useful to replace α with a 'specific duration'[18] parameter, defined as $\Delta t = \frac{\ln(81)}{\alpha}$. Having Δt, it is easy to approximate the time needed for x to grow from 10 to 90 % κ. The midpoint (β) describes the point in time at which the logistic growth starts to level off. Mathematically, the midpoint stands for the inflection point of the logistic curve. Incorporating Δt and (T_m) into Eq. (3.15), entails:

$$N_x(t) = \frac{\kappa}{1 + exp\left[-\frac{\ln(81)}{\Delta t}(t - T_m)\right]}. \tag{3.16}$$

A generalized version of the logistic function (Kudryashov 2013) including more than one explanatory variable of $N_x(t)$, is as follows:

$$N(Z) = \frac{expZ}{1 + expZ} = \frac{1}{1 + exp^{-Z}}, \tag{3.17}$$

with $Z = x^T\gamma$, where x stands for all covariates and γ is the coefficient of x.

Given that different growth processes are decomposable into *sub*-process, the model in Eq. (3.15) can easily be transformed into a multiple growth 'pulses' model. Assuming we are dealing with just two recognizable 'pulses' (*sub*-processes of growth), this gives rise to the expression:

$$N_x(t) = N_1(t) + N_2(t). \tag{3.18}$$

Hence, $N_1(t)$ and $N_2(t)$ yield: $\left[\frac{\kappa_1}{1+exp\left(\frac{\ln(81)}{\Delta t_1}\left(t-T_{m_1}\right)\right)}\right]$ and $\left[\frac{\kappa_2}{1+exp\left(\frac{\ln(81)}{\Delta t_2}\left(t-T_{m_2}\right)\right)}\right]$ respectively. The model defined in Eq. (3.18), is commonly known as a *bi*-logistic growth equation. The generalized version of Eq. (3.18) for multiple (→'z') logistic growth *sub*-processes follows the *z-component* logistic growth model:

[16] Also labelled 'width'.

[17] The parameter α as such, is not economically interpretable, thus it is exclusively estimated to calculate the 'specific duration'.

[18] Also labelled 'characteristic duration' or 'specific time'.

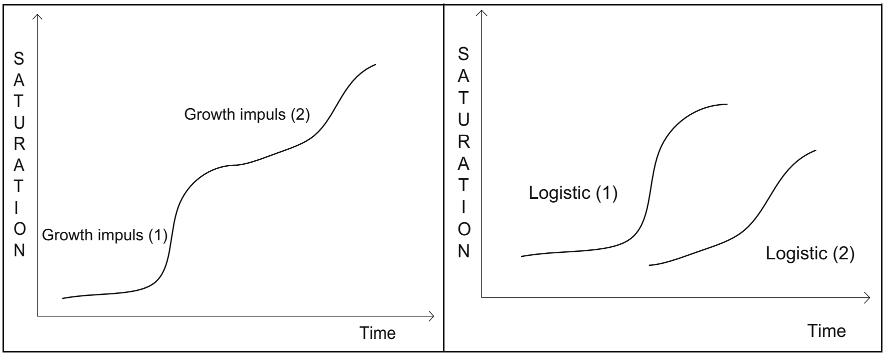

Fig. 3.4 Component logistic model decomposition into *bi*-logistic growth. Theoretical specification

$$N(t) = \left[\frac{\kappa_1}{1 + exp\left(\frac{\ln(81)}{\Delta t_1}\left(t - T_{m_1}\right)\right)}\right] + \ldots + \left[\frac{\kappa_i}{1 + exp\left(\frac{\ln(81)}{\Delta t_i}\left(t - T_{m_i}\right)\right)}\right]$$
$$= \sum\nolimits_{i=1}^{z} N_i(t), \tag{3.19}$$

if:

$$N_i(t) = \frac{\kappa_i}{1 + \exp(-\alpha_\mathrm{i}(\mathrm{t} - \beta_\mathrm{i}))}. \tag{3.20}$$

The concept formalized in Eq. (3.18) is graphically displayed in Fig. 3.4 (see below).

The left-hand side of Fig. 3.4, shows a component logistic curve with two clearly distinguishable growth phases (growth impulse (1) and growth impulse (2)). The left-hand curve is the approximated sum of two discrete 'wavelets' (Meyer et al. 1999), and can be decomposed into two separate three-parameter logistic functions. The curves on the right, instead, present the two distinct growth *sub*-impulses. Such decomposition allows for detailed analysis of the behaviour of the relevant technology in each phase of growth.[19]

Most technology diffusion models deal with strictly one technology (innovation) and describe its in-time behaviour. However, if another technology arrives there emerges a competition between the 'old' and 'new' technologies. Hence, the technological substitution process is revealed, which explains the life cycle of certain technologies, distinguishing certain phases of growth and decline. Hereafter, Sect. 3.2.3 briefly describes technological substitution theories and models.

[19] If a Fisher-Pry transform is applied for normalization, then the logistic curves become linear, which additionally facilitates further analysis of growth *sub*-phases.

3.2.3 Technological Substitution

Technologies rise, saturate and finally decline when new and better ones emerge. The process of continuous replacement of ‘old’ technologies by ‘new’ technologies is labelled technological substitution, and can easily be encountered in various systems and under different circumstances (Fisher and Pry 1972). Technological substitution is evolutionary or revolutionary in its nature. It brings significant changes to societies (Kucharavy and De Guio 2011), and it may be perceived as a consequence of technology development marked by a stream of ‘discontinuities’ (Miranda and Lima 2013), and leading to replacements of ‘old’ technologies by ‘new’ ones. Generically, the process of technological replacement resembles competition between the ‘old’ and ‘new’ technology, in which the ‘old’ technology is initially a dominant competitor in the market and the ‘new’ ‘invading’ one fights for a growing market share (Morris and Pratt 2003).

By definition, the technological substitution model (also labelled logistic substitution model) explains the competitors’ changing market shares (fractions) along the competition process, which is attributed to time. Technological replacement is gradual (Wang and Lan 2007), and, as broadly observed, the time behaviour of competing technologies follows a logistics trajectory. In a competitive system, each technology passes through three characteristic phases: a logistic growth phase (P1)—the prime phase of growth, when initially growth rates are slow, but they then enter an exponential growth phase (this results in fast diffusion of the technology); a saturation phase (P2)—the technology reaches the maximum of its market share and thus follows a non-logistic pattern; and a logistic decline phase (P3)—the technology is fading away from the market, its market share is gradually declining as it is substituted by new technology, which is in the logistic growth phase.

Most contemporary empirical works considering the process of gradual substitution between two competing technologies[20] can be traced back to the influential models proposed by Fisher-Pry (1972), Marchetti and Nakicenovic (1980), and Nakicenovic (1987). The Fisher-Pry model of technological substitution is based on three general assumptions (Fisher and Pry 1972; Bhargava 1995; Kumar and Kumar 1992): (1) many technological advances can be considered competitive substitutions of one method of satisfying a need with another; (2) if a substitution has progressed as far as a few percent, it will proceed to completion; (3) the rate of fractional substitution of new for old is proportional to the remaining amount of the old left to be substituted.

Technically, the technological substitution model explains changing shares of the market that competitors take over, and it relies on the assumption that the total

[20] Conceptually, technological substitution models refer to the seminal works of Alfred Lotka (1920) and Vito Volterra (1926), who were the first to introduce a generalized version of the logistic growth equation. They developed a model of competition among different species in biological systems (Voltera) and chemical chain reactions (Lotka). Today, the Volterra-Lotka competition equation is widely adopted for qualitative analysis of technological substitution if at least two competing technologies are involved.

sum of users of the two competing technologies is fixed.[21] Blackman (1971) and Marchetti and Nakicenovic (1980) formalize the original technological substitution model developed by Fisher and Pry, and develop a three-parameter logistic substitution model describing the behaviour of two competitors along the time path. The technological substitution model is based on the following assumptions:

- There are n competing technologies;
- Once a 'new' technology has invaded the market, it grows at logistic rates;
- The 'old' technology fades away also at logistic rates, but the speed of decline is predominantly affected by the speed of diffusion of the 'new' technology[22];
- It is possible for only one technology (out of two or more competitors) to be in the saturation phase at a given point of time;
- A technology in the saturation phase follows a non-logistic pattern.

Let us assume a competitive system and consider the technology substitution model with two technologies replacing each other. Assume that N is the total population, where N_i represent the users of the two technologies, so that the share of the population using i-technology at time t is:

$$f_i(t) = \frac{N_i(t)}{N}. \tag{3.21}$$

To avoid unrealistic estimates, it is presumed that the number of users is fixed and each deploys one out of the two available technologies (Morris and Pratt 2003), which implies an obvious constraint like:

$$f_i(t) + f_j(t) = 1, \tag{3.22}$$

where $'i'$ and $'j'$ are competing technologies. By convention, the technologies follow a logistic growth trajectory (Kwasnicki 1999) defined as:

[21] Relaxing the assumption of a fixed total number of users would allow the system to grow infinitely, which is not the case in real-data based empirical studies.

[22] Theodore Modis (2003) distinguishes six ways that two competitors can affect the growth rate in a competitive system. These are: (1) pure competition (competitors need to fight to survive in the same environment, as they use the same resources, which are limited); (2) predator-prey competition (one competitor is labelled prey and the second the predator—the 'predator' population grows as there are abundant 'preys'; this kind of competition generates cyclical growths and declines in populations of 'predators' and 'preys'. Lotka-Volterra equations are applied to describe this kind of competition; (3) symbiosis (competitors are interrelated as the existence of the first is totally dependent on the existence of the second); (4) parasitic (the first competitor benefits from the second, but is does not affect the latter's existence, also labelled 'win-impervious' competition); (5) symbiotic (the first competitor benefits from the second, but the latter is negatively affected by the competition but remains indifferent to the loses, also labelled 'loss-indifferent'); (6) no competition (the two competitors are not overlapping each other as they use different resources to survive.

$$f_i(t) = \frac{1}{1 + \exp(-a - bt)}, \tag{3.23}$$

where value a is defined for the initial year $(t = 0)$. To indicate the market share $(y_i(t))$ possessed by technology $'i'$ (either a declining or growing technology), we adopt a Fisher-Pry transform (1972) so that Eq. (3.23) yields $y_i(t) = ln\left[\frac{f_i(t)}{1 - f_i(t)}\right]$. Respecting the assumption defined in Eq. (3.22), we find that:

$$y_i(t) + y_j(t) = 1. \tag{3.24}$$

If Eq. (3.24) is satisfied, the market share of technology $'j'$ in the non-logistic saturation phase (P2) is given by:

$$f_j(t) = 1 - \sum\nolimits_{j \neq i} f_i(t). \tag{3.25}$$

Thus, the share of the market possessed by technology $'i'$ is strictly subject to the share of the market possessed by technology $'j'$.

For an economic interpretation of the process of technological substitution, it is essential to determine the point in time when certain phases of substitution begin or end. Following Meyer et al. (1999), the estimate of the point in time when the saturation phase stops is given by:

$$\frac{y_i^{''}(t)}{y_i^{'}(t)} \rightarrow min. \tag{3.26}$$

Having y_i and thus $y_i^{'}$, it is possible to estimate the two parameters of the logistic curve for technology $'i'$, which can be mathematically expressed as:

$$\Delta t_i = \frac{\ln(81)}{y_i^{'}(t)}, \tag{3.27}$$

and:

$$T_{m_i} = ln\left[\frac{\left(y_i(t) - \frac{\ln(81)}{\Delta t}\right)}{\frac{\ln(81)}{\Delta t}}\right]. \tag{3.28}$$

Δt_i is labelled 'takeover' (Fisher and Pry 1972) and it indicates the time needed for technology $'i'$ to increase its market share from $y_i(t) = 0.1$ to $y_i(t) = 0.9$. $T_{m_{is}}$ explains the specific point in time (e.g. year) when the substitution process between the competing technologies is half-complete; thus $y_i(t) = y_j(t) = 0.5$.

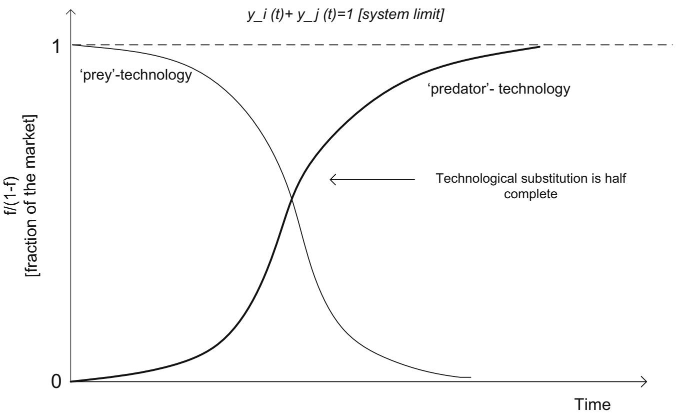

Fig. 3.5 Technological substitution process. Theoretical specification

Figure 3.5 graphically presents the mechanism of technological substitution, which combines two substitution curves with deterministic asymptotic behaviour.

Figure 3.5 shows the life cycles of both the 'predator' and 'prey' technologies, and three distinct phases are detectable: logistic growth, saturation and logistic decline. It is easy to note that once the 'predator' technology is in its logistic growth phase, the 'prey' technology follows a logistic decline. The intersection point depicts the specific time (i.e. the year) when the technological substitution process is half complete. Thus both the 'predator' and 'prey' control 50 % of the total market ($\rightarrow y_i(t) = y_j(t) = 0.5$).

3.3 The '*Critical Mass*': What Stands Behind?

3.3.1 The '*Critical Mass*'. Explaining the Concept

Technology diffusion is strictly attributed to network externalities (network effects), which emerge as positive feedback from random contacts between society members, giving rise to exponential growth of the network itself. Carrington et al. (2005) and Villasis (2008) argue that 'network' stands for an interconnected chain or group, while the 'social network' '*is a social structure made of nodes tied by one or more types of relations (...)*'. If social networks give positive feedback, then network effects (externalities) may emerge, showing the value of potential connectivity exponentially increasing with the number of users of a new technology (Economides and Himmelberg 1995a, b; Villasis 2008). Katz and Shapiro (1985) and Shapiro and Varian (1998) define network effects as an increasing utility of using the product when the absolute number of users of this product increases. However, the positive effects of networks may arise only if the social system achieves a certain '*critical mass*', ensuring a further sustainable multiplication of users (Katz and Shapiro 1985, 1986, 1992; Markus 1987; Oliver et al. 1985).

In other words, a positive re-alimentation schema of revealing network effects is conditioned on the society reaching a certain '*critical mass*'. The notion of '*critical mass*' might be confusing, since it has multiple meanings. It originates from physics, and in its generic sense denotes the amount of radioactive material necessary for nuclear fission to take place (Oliver et al. 1985). Mancur Olson (1965) was the first to introduce the concept of '*critical mass*' to the social sciences, and he defines '*critical mass*' as the *critical* number of early adopters which is necessary to lead the rest of the population in collective actions.[23] Rephrasing this, '*critical mass*' theory leads to the *critical* (threshold) conditions for collective actions to emerge, and then continue as self-perpetuating[24] and profitable[25] (Marwell and Oliver 1993; Molina et al. 2001; Puumalainen et al. 2011).

To a certain extent, the '*critical mass*' concept has also been discussed in the literature on technology diffusion. The process of technology diffusion follows the third-order (S-shaped) time path, and so the main emphasis in analyzing the diffusion process is put on estimating the inflection point of the curve. By definition, the inflection point on an S-shape trajectory denotes the specific time period when saturation reaches 50 % of the population and the rate of diffusion starts to slow down. However, when considering the '*critical mass*' concept in reference to the diffusion process, it might be relevant to identify the *critical* (threshold) level of saturation of a given technology, at which the further process of diffusion becomes self-perpetuating. Rogers (2010) argues that at the '*critical mass*' 'diffusion becomes self-sustaining'. However, the concept of '*critical mass*' that Rogers (2010) uses is based on the assumption that the diffusion process will continue endogenously at exponential rates, finally reaching the stabilization phase once the '*critical mass*' of users is achieved (see Fig. 3.6) This therefore relaxes the assumption that the diffusion process of, e.g., a new product is determined by changes in relative prices or shifts in quality.

Similar explanations of significance of the '*critical mass*'[26] in the continuous diffusion process characterized by multiple equilibria states are given by Cabral (1990, 2006), Economides and Himmelberg (1995a, b), and Evans and Schmalensee (2010). For instance, Economides and Himmelberg (1995a, b) propose that the '*critical mass*' constitutes the smallest possible (minimal non-zero) equilibrium assuring the stability of a further diffusion process[27] at an exponential rate, while

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[23] Oliver et al. (1985) recall that the *critical mass* effect is also known as the 'snob and bandwagon effect', the 'free rider problem' or the 'tragedy of commons'.

[24] Self-sustaining.

[25] Many claim (see, e.g. Bonacich et al. 1976; Frohlich et al. 1971; or Hardin 1982) that Olson's concept of *critical mass* was too general and unconditional and so it did not allow for any mathematical formalization. Additionally, their experiments have proved that Olson's concepts was not correct, as in many cases people's real behaviour does not confirm Olson's assumptions.

[26] The notion of *critical mass* is also known as 'installed base' (Grajek and Kretschmer 2012).

[27] In fact, they precondition the value of *critical mass* on prices, arguing that lower prices require lower *critical mass*, to assure sustainability of the diffusion process.

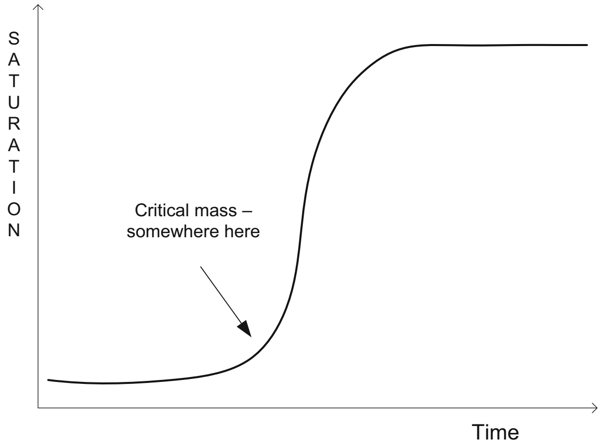

Fig. 3.6 '*Critical mass*' on the S-shaped diffusion trajectory

Evans and Schmalensee (2010) show that the level and diffusion of the '*critical mass*' are heavily determined by the nature of networks and individual consumer preferences.

In analyzing the phenomenon of '*critical mass*' as proposed by Rogers (2010), the theory of the diffusion of innovation becomes an obvious conceptual background. In diffusion theory, the very first adopters (innovators) of a new product do so because they benefit from the new product. Whether the rest of the society members will follow them or not usually depends on a *threshold,* defined as the number of people who have already adopted the new product. The central presumption of diffusion theory is that the process of diffusion follows a sigmoid pattern. Hence, identification of the '*critical mass*' might be strictly related to examining when and at what saturation level diffusion accelerates and the 'take-off' emerges. It is thus possible to state that diffusion accelerates once the '*critical mass*' is reached (Allen 1988a; Rogers 2010; Schoder 2000). Cabral (1990, 2006) claims that '*critical mass*' occurs if network effects are sufficiently strong and diffusion is endogenously driven. He also states that the '*critical mass*' point depicts the 'catastrophe point' on the diffusion time path, which corresponds to low-level equilibrium. Loch and Huberman (1999), in their work '*A Punctuated-Equilibrium Model of Technology Diffusion*', propose an evolutionary model where two competing technologies (old and new) are available. Assuming that both technologies demonstrate network externalities and generate benefits from their use, consumers will switch to the new technology only if the technology diffuses at high speed. They also presume that other factors like, e.g., uncertainty, cultural 'openness' or personal preferences play a crucial role in the diffusion process, being strong incentives or barriers for new technologies to reach a '*critical mass*' and spread throughout society.

The works of Lim et al. (2003) and Kim and Kim (2007) attempt to identify the '*critical mass*' from the S-shaped diffusion pattern. Implementing the Bass diffusion model,[28] they develop the concepts of 'early take off' (Kim and Kim 2007) and

[28] For the formal specification, see Sect. 3.2.

'late take off' (Lim et al. 2003) with respect to diffusion studies. Adopting the formal specification of non-cumulative and cumulative adoption curves, they calculate the specific periods of time indicating the beginnings of the 'early take off' and 'late take off' phases. Assuming that t is time, that $(C(t))$ describes the cumulative curve and $(nonC(t))$ is the non-cumulative one, then:

$$\mathrm{C(t)} = \kappa \frac{1 - \mathrm{e}^{-(\mathrm{p+q})\mathrm{t}}}{1 + \frac{\mathrm{q}}{\mathrm{p}}\mathrm{e}^{-(\mathrm{p+q})\mathrm{t}}}, \tag{3.29}$$

and:

$$nonC(t) = \kappa \frac{p(p+q)^2 e^{-(p+q)t}}{\left(p + qe^{-(p+q)t}\right)^2}, \tag{3.30}$$

where κ is the saturation level, and p and q explain the external and internal influence respectively. Mathematically (Kim and Kim 2007), the inflection points of the curves specified in Eqs. (3.29–3.39) correspond to:

$$t_{infl(C(t))} = -\frac{1}{p+q}\ln\frac{p}{q}, \tag{3.31}$$

and:

$$t_{infl(nonC(t))} = -\frac{1}{p+q}\ln[(2+\sqrt{3}frac\,pq)]. \tag{3.32}$$

The inflection point defined as in Eq. (3.31) denotes entry into the exponential growth phase on the S-time path. By convention, by using the value of the inflection point we can determine the number of adoptions, which refers to $t_{infl(C(t))}$. Therefore, the number of adoptions at $t_{infl(C(t))}$ would presumably determine the level of the '*critical mass*'. However, as Valente (1996, 2005), Mahler and Rogers (1999), and Lim et al. (2003) argue, it may be highly controversial whether the point $t_{infl(C(t))}$ unquestionably denotes the '*critical mass*'. The question is whether, after passing the $t_{infl(C(t))}$ point, the diffusion turns out to be a self-sustaining process or not. If not, there is no justification for treating $t_{infl(C(t))}$ as the '*critical mass*' point. Thus, the conviction that the '*critical mass*' is easily detectable might be misleading and confusing.

Different approaches to the identification of '*critical mass*' are offered by Grajek (2003, 2010), Grajek and Kretschmer (2011, 2012), Baraldi (2004, 2012), Arroyo-Barrigüete et al. (2010) and Villasis (2008). To quantify '*critical mass*', Grajek and Kretschmer (2012) define it as a function of the installed base and price. Following, e.g., Cabral (1990, 2006), they presume that due to the installed base effect the diffusion of products should continue even if prices remain unchanged. Consequently, Grajek and Kretschmer (2012) develop a structural model of demand with installed base effects. To estimate the threshold level of the '*critical mass*', they suggest that diffusion is highly endogenous and the process as such can be identified as multi-equilibrating. Their seminal findings, examining the case of the global cellular telephony market over the period 1998–2007,[29] suggest that the '*critical mass*' can be predominantly attributed to the size of the installed base, prices and the market size. Strong network effects allow for a lower installed base and higher prices to assure the sustainability of further diffusion, and the opposite is true in the case of weak network effects. Additionally, Grajek and Kretschmer (2012) report that the '*critical mass*' phenomenon is only revealed in the case of emerging (pioneering markets). The model they propose for the identification of the '*critical mass*' combines an installed base effect, the current installed base and prices. If the '*critical mass*' occurs under certain threshold conditions, then the diffusion becomes self-sustaining. In this spirit, they define the '*critical mass*' point as a combination of the three factors previously listed. Considering the assumptions in the Grajek and Kretschmer (2012) model, in certain societies (countries) the diffusion of innovation will never occur unless the '*critical mass*' is reached. This would imply that some societies might be stuck in a 'low-equilibrium trap' and unable to 'take-off'. Baraldi (2012) provides new insights into the estimation of the *size* of the '*critical mass*' rather than concentrating exclusively on its determinants (recall the works of, e.g., Grajek and Kretschmer 2012). Baraldi (2012) argues that the size of the '*critical mass*' is determined by the strength of network effects. To detect the strength of the network effects, she adopts a concave demand curve. Hence, the occurrence of the '*critical mass*' (regardless of the price of the new product) takes place the sooner the stronger the network effect is and the opposite otherwise.[30]

Similar to Baraldi (2012), Arroyo-Barrigüete et al. (2010) offer a conceptualization of the '*critical mass*'. They use a convex demand curve to depict the '*critical mass*' point. Arroyo-Barrigüete et al. (2010) follow Oren et al.'s (1982) concept of '*critical mass*', arguing that it explains the minimum size of the network that encourages new users to join the network and adopt the new product. Once the '*critical mass*' of users is achieved, the process of diffusion is self-perpetuating. Following Katz and Shapiro (1985), who define the network effects as an increasing

[29] Similar evidence on the role of the installed base is offered by Gruber and Verboven (2001), Koski and Kretschmer (2005), and Grajek (2010).

[30] Baraldi (2012) specifies the network effects as: $X_{i,t} = f\left[\left(\frac{GDP}{population}\right)_{i,t}, \ p_{i,t}, \ g(X_{i,t-1})\right]$, where i denotes country, and t the time period. $X_{i,t}$ is thus the installed base, $p_{i,t}$ is price, $\left(\frac{GDP}{population}\right)_{i,t}$ is GDP *per capita,* and $g(X_{i,t-1})$ reveals network externalities in country i at time t. To control for concavity, $g(X_{i,t-1})$ includes a squared term for the lagged installed base. To estimate the size of the *critical mass*, Baraldi (2012) follows Rohlfs (1974), Katz and Shapiro (1985) and Economides and Himmelberg (1995a) and formalizes the inverse demand function as $p_{i,t} = \alpha + \beta_1 base_{i,t} + \beta_2 \ln(base_{i,\ t-1}) + \beta_3 X_{i,t} + \varepsilon_{i,t}$, where $X_{i,t}$ captures control variables. To assure concavity, $\beta_2 > 0$, and $\beta_1 < 0$ must be satisfied. If $\beta_2 > 0$ and $\beta_2 > \beta_1$, the network externalities are revealed and the upward slope of the demand curve emerges. The higher β_2, the sooner the *critical mass* point is reached.

utility of using a product as the total number of users grows, Arroyo-Barrigüete et al. (2010) suggest that new users will arrive once the utility obtained from the product is higher than its price.[31] However, Arroyo-Barrigüete et al. (2010) claim that direct estimation of the '*critical mass*' point is hardly possible, as the process of diffusion of new products is preconditioned by individual choices (not always rational) and preferences, market structure, legal conditions and other unquantifiable effects.

It is worth underlining that despite a relatively well-developed theoretical framework and conceptual background aiming to explain the '*critical mass*'-like phenomenon, the number of empirical works seeking a quantitative assessment of it is very limited. This may be a consequence of the great heterogeneity of the proposed theoretical specifications without any clear and well-established definition of '*critical mass*'.

Few empirical works provide quantitative identification of the *critical mass* in its generic sense. Some examples are the works of Mahler and Rogers (1999), who study telecommunication services in 392 German banks, and Cool et al. (1997), who analyze the diffusion of innovation in an intra-organizational context, providing evidence on the *threshold share* of the population that has already adopted the new product which can ensure the further process of diffusion is self-sustaining. Mahler and Rogers (1999) suggest that keeping diffusion at very low levels makes it impossible to reach the '*critical mass*', which hinders the broad spread of innovations. Cool et al. (1997) find that the '*critical mass*' can be reached in different organizational regimes. They also underline that before reaching the '*critical mass*' point, diffusion is predominantly driven by supply factors, while after passing the '*critical mass*' point further diffusion is mainly pushed by growing demand.

Most presented concepts of the '*critical mass*' consider the phenomenon in a microeconomic rather than a macroeconomic perspective. This is a serious limitation, as reaching a '*critical mass*' might be strongly affected by social, economic, institutional, cultural or legal prerequisites.

The following Sect. 3.3.2 is intended to explain a novel conceptualization of the '*critical mass*' regarding technology diffusion process.

3.3.2 The '*Technological Take-Off*' and the '*Critical Mass*'. A Trial Conceptualisation

As was previously discussed, the '*critical mass*', may be defined as the minimal necessary number of user of new technology, which ensure the emergence of the '*take-off*' period along the diffusion trajectory, at which the further process of diffusion becomes self-perpetuating (see Fig. 3.3).

[31] The condition follows: $U = a + b(n^e) > P$, where U is the utility function and P is the product price.

The term 'take-off' itself, however has been originally introduced to the economic literature by Walt Rostow, who, in his founding paper '*The take-off into self-sustaining growth*' (1956), claimed that the process of economic growth is characterised by discontinuity '*centering on a relatively brief time interval of two or three decades when the economy and the society of which it is a part transforms themselves in such ways that economic growth is, subsequently, more or less automatic*' (Rostow 1956, p. 1). He labelled this transformation the '*take-off*'. Rostow (1956, 1963, 1990) also wrote that identifying the '*take-off*' entails seeking to isolate the specific period (interval) in which '*the scale of productive activity reaches a critical level, (...) which leads to a massive and progressive structural transformation in economic, better viewed as change in kind than a merely in degree*' (Rostow 1956, p. 16). The concept of the '*take-off*' was then developed and implemented in the works of, e.g., Hoselitz (1957), Ranis and Fei (1961), Bertram (1963), Azariadis and Drazen (1990), Becker et al. (1994), Evans (1995), Baldwin et al. (2001), and Easterly (2006). In most of the cited works, the notion of the 'take-off' was, however, combined with Rosenstein-Rodan's (1943) 'Big Push' doctrine, which was predominantly applied to describing and explaining the stages, patterns and determinants of economic development and growth.

Similar to economic growth, the process of technology diffusion may well be approximated by easily distinguishable phases (stages) (see Fig. 3.2). During the initial phase, the process of diffusion slows, whereas subsequently, under favourable circumstances, it accelerates and proceeds at an exponential growth rate, ultimately approaching relative stabilisation (maturity) when the growth rates gradually diminish.

In Sect. 3.3.2, we propose a novel trial conceptualisation of how to identify the '*take-off*' period and the '*critical mass*' regarding technology diffusion process. The presented throughout the Sect. 3.3.2 theoretical framework has been developed based on the previously run empirical analysis which outcomes are extensively discussed in Chap. 5 (see also Appendices F and G for detailed calculations).

To meet the objective of this work, we adjust the conceptual background provided by Rostow (1956, 1990) and develop the term '***technological take-off***' and define it the time interval when the nature of the diffusion process is radically transformed due to shifting the rate of diffusion and forcing the transition from condition of stagnation into dynamic and self-sustaining growth (diffusion) of new technology. In this sense, the emergence of the '*technological take-off*' is essential for ensuring the sustainability of technology diffusion and enabling the widespread adoption of new technology throughout society. Generally, before the '*technological take-off*', diffusion proceeds slowly, but once the '*technological take-off*' is achieved, diffusion proceeds more rapidly and the number of new technology adopters begins to expand fast, typically at an exponential rate. Finally, in the maturity phase, the number of new technology users reaches system carrying capacity (saturation) and stabilises. To remain in line with the previous, the long-term process of technology diffusion may be arbitrarily divided into four separate phases (stages). Firstly, the initial (early) phase is when the technology diffusion is initiated, but the annual growth and penetration rates are typically negligible. In the early stage of diffusion, the preconditions for the '*technological take-off*' are also established. The second phase constitutes the '*technological take-off*' itself; then, in the third phase—'*post technological take-off*'—the increase in users of the new technology is self-perpetuating and becomes a normal condition in a given economy. Finally, the fourth phase occurs when diffusion significantly slows down, approaching saturation (maturity).

However, the emergence of the '*technological take-off*' is intimately related to and preconditioned by achieving the '*critical mass*', which has yet to be defined. With this aim, we develop the following terms: the technology replication coefficient ($\Phi_{i,y}$) (hereafter, the replication coefficient), marginal growth in technology adoption ($\Omega_{i,y}$) (hereafter, marginal growth), critical year ($Y_{crit,i,y}$), and critical penetration rate ($critICT_{i,y}$), where i denotes country and y year.

Assume that for a given country (i) and a given technology (ICT), the term $N_{i,y}$ stands for the level of technology (ICT) adoption in y year. By definition, $N_{i,y} > 0$, because negative adoption is not possible, and if $N_y = 0$, the diffusion process is not reported. Along this line, the technology replication coefficient ($\Phi_{i,y}$) follows:

$$\Phi_{i,y} = \frac{N_{i,y}}{N_{(i,y-1)}}, \tag{3.33}$$

then:

$$N_{i,y} = \Phi_{i,y}\left[N_{(i,y-1)}\right], \tag{3.34}$$

if $N_{i,y} > 0$ and $N_{(i,y-1)} > 0$, and $\Phi_{i,y} \in (0;\infty)$. The replication coefficient for respective technology (ICT) explains the multiplication of technology users that occurs because of the emerging '*word of mouth*' effect (Geroski 2000; Lee et al. 2010). Suppose that for y year, the $\Phi_{i,y}$ =3. This shows that in $(y-1)$ year, each user of the given technology has 'generated' two **additional** new users of the new technology. In this sense, the replication is the cornerstone of the diffusion process itself. Figure 3.7 illustrates how respective values of $\Phi_{i,y}$ determine $N_{i,y}$ over time.

If $\Phi_{i,y} > 1$, it implies that in each consecutive year, the number of users of new technology increases, so that $N_{i,y} > N_{i,y-1}$. This indicates that the values of $\Phi_{i,y}$ must be higher than 1 to ensure diffusion. If $\Phi_{i,y} = 1$, the number of new technology users is constant over time, and thus $N_t = N_{(t+1)} = \ldots = N_{(t+n)}$ and no diffusion is reported. Finally, $\Phi_{i,y} < 1$ would imply that the number of users of new technology is decreasing over time, so that $N_{i,y-1} > N_{i,y}$. It may be argued that the replication coefficient ($\Phi_{i,y}$) exhibits the dynamics of the diffusion process and—to some degree—demonstrates the strength of the network effects that enhance the spread of new technology over society.

As was already claimed, if $\Phi_{i,y} > 1$, the number of new technology users is constantly increasing, so that $N_{i,y} > N_{i,y-1}$. Based on the latter, we propose the

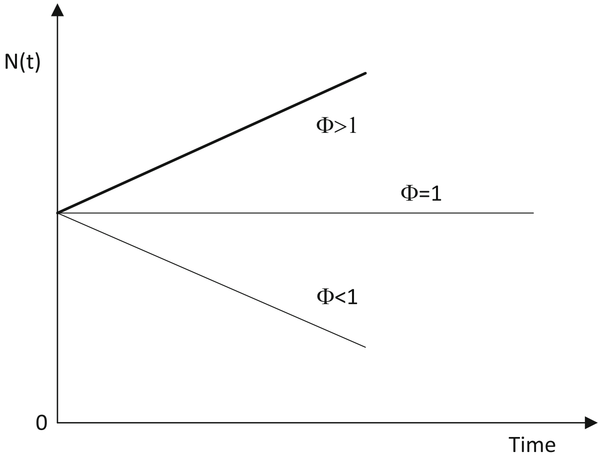

Fig. 3.7 Changes is number of technology users *versus* replication coefficients. Source: Author's elaboration

term 'marginal' growth in technology adoption ($\Omega_{i,y}$), which formally may be expressed as:

$$\Omega_{i,y} = N_{i,y} - N_{i,y-1}, \tag{3.35}$$

under the conditions that $N_{i,y} > 0$ and $N_{i,y-1} > 0$. The value of $\Omega_{i,y}$ expresses the change in the total number of users[32] of new technology over two consecutive years.

It is easily observed that these two coefficients—$\Phi_{i,y}$ and $\Omega_{i,y}$, are closely interrelated. Assuming that $\Phi_y > 1$, the level of marginal growth in i country and in y year is:

$$\Omega_{i,y} = N_{(i,y-1)}\left[\Phi_{i,y} - 1\right], \tag{3.36}$$

or:

$$\Omega_{i,y} = -N_{(i,y-1)}\left[1 - \Phi_{i,y}\right]. \tag{3.37}$$

Simply transforming Eq. (3.35) yields:

$$\frac{\Omega_{i,y}}{N_{i,y-1}} = \left[\Phi_{i,y} - 1\right]. \tag{3.38}$$

Generally, the $\Omega_{i,y}$ depends directly on the strength of the replication process that is expressed through the $\Phi_{i,y}$.

Examining the $\Phi_{i,y}$ and $\Omega_{i,y}$ simultaneously, it is easy to conclude that:

[32] In our case, expressed as number of users per 100 inhabitants.

1. If ($\Phi_{i,y} > 1$ then $\Omega_{i,y} > 0$), the replication process is sufficiently strong and the diffusion proceeds, which is demonstrated in the increasing number of new technology users $\left(N_{i,y} < N_{(i,y+1)}\right)$;
2. If ($\Phi_{i,y} = 1$ then $\Omega_{i,y} = 0$), the diffusion does not proceed, which results in a constant number of users of new technology $\left(N_{i,y} = N_{(i,y+1)} = \ldots = N_{(i,y+n)}\right)$;
3. If ($\Phi_{i,y} < 1$ then $\Omega_{i,y} < 0$), the replication process is so weak that the diffusion is limited, and there will be a decreasing number of users of new technology $\left(N_{i,y} > N_{(i,y+1)}\right)$.

If the replication coefficient is constant over time $\left(\Phi_{i,y} = \Phi_{i,y+1} \ldots . = \Phi_{i,y+n}\right)$, then in each consecutive period, the marginal growths in technology adoption are equal $\left(\Omega_{i,y} = \Omega_{i,y+1} \ldots = \Omega_{i,y+n}\right)$; and the diffusion proceeds linearly. However, as was already discussed in Sect. 3.2, the technology diffusion process is far from linear but rather follows an S-shaped trajectory instead.

In this vein, we intend to examine the behaviour of respective coefficients—$\Phi_{i,y}$ and $\Omega_{i,y}$—along the sigmoid technology diffusion pattern (for visualisation, see Fig. 3.8), which allows for determining the critical year ($Y_{crit,i,y}$) and critical penetration rate ($critICT_{i,y}$), and finally for identifying the '*technological take-off*' interval.

In the early (initial) diffusion phase, the replication coefficient tends to be higher than marginal growth $\left(\Phi_{i,y} > \Omega_{i,y}\right)$, and thus, a gap emerges between $\Phi_{i,y}$ and $\Omega_{i,y}$. However, as the diffusion proceeds and the replication process is gains strength (so that $\Phi_{i,y} > 1$ and $\Omega_{i,y} > 0$), the $\Omega_{i,y}$ ultimately increases gradually while the $\Phi_{i,y}$ decreases in consecutive years, which will inevitably lead to closing the gap between $\Phi_{i,y}$ and $\Omega_{i,y}$ (the paths that show the changes in $\Phi_{i,y}$ and $\Omega_{i,y}$ are converging; see Fig. 3.8). If the latter is satisfied, the paths that show changes in $\Phi_{i,y}$ and $\Omega_{i,y}$ finally intersect (the gap between $\Phi_{i,y}$ and $\Omega_{i,y}$ is closed), so that in the next years, the replication coefficients are *lower* than marginal growth $\left(\Phi_{i,y} < \Omega_{i,y}\right)$, and the paths that show changes in $\Phi_{i,y}$ and $\Omega_{i,y}$ diverge. The specific time when the gap between $\Phi_{i,y}$ and $\Omega_{i,y}$ is closed (theoretically, $\Phi_{i,y} = \Omega_{i,y}$) we label the critical year ($Y_{crit,i,y}$); meanwhile, the penetration rate of new technology in $Y_{crit,i,y}$ we name the critical penetration rate ($critICT_{i,y}$). Technically, the critical year denotes the specific time period when the dynamic of the diffusion process is transformed, as the early diffusion phase is left behind and the new technology begins to diffuse exponentially; the '*critical penetration rate*' we define as the *threshold* that, once passed, provokes the diffusion to become self-perpetuating, which implies overcoming the '*resistance to steady growth*' (Rostow 1990). The '*critical penetration rate*' traces the number of individuals—'innovators'—who demonstrate little risk aversion and high propensity to acquire novelties and who thus are the first new technology adopters and the ones who propagate its further diffusion throughout society. Finally, we argue that the '*critical penetration rate*' approximates the '*critical mass*' of new technology adopters, which preconditions

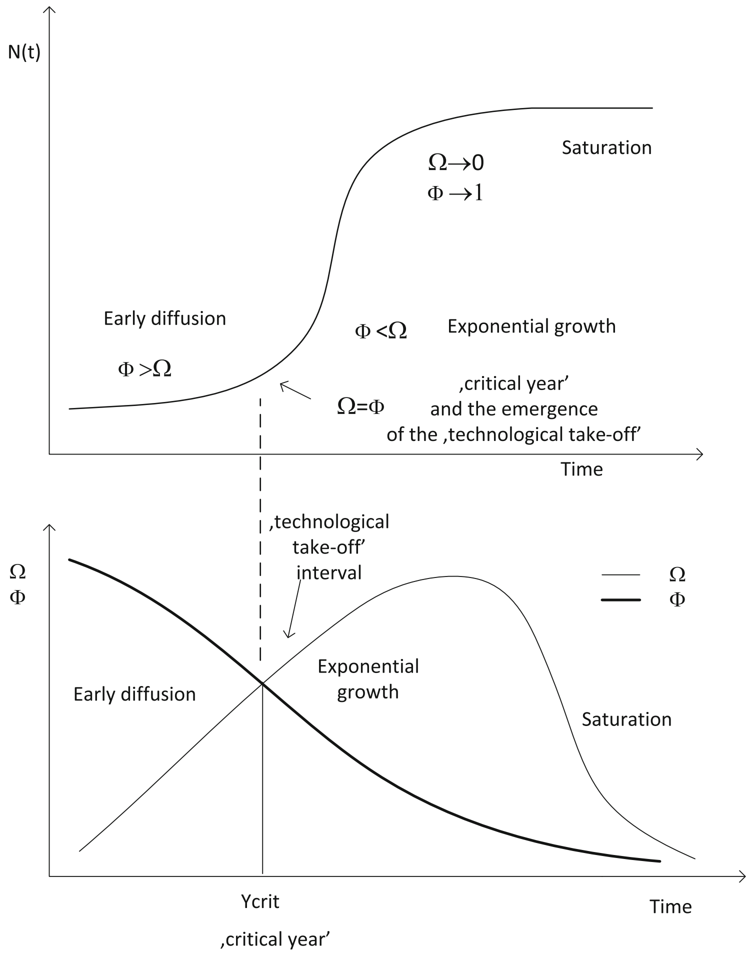

Fig. 3.8 Relationships between technology replication coefficient ($_{i,y}$), 'marginal' growth in technology adoption ($_{i,y}$), critical year ($Y_{crit,i,y}$) along the S-shaped technology diffusion trajectory. Source: Author's elaboration

the further spread of technology and forces the emergence of the '*technological take-off*'.

It is important to note that following this procedure would yield rigid identification of the exact date when $\Phi_{i,\,y} = \Omega_{i,\,y}$. However, to satisfy the latter, daily data on new technology penetration rates would be required, which for obvious reasons is scarcely possible. To challenge this obstacle, we choose to treat as the critical year ($Y_{crit,i,y}$) the first year when $\Phi_{i,\,y} < \Omega_{i,\,y}$, **if** in the previous year, the $\Phi_{i,\,y-1} > \Omega_{i,\,y-1}$ was reported. As was already mentioned, once it passes the $Y_{crit,i,y}$, the new technology begins to diffuse at an exponential rate, which is exhibited in the increasing values of $\Omega_{i,y}$. Finally, the process of diffusion slows and inevitably approaches the maturity phase when the desired saturation ($N_{y,i}$) is achieved. The slow-down and maturity phase $\Phi_y \rightarrow 1$ and $\Omega_y \rightarrow 0$ determines the termination of the diffusion process.

Finally, we propose labelling the 2-year interval right after the $Y_{crit,i,y}$ as the '*technological take-off*', which, as was previously defined, denotes the time period when the nature of the diffusion process is transformed because the diffusion rate shifts and forces the transition from stagnation to the dynamic and self-sustaining growth (diffusion) of the new technology.

Presuming that y stands for $Y_{crit,i,y}$ and to address the assumption that the '*technological take-off*' is the period during which the rate of diffusion is radically shifted, we suggest the following formalization of the conditions under which the '*technological take-off*' emerges:

$$\begin{cases} \Omega_{i,(y+1)} > 0 \\ \Omega_{i,(y+2)} > 0 \\ \Omega_{i,(y+1)} > \Omega_{i,(y)} \\ \Omega_{i,(y+2)} > \Omega_{i,(y)} \end{cases} . \tag{3.39}$$

Following Eq. (3.38) we argue that if y stands for $Y_{crit,i,y}$, the '*technological take-off*' interval occurs during the period $< y+1; y+2 >$.

If the critical year ($Y_{crit,i,y}$) is not identified, the conditions specified in Eq. (3.39) are also not satisfied, and this implies that the emergence of the '*technological take-off*' has been restricted. Technically, the previous indicates that during the initial diffusion phase, the replication lacked the strength to ensure gradual increases in $\Omega_{i,y}$, which would allow for closing the gap between $\Phi_{i,y}$ and $\Omega_{i,y}$ (see Fig. 3.9). As result, the paths that show the changes in $\Phi_{i,y}$ and $\Omega_{i,y}$ diverge rather than converge, and the critical year does not emerge. If $\Phi_{i,y} = 1$ or $\Phi_{i,y} < 1$, the situation is similar, and the technology diffusion is impeded. The countries where the $Y_{Crit,i,y}$ has not been identified are those where the process of entering exponential growth has been restrained and they remained virtually locked in the 'low-level-technology' trap, becoming latecomers in this respect.

Finally, we strongly argue that the '*critical year*', the '*critical penetration rate*' and the '*technological take-off*' do not emerge unconditionally or in isolation but are heavily predetermined by multiple social, economic and instructional prerequisites. The '*technological take-off*' is preconditioned and induced by strong stimuli that are typically well-established in the early diffusion phase. In this vein, we claim that the analysis of the '*critical mass*' should be considered in a broad context that allows for capturing a broad array of factors that could potentially foster or impede the '*technological take-off*'. We suggest that identifying both the critical penetration rate and the '*technological take-off*' interval should be complemented by broad analysis of the socio-economic and institutional conditions under which the '*technological take-off*' emerged. This approach places the purely numerical analysis in the broad macroeconomic perspective and is essential for capturing those factors that potentially foster or hinder the emergence of the

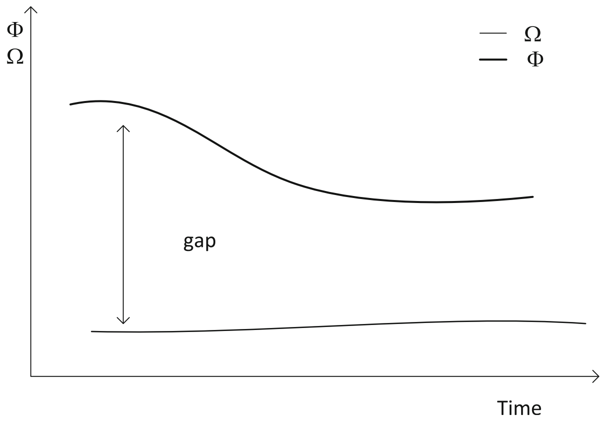

Fig. 3.9 The 'low-level-technology' trap. Source: Author's elaboration

'*technological take-off*'; and proposed broadening of the '*critical mass*' analysis sheds light on countries' socio-economic and institutional characteristics and situates the analysis in a broad macroeconomic perspective. These preconditions generally combine institutional change, economic performance, political regimes, social norms and attitudes, and the state of development of any backbone infrastructure. In a broad sense, the '*technological take-off*' requires that a society and an economy be prepared to actively respond to newly emerging possibilities (Rostow 1956). If these requirements are not sufficiently fulfilled, the '*technological take-off*' will not occur. Our concept of '*critical mass*' is, to a point, related to what was stressed in the works of Baumol (1986), Perez and Soete (1988), and Verspagen (1991), that a country's ability to adopt new technologies is preconditioned by a wide array of factors. Societies assess and assimilate technological novelties by relying upon 'intellectual' capital (Soete and Verspagen 1994) and institutional, governmental and cultural conditions. Some empirical evidence shows that the most prominent factors in a country's ability to adopt and effectively use new technologies are education and the skills of the labour force (Baumol 1986). Countries that experience significant lacks in these factors will likely never be able to ensure the widespread use of new technologies and use the full potential of technological change. As a result, they will never catch up with richer countries and will continue to lag behind as technologically disadvantaged regions.

3.4 Technology Convergence and Technology Convergence Clubs

Dynamic technology diffusion, accompanied by fundamental shifts in technology adoption and use, should inevitably lead to a significant reduction in cross-country technology gaps and growing cohesion. In other words, if countries experience growing levels of technology adoption, cross-country convergence should be exhibited. In this vein, we define 'technology convergence'[33] as a process leading to the 'technology gap' narrowing, and eradicating different forms of exclusion from access to and use of basic ICTs (Lechman 2012a, b). In this sense, technology convergence should fundamentally decrease cross-country inequalities in access to and use of ICTs,[34] as countries which are initially technologically-poorer shall exhibit relatively higher average annual growth rates of ICTs adoption, compared to countries which are initially better off with this respect. We intentionally encourage technology convergence unconditionally, leaving aside all factors which hypothetically might enhance or hinder the process. Still, our main attention shifts to providing an analytical framework to answer the prominent question of whether countries exhibit growing cohesion (decreasing technology gaps) in terms of their level of adoption and use of ICTs. So far, the approach to technology convergence analysis that we suggest is not commonly recognized, and the empirical evidence in the field remains relatively poor. Some evidence can be traced in the works of Comin and Hobijn (2004, 2011), Comin et al. (2006), Castellacci (2006a, 2008), Castellacci and Archibugi (2008), Castellacci (2011) and Lechman (2012a, b). Comin and Hobijn (2004) provide extensive analysis of technology convergence over the period 1788–2001. Their study covers 20 technologies in 23 different countries and tests the convergence hypothesis applying beta- and sigma-convergence procedures. Comin et al. (2006) perform similar exercises to Comin and Hobijn (2004). They test beta- and sigma-convergence using the CHAT (Cross-Country Historical Adoption of Technology) dataset, additionally separating within-technology and across-technologies effects. Castellacci (2006a, 2008) and

[33] In the literature discussing 'technological catching-up', the term is often confused with 'technology convergence'. In effect, it is misleading to use these two terms alternatively. Technological catching-up is the process through which countries benefit from the stock of knowledge available in the rest of the developed world, and goes far beyond simple technology convergence (Rogers 2010). The technological catching-up theories instead seek to answer how technologically backward countries may benefit from their underdevelopment and by diminishing the relative gap in Total Factor Productivity (TFP) experience economic growth (Soete and Turner 1984). The idea of incorporating different aspects of 'technology' into growth models traces back to pioneering works by Veblen (1915), Nurkse (1955), Gerschenkron (1962), Rostow (1971), Schumpeter (1984). Nelson and Phelps (1966) were the first to formalize the Veblen-Gerschenkron 'relative backwardness' idea and they introduced the idea of the function of technological catching-up depending on human capital and its absorptive capabilities (also argued by Abramovitz (1986)): $\frac{dA}{dt} / A = \varnothing(.)\left(\frac{T-A}{A}\right)$, where T stands for the level of the best practice technology, A is the level of technology in a backward country, and $\varnothing(.)$ is the function of absorptive capacities. Recently the literature treating international technological catching-up, and technology diffusion and transfer as factors contributing to rapid economic growth is pervasive. The most prominent evidence can be found in works by, *inter alia*, Fagerberg (1987, 1994), Perez and Soete (1988), Verspagen (1994), Dowrick (1992), Ben-David (1993), Coe and Helpman (1995), Barro and Sala-i-Martin (1990), Keller (1996), Bassanini et al. (2000), Dowrick and Rogers (2002), Castellacci (2002, 2006a, b, 2008, 2011), Liebig (2012), Stokey (2012), Shin (2013) and Serranito (2013).

[34] Apart from some empirical evidence on 'technology convergence' with respect to ICTs, there exist numerous studies where an analogous problem is tackled, but is labelled 'closing the digital divide' (see e.g. Servon 2008; James 2003, 2011; Vicente and López 2011).

Castellacci and Archibugi (2008) detect technology convergence clubs along with technology convergence testing. Castellacci (2008) reports on technology convergence and technology convergence clubs for 149 countries over the period 1990–2000. He additionally tests for 'technological capabilities' which may enhance or hinder the process of closing cross-country technology gaps. Additional evidence on the process of closing technology gaps is also reported by Castellacci (2011). Castellacci and Archibugi (2008), using data from the ArCo database (Archibugi and Coco 2004a, b, 2005) provide similar evidence over an analogous time period but they include 131 countries in their analysis. The empirical analysis found in works by Lechman (2012a, 2012b) reports on technology convergence exclusively for Information and Communication Technologies, for 145 countries over the period 2000–2010, and the technology convergence is tested adopting beta-, sigma-, and quantile-convergence approaches.

Originally, the concept of 'convergence' referred to growing cross-country cohesion in terms of economic development, approximated by *per capita* income level. Thus, the conceptual background for technology convergence analysis is derived from endogenous growth theories. These are explained in Sects. 3.4.1 and 3.4.2.

3.4.1 Convergence: Theoretical Specification

Following neoclassical growth theory (Solow 1956), countries follow a convergence pattern heading for common equilibrium in *per capita* income (Barro and Sala-i-Martin 1990; Barro et al. 1991, 1995). In other words, countries tend to converge toward a 'steady-state' equilibrium, but they experience gradual decreases in their rate of growth (Kangasharju 1999), however, under the rigid assumption of identical cross-country growth rates. In other words, the convergence process implies that initially poorer countries experience a relatively higher average annual growth rate, and thus catch up with the rich ones. The idea that poor countries tend to grow faster than rich ones is strictly attributed to Gerschenkron's[35] pioneering hypothesis of 'relative backwardness' (1960, 1962). Gerschenkron argues that backward economies take advantage of their economic underdevelopment[36] and by assimilating technology spillovers into high growth rates they catch up with the rich countries[37] (Verspagen 1994). Thus, the Veblen-Gerschenkron

[35] Although in many works Alexander Gerschenkron is cited as the first to introduce the idea of 'relative backwardness', the term was also used by Thorsten Veblen (1915) and Leibenstein (1957).

[36] Similarly, Findlay (1978a), Baumol (1986) and Romer (1993) consider relative backwardness to be a convergence facilitating factor.

[37] Gerschenkron's 'relative backwardness' idea (1962) was formalized in a model by Nelson-Phelps (1966), who argued that the growth of technology in an economically backward country is proportional to the gap between the backward country and the country using the most advanced technological solutions (located close to the Technology Frontier Area) (Gomulka 2006).

hypothesis links economic convergence[38] with the initial size of the gap with world technology frontiers (Stokke 2004)[39]; while Abramovitz (1986) points out that backward countries have a potential for rapid advances, but he also stresses the importance of social capabilities which can enhance or hinder the catching-up process (Abramovitz 1989).

Technically speaking, convergence occurs if average annual growth rates are inversely correlated with initial *per capita* income. A straightforward implication of undisturbed convergence is that—in a long-term perspective—cross-country disparities should inevitably be eradicated. If this is not the case, countries instead experience divergence and the gap between 'rich' and 'poor' enlarges. Empirically, the convergence can be tested using two standard approaches, namely sigma (σ)-convergence and beta (β)-convergence. σ-convergence is exhibited once disparity in *per capita* income decreases over time, which is measured by changes in the standard deviation (absolute approach) or the coefficient of variation (relative approach).[40] The standard deviation for country i in country set n and year t is as follows (Rodrik 2013; Thirlwall 2013):

$$\sigma_{i,t} = \left[\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(log\left(\frac{y_i}{y^x}\right)\right)^2\right]^{1/2}, \tag{3.40}$$

if $y^x \equiv \frac{1}{n}\sum\nolimits_{i=1}^{n} log(y_i)$, and y stands for *per capita* income. Over the period analyzed, the σ-convergence hypothesis is verified positively if $\sigma_{i,t} \to 0$ is satisfied.[41] This approach to convergence testing, although very interpretive and simple, has one main disadvantage: the standard deviation reveals a high sensitivity to the inclusion of outliers in the country set tested, and additionally it does not allow any causal mechanism provoking economic convergence among countries to be captured.[42]

[38] Productivity convergence.

[39] Findlay (1978a), however, argues that the gap to the world technology frontier cannot be *too* large, and countries located below a threshold value of the gap will not be able to catch-up economically.

[40] The coefficient of variation is highly useful in σ-convergence testing if two or more country groups are compared in terms of their internal convergence.

[41] If σ-convergence is tested with regard to the coefficient of variation, then the coefficient of variation is $\frac{\sigma_{i,t}}{\vartheta_{i,t}}$, where $\theta_{i,t}$ is the mean of the tested variable over the whole sample.

[42] The σ-convergence hypothesis was tested, *inter-alia*, in works by de la Fuente (2003), Canaleta et al. (2002), Rey and Dev (2006), Young et al. (2008), Egger and Pfaffermayr (2009), Garrido-Yserte and Mancha-Navarro (2010), Schmitt and Starke (2011), Smetkowski and Wójcik (2012), Delgado (2013) and Thirlwall (2013).

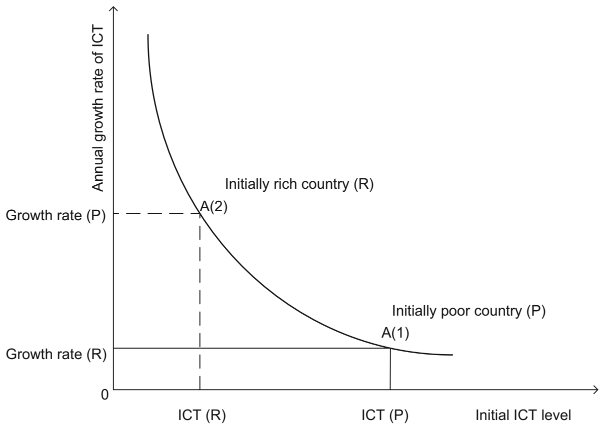

Fig. 3.10 Unconditional (absolute) convergence. Note: the figure refers to 'technology (ICT) convergence'; *P* poor country; *R* rich country

Following the neoclassical growth model (Sala-i-Martin 1995), the conditions for absolute (unconditional) β-convergence can be formulated as a regression equation[43]:

$$\mathrm{g_i} = \mathrm{a} + \mathrm{bv}_{\mathrm{i},\mathrm{t}_0} + \varepsilon_{\mathrm{i}}, \tag{3.41}$$

where i denotes the country, t_0 is the initial year in the time span for the convergence test, v_{i,t_0} is the level of *per capita* income in t_0 expressed as its natural logarithm, and ε_i is a random error term. The coefficient b[44] in Eq. (3.41) stands for the convergence coefficient, indicating the speed of the process. Consider that, for example, $b = 1.5$, then one unit increase in $\ln(v_{i,t_0})$ provokes an average annual growth in *per capita* income approximately 1.5 % higher in initially poorer countries. For economic interpretation, the sign—positive or negative—of b is crucial, since negative b indicates convergence (see Fig. 3.10), but positive b means divergence, yielding growing disparities between countries. Formally, if coefficient $b = 0$, then neither convergence nor divergence is reported and the gaps between countries are maintained over time.

Using the coefficient b from Eq. (3.41), the speed of convergence can be estimated. Assume that over the given time period $T = 0 \ldots\ldots t$, so that:

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[43] Conventionally, Eq. (3.41) is estimated applying OLS. However, if we relax the assumption that the variables are normally distributed, the estimated coefficients might be biased and inefficient. Koenker and Bassett (1978) suggest the adoption of non-parametric quantile regression to avoid the problem. The quantile regression approach is highly useful when the original variable distribution is highly skewed (asymmetric). Standard β-convergence estimates allow for assessment of variable behaviour but are based on the conditional mean, while quantile regression (q-regression, q-convergence) introduces estimates in non-central locations (Koenker 2004; Hao and Naiman 2007). Using the quantile regression approach, it is possible to determine any number of quantiles for estimation, which allows modelling of variable behaviour in any pre-defined location of variable distribution.

[44] Also explaining the partial correlation between a variable growth rate and its initial level.

$$b = -\left(1 - e^{-\beta T}\right). \tag{3.42}$$

By extracting β from Eq. (3.42), we obtain:

$$\beta = -\ln(1 + b)/T, \tag{3.43}$$

where β indicates the rate at which convergence proceeds and countries head toward a steady state of *per capita* income. Consequently, we calculate the time span necessary for actual inter-country disparities to be halved:

$$HL_i = [-\ln(2)]/\beta. \tag{3.44}$$

Suppose that HL_i is 10 years. This implies that if the current convergence rate is maintained over the period the inter-country gaps will be halved within a 10-year period.

The concept of unconditional convergence (both σ and β) is built on the rigid assumption that the process of convergence is 'automatic' and is not pre-conditioned by any country's individual characteristics. However, it is reasonable that the tendency of countries to converge (diverge) toward a steady state is conditioned by factors unobservable from their absolute convergence (Galor 1996; Quah 1996; Rodrik 2013). These can be technological development, social capital, institutional constraints, culture or many others.[45] The formalization of conditional convergence, however, requires that Eq. (3.41), needs to be modified by adding a vector (V_i) explaining a country's individual features. Thus, the regression is estimated as:

$$g_i = a + bv_{i,t_0} + \alpha V_i + \varepsilon_i, \tag{3.45}$$

with notation as in Eq. (3.41). The economic interpretation of b is analogous to that in the case of unconditional convergence.

σ-, and β-convergence testing (both unconditional and conditional) is based on econometric procedures with cross-sectional data application (de la Fuente 2000). However, Bernard and Durlauf (1995) and Bernard and Jones (1996) argue that convergence is a dynamic process. They suggest an alternative approach to convergence analysis which is based on a time series.[46] They claim that economies should stochastically converge under the assumption that long-term growth forecasts for each country are close to equal.[47] Assume we have just two countries *a* and *b*, and

[45] The body of evidence on conditional convergence is *mass*ive. Seminal contributions in the field were made by, *inter alia*, Dowrick and Nguyen (1989), Barro and Sala-i-Martin (1990); Mankiw et al. (1992), Quah (1993, 1999), Pritchett (1997), Del Bo et al. (2010), Schmitt and Starke (2011), Barro (2012), and Yorucu and Mehmet (2014).

[46] Also labelled 'stochastic convergence' (see i.e. McGuinness and Sheehan 1998).

[47] The approach for convergence testing using a time-series has been applied in a multitude of studies, e.g. using empirical evidence on inter-regional stochastic convergence, by *inter alia*, Johnson (2000), Drennan et al. (2004), Alexiadis and Tomkins (2004), Herrerías and Monfort

for both the long-run GDP *per capita* forecasts are equal. Thus, the condition for absolute convergence can be expressed as (Bernard and Durlauf 1995):

$$\lim_{k \to \infty} E\Big(\ln(GDPpc)_{a,t+k} - \ln(GDPpc)_{b,t+k} / \Pi_t\Big) = 0, \tag{3.46}$$

where t denotes time and Π is the stock of information which is available at a given point in time. The formula in Eq. (3.46), can be easily extended to any number of countries in the sample for which the absolute convergence hypothesis is to be tested.[48]

3.4.2 Convergence Clubs Hypothesis

Apart from the growing body of theoretical and empirical evidence on the convergence process, the concept of 'convergence clubs' has emerged. It was initially proposed and conceptualized by Baumol (1986) and consequently developed by Baumol and Wolff (1988), and Baumol et al. (1989). The 'convergence clubs' hypothesis assumes that a sub-set of countries (of the full sample) experience convergence[49] and head toward a common steady state (Alexiadis and Tomkins 2004; Alexiadis 2013a), while the 'rest' of the countries are left outside the 'club' and gradually diverge. The general message is that convergence occurs only for a subset of countries, while the 'rest' are excluded from the 'very exclusive organization' (Baumol 1986). Alexiadis and Alexandrakis (2008) argue that convergence clubs arise as some economically backward countries do not satisfy certain initial conditions and cannot fully realize their potential of catching-up with rich countries (Easterly et al. 1993; Ocampo et al. 2007). Thus, a group of initially poor countries grows at lower rates than rich countries, and the gap between the two increases.[50]

In the literature, there exist two main approaches providing a theoretical framework for the detection of convergence clubs. The first one, proposed by Baumol (1986), derives from the absolute convergence to 'steady state' approach (see, e.g., Barro and Sala-i-Martin 1990; Barro et al. 1991, 1995), and the second—developed

(2013), Lin et al. (2013); or inter-country stochastic convergence as in the works of Datta (2003), Bentzen (2005), and Canarella et al. (2010).

[48] The possibility of applying the formula in Eq. (3.46) to use it for absolute convergence testing, however, is determined by specific econometric tests. The most commonly used for this purpose is the Augmented Dickey Fuller test (1979, 1981), which introduces cointegration and unit root procedures to the empirical analysis of time-series.

[49] Generally in terms of β-convergence.

[50] Quah (1997, 1999) argues that countries may form 'coalitions' and behave non-linearly in their convergence patterns for three main reasons: countries' behaviour along their development paths are heavily preconditioned by other counties (e.g. by trade flows, human labour flows); countries tend to specialize to boost economies of scale; and human capital, culture, social and absorptive capabilities matter for development (see also Abramovitz 1989).

by Chatterji (1992)—is based on 'convergence in gaps'.[51] Formally, the test for the existence of convergence clubs in a set of countries consists in augmenting the standard procedure for β-convergence testing (see Eq. (3.41)) by introducing the square term of the explanatory variable. Inserting these square terms into Eq. (3.41), generates the possibility of identifying multiple *equilibria* (Alexiadis 2013a) as the convergence path exhibits non-linearities (Desdoigts 1999; Quah 1997, 1999; Fiaschi and Lavezzi 2007; Artelaris et al. 2011). Following the theoretical specification developed by Baumol (1986) and Baumol and Wolff (1988), the basic condition for convergence club emergence is expressed in a quadratic model:

$$\mathrm{g_i} = \mathrm{a} + \mathrm{b_1 v_{i,t_0}} + \mathrm{b_2 v^2_{i,t_0}} + \varepsilon_\mathrm{i}. \tag{3.47}$$

Equation (3.47) is an augmented version of the standard regression (see Eq. (3.41)) applied for β-convergence testing. The hypothesis on convergence clubs is supported only in the case that the coefficients b_1 and b_2 emerge as negative and positive respectively. The model defined in Eq. (3.47) has several important implications. First, it shows that the convergence pattern with respect to a set of countries might not be linear, and the convergence as such is identified only in a subset of countries, while the rest are left behind (see Fig. 3.11). The function defined in Eq. (3.47) reaches its maximum when the first derivative of Eq. (3.48) reaches zero. Thus:

$$f'_{g_i, v_{i,t_0}} = \frac{dg_i}{dv_{i,t_0}} = 0. \tag{3.48}$$

Extracting v_{i,t_0} from Eq. (3.48), gives the level of *per capita* income corresponding to the maximum of the function in Eq. (3.47), which can be calculated as:

$$v_{threshold} = \frac{-b_1}{2b_2}. \tag{3.49}$$

The *per capita* income in (t_0) calculated applying Eq. (3.49) stands for the '*threshold value*' ('*threshold condition*') (Alexiadis 2013a) and enables the identification of convergence club members.

Thus, in the case of countries that initially exceed the '*threshold value*' of *per capita* income $(v_{i,t_0} - v_{threshold} > 0)$ the relationship between the average annual growth rate and the level of *per capita* income in (t_0) is negative. Hence β-convergence is confirmed, and they form a convergence club. However, for

[51] The evidence on convergence club identification, mainly with respect to *per capita* income, can be found in works by, *inter alia*, Ben-David (1994, 1998), Armstrong (1995, 2002), Dewhurst and Mutis-Gaitan (1995), Fagerberg and Verspagen (1996), Verspagen (1997), Desdoigts (1999), Baumont et al. (2003), Durlauf (2003), Su (2003), Canova (2004), Fischer and Stirböck (2006), Le Gallo and Dall'Erba (2006), Alexiadis (2013b), Lechman (2012c), Song et al. (2013), Brida et al. (2014) and Fischer and LeSage (2014)

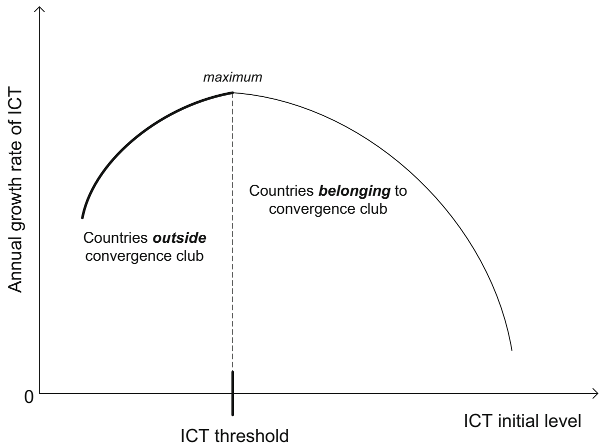

Fig. 3.11 Convergence clubs—theoretical specification. Source: own elaboration based on Baumol (1986) and Alexiadis (2013a) concepts. Note: the figure refers to 'technology (ICT) convergence clubs'

countries that were initially located below the '*threshold value*' of *per capita* income $(v_{i,t_0} - v_{threshold} < 0)$, the relationship between the average annual growth rate and the level of *per capita* income in (t_0) is positive and β-convergence is not reported.[52] Hence, these are left outside the club.

Following the original concept of technology gaps developed, *inter alia*, by Gomulka (1971, 1986), Chatterji (1992) proposed a different approach to convergence club detection. He argues that positive verification of the β-convergence hypothesis is not sufficient for the reduction of gaps among countries. Cross-country disparities may grow over time and thus convergence 'in gaps' is not reported. The procedure proposed by Chatterji (1992) for the detection of convergence clubs may be treated as an enriched and more sophisticated version of σ-convergence. Its theoretical specification is the following. Assume we have a set of countries over the period $(t_0 \ldots\ldots. T)$ with a leading economy (L). We follow the rigid assumption that both in the initial and the terminal year the leading economies remain unchanged. The gap (divide) between the L-economy and any other country in the set is defined as (Chatterji and Dewhurst 1996; Kangasharju 1999):

$$G_{i,t_0} = ln\left(\frac{V_{leader,t_0}}{V_{i,t_0}}\right), \tag{3.50}$$

in the initial year (t_0), and in the terminal year (T) it is:

$$G_{i,\mathrm{T}} = ln\left(\frac{V_{leader,\mathrm{T}}}{V_{i,\mathrm{T}}}\right). \tag{3.51}$$

[52] It is important to note that Baumol (1986) approach to convergence club identification is heavily pre-conditioned by the initial level of *per capita* income.

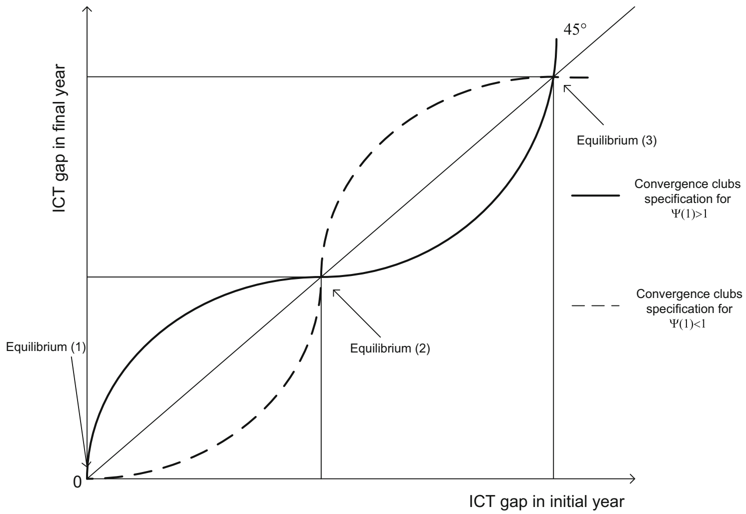

Fig. 3.12 Convergence clubs—theoretical specification. Source: own elaboration based on concepts by Chatterji (1992), Kangasharju (1999) and Alexiadis (2013a). Note: the 45° line indicates whether $G_{i,t_0} = G_{i,T}, G_{i,t_0} > G_{i,T}$ or $G_{i,t_0} < G_{i,T}$. Points below 45° indicate convergence and above 45° divergence. The figure refers to 'technology (ICT) convergence clubs'

Following Kangasharju (1999), the condition for the identification of convergence clubs in a given country set is defined as a three-equilibria model:

$$G_{i,T} = \Psi_1\,(G_{i,0}) + \Psi_2(G_{i,0})^2 + \Psi_3\,(G_{i,0})^3. \tag{3.52}$$

The third degree polynomial[53] (Eq. 3.52) yields the existence of three different equilibrium (see Fig. 3.12) satisfying $G_{i,0} = G_{i,T}$. This also suggests that convergence follows a cubic behaviour, and at every equilibrium the gap between economy i and economy L is constant.

Following Chatterji (1992) and Alexiadis (2013a), the steady-state values ($G_{1,t_0} \rightarrow$ Equilibrium (1), $G_{2,t_0} \rightarrow$ Equilibrium (2), and $G_{3,t_0} \rightarrow$ Equilibrium (3)) that determine club membership are defined as:

$$\begin{aligned} G_{2,t_0} &= \frac{-\Psi_2 - \sqrt{(\Psi_2)^2 - 4\Psi_3(\Psi_1 - 1)}}{-2\Psi_3} \\ G_{3,t_0} &= \frac{-\Psi_2 + \sqrt{(\Psi_2)^2 - 4\Psi_3(\Psi_1 - 1)}}{-2\Psi_3} \end{aligned} \tag{3.53}$$

and G_{1,t_0} is zero by definition.

[53] Cubic specification.

Convergence behaviour and convergence club formation strictly depend on the value Ψ_1. If $\Psi_1 < 1$, then countries with an initial gap lower than G_{2,t_0} exhibit convergence. Thus for a convergence club the gap between country i and economy L is gradually decreasing. Conversely, countries with an initial gap between G_{2,t_0} and G_{3,t_0} are instead diverging from economy L and are excluded from the club, increasing their distance to economy L. The most backward economies with an initial gap above G_{3,t_0} may converge, but only toward the third equilibrium point. If $\Psi_1 > 1$, the situation is just the opposite. Countries exhibiting convergence (forming convergence clubs) are those with an initial gap varying from G_{2,t_0} to G_{3,t_0}, while countries with an initial gap below G_{2,t_0} instead tend to diverge from economy L. Again, the poorest countries, with initial gaps above G_{3,t_0}, converge, but toward the 'lower' equilibrium.

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