Environmental policy and technology diffusion under imperfect competition

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Chapter 3

Diffusion models: an overview

3.1 Introduction

The body of literature that discusses the diffusion of technology is vast and, for this reason, it is inevitable to demarcate. The aim of this chapter is not to give an extensive overview of all the different types of models but rather to determine how and to what extent evolutionary game theory can contribute to the existent types of diffusion models. To do so, we will first give an overview of the more conventional types of diffusion models. Given the purpose of this dissertation, it is sufficient to touch the most influential models only briefly. This is the subject of section 3.2. Readers interested in a more thorough treatment of the most influential diffusion models are referred to the recent study of Geroski (2000).

Section 3.2 contains an overview of classical diffusion models. In section 3.3, a broad sketch of the evolutionary theory of technological change is provided. The chapter ends with concluding remarks in section 3.4.

3.2 Classic diffusion models: a bird's eye view

Empirical evidence shows that over time the market penetration of a new technology in many cases follows a S-shaped pattern (e.g. Karshenas and Stoneman, 1995; Geroski, 2000). Moreover, the evidence reveals that diffusion is a rather slow process and that the spreading of new technologies simply takes time. The S-shaped diffusion pattern reflects an initially low, but increasing adoption rate

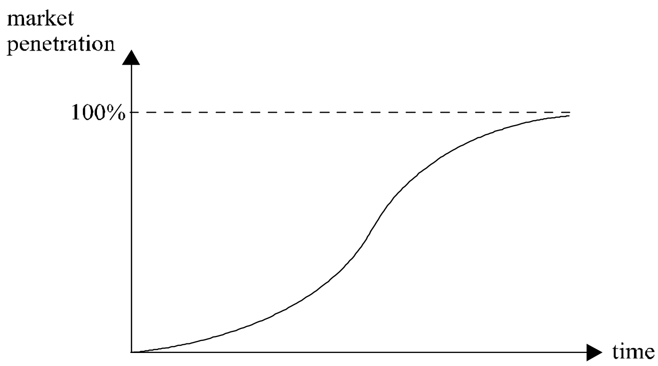

Figure 3.1: *Logistic diffusion curve.*

in the population of potential users in the first stage, followed by a high rate of adoption in the second stage approaching the final stage of the diffusion process where the maximum share of entire population has switched to the new technology. Figure 3.1 gives an illustration of this well-known sigmoid market penetration pattern represented by the logistic function[1].

The oldest branch of models that tried to capture the sigmoid diffusion pattern are the epidemic models. The classic epidemic diffusion model originally finds its roots in the science addressing the spreading of diseases, as the word 'epidemic' suggests. Seminal economic studies that make use of the model for shedding some light on the diffusion of technology at the sectoral level are Griliches (1957) and Mansfield (1961). Later applications and extensions are e.g. Bass (1969) and Rogers (1995). They will not be examined in detail, but we rather point to the main diffusion dynamic around which they center their analysis. These studies, among others, share the use of one of the most conventional functions for generating an S-shape diffusion pattern, namely the logistic function expressed by the ordinary differential equation:

$$\frac{ds}{dt} = \xi s(1 - s). \tag{3.1}$$

Equation (3.1) determines how diffusion develops over time with $s \in [0, 1]$ as the fraction of the population which has adopted the technology and $\xi > 0$ determining the speed of diffusion. Parameter ξ describes the transmission of information in the population of potential adopters by means of contact. In this classic epidemic model ξ is exogenous. This was one of the main critiques

[1] In figure 3.1 the saturation level is set at 100%, but might as well lie at any other level.

on this specification (e.g. Davies, 1979; Dixon, 1980). Some important studies (basically developed in the marketing and management sciences) are e.g. Chow's (1967), Glaister (1974), Hernes (1976), Bass (1980), Easingwood *et al.* (1983), Horsky and Simon (1983), Kalish (1985) and Karshenas and Stoneman (1992). The book of Kemp (1997) includes a good summary of this work. But despite allowing for a varying speed of adjustment, the mentioned studies are not based upon a profound decision-theoretic framework (e.g. Davies, 1979; Kemp, 1997). That is, they do not consider the individual decision making processes in determining whether or not to adopt a particular technology. The new technology is supposed to spread like an epidemic among the population simply by means of information transmission. The transmission accelerates in the first stage as more and more members have become a source of information. In the second stage, the spread of information slows down since there are less and less people to be found who are still uninformed. The general shortcoming of epidemic models is that they 'abstract from differences in the goals, capabilities or actions of individual members of the population in order to focus on the diffusion of information in a simple, tractable, non-strategic setting' (Geroski, 2000, p.610). In the spirit of this thesis, it is essentially diffusion in a strategic environment in which we are interested and we thus have to incorporate an explicit market structure, which, at the same time, accounts for economic variables as well.

A reaction to this lack of account for economic variables and the lack of an explicit decision making framework behind the adoption rationales, are the so-called rational choice diffusion models. The class of rational choice models can broadly be divided into two groups: probit models and game theoretic models (e.g. Kemp, 1997). Both types of models aim at incorporating economic variables into the individual decision making process. We shall first discuss probit models; it is followed by a discussion on game theoretical diffusion models[2].

Probit models (e.g. Bain, 1964; David, 1969; Bonus, 1973) analyze the individual adoption decision by using a threshold level of adoption. The threshold is a critical adoption level and the decision to adopt occurs once a stimulus variate exceeds this threshold value. While epidemic models explain the diffusion pattern by directly focusing on the aggregate level, probit models allow for differences in the individuals' characteristics. Instead of focusing on the

[2]See e.g. Beath *et al.* (1995) for a general overview of game theoretic approaches to technological change. Not only do they discuss the subject of technology diffusion based on game theory, but also cover topics as tournament and non-tournament R&D models, as well as licensing issues.

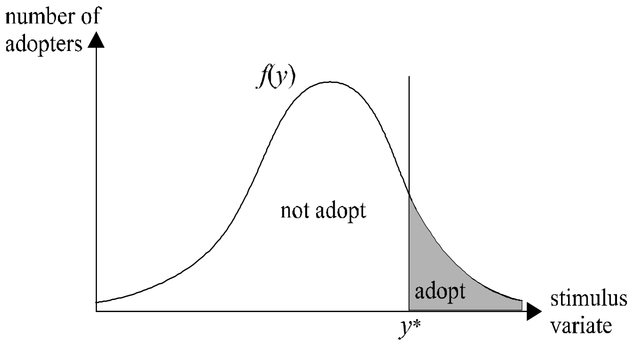

Figure 3.2: *Normal frequency distribution of stimulus variate y_i.*

aggregate level, the focal point in probit models is to analyze the individual adoption decision.

Suppose an individual in a population of potential users of a certain technology differs in some characteristic (stimulus variate) y_i. The *expected* payoff or profitability of adopting the new technology is contingent on y_i. Furthermore, assume adoption takes place when y_i exceeds some critical level y^*. The final ingredient is a density function which describes how y_i is distributed across the population. In practice, any kind of distribution may be applicable, but for now assume y_i is normally distributed described by the function $f(y)$ as pictured in figure 3.2. The shaded area in the figure represents the adopters of the new technology; for those individuals $y_i > y^*$. The non-shaded area represents the non-adopters for which $y_i < y^*$ applies. Actually, the case is a picture at a given moment in time, i.e., both y^* and y_i may fall or rise in the course of time. When an individual does not adopt the technology, it waits until either y^* falls or its y_i rises and then again determines whether or not to adopt. So, both y_i and y^* may vary over time.

Two concrete classic examples of the application of probit models to analyze the diffusion of process innovations are David (1969) and Davies (1979) in which the individual characteristic is firm size. Let's focus on the Davies model. The adoption decision here depends on whether the expected returns of adoption exceed a certain threshold value of returns. However, Davies faces the problem of both these variables being unobservable. He solves the adoption decision problem by assuming that both are a function of firm size with increasing expected returns relative to the threshold returns when firm size increases.

Subsequently, the critical level of firm size at which the expected return equals the critical level of returns is determined. Hence the decision implies adoption when the firm size exceeds the critical value of firm size or otherwise non-adoption.

In a nutshell, probit models try to underpin the diffusion process with a base of economic decision making processes. However, as Adeoti (2001, p.30) points out: '[..] the models are models of decision under uncertainty based on the assumption of a heterogeneous adopting population and non-declining benefit to adoption as adoption widens.' The uncertainty comes from the fact that the decision to adopt is based on *expected* returns. The diffusion is driven by exogenous changes in factor prices and the model lacks an information spreading device, which is explicitly present in the epidemic model. Moreover, the probit model is a static one; i.e., it is an equilibrium model in the sense that it does not provide any insight into how a possible saturation level of diffusion is reached (*cf.* Thirtle and Ruttan, 1987). Finally, there is hardly any account for social interaction and learning (Kemp, 1997).

The other member of the class of rational choice diffusion models are models based upon game theoretic concepts (e.g. Reinganum 1981a, 1981b, 1983). Game theoretic models investigate the individual decision making and so base, just as probit models, the aggregate 'macro' level of diffusion on the individual 'micro' structure. In Reinganum's models, firms play an oligopoly game and act strategically by considering the adoption of a new technology. She assumes that the identical firms maximize present value, given the availability of perfect information about the new technology. Moreover, it is assumed that the later a firm adopts the new technology, the lower the costs of adoption will be. Furthermore, as usual, profits are assumed to be decreasing in the number of adopters. By delaying adoption, a firm does not save an adoption cost, but the profits of adoption will also be lower due to earlier adoption by other firms. The game in which the firms participate is a one-shot game, i.e., when the new technology appears, it is played only once. Reinganum (1981a) finds a Nash equilibrium implying different dates of adoption for the various firms in the industry. So, the general result is that firms adopt sequentially and the difference in adoption dates generates the diffusion pattern. One of the main results of the game theoretic analysis of diffusion as derived by Reinganum is that when all firms instantly adopt a technology this might not be profitable, but that eventually diffusion develops to a state where the fraction of adopters approaches unity. The approach of Reinganum is interesting in the sense that she illustrates the relevancy of the oligopoly game and so the strategic environment for the diffusion process. However, a shortcoming is that the approach is not completely dynamic. As stated above, she considers a one-shot game and this type of game is by definition static. How diffusion evolves over time is completely determined by decisions taken prior to the initiation of the diffusion process.

Like probit models, the game theoretic approach too ignores the information spreading factors. However, in contrast to probit models there is some form of social interaction in terms of players acting strategically to one another. Kemp (1997) notes some shortcomings of game theory as a method for analyzing technology diffusion. He argues that '[..] the practical meaning of game theoretic diffusion models is believed to be limited. The models are not able to derive sigmoid diffusion curves that are commonly observed. Moreover, learning and risk reduction in the presence of technological uncertainty are given a minor role, if any, in the models' (Kemp, 1997, p.84).

The remarks of Kemp are not completely justified. For instance, in Reinganum (1983) technological uncertainty is explicitly modelled and is an important feature of the model. However, one has to admit that uncertainty is brought in as a distribution of expected outcomes and therefore can be included in the economic calculations. When uncertainty is fundamental in the sense of having limited information, we can have cases of myopic actors simply reacting to actual outcomes. In chapter 6, we shall elaborate on a dynamic diffusion model based on economic decisions under such myopic decision making. Finally, both probit and game theoretic models are essentially demand oriented. There is less room for supply side factors, both on the technology and economic side of the market.

Next to the epidemic and rational choice diffusion models, one can distinguish a third class of models labeled as an evolutionary or neo-Schumpeterian approach. This is the next subject we will turn to.

3.3 Diffusion: evolutionary approaches

The key element in the evolutionary or so-called neo-Schumpeterian approach of technological change is the interaction between technology and the economy, thus emphasizing the *processes* in finding the answers to the main question: why is it that some innovations survive while others don't? (Freeman, 1991). As Freeman continues, whether innovations survive or not, implies the existence of a selection environment. This selection environment is shaped by the whole complex set of interactions within the technology-economy framework. As a consequence, in contrast to neoclassical theory in which the individual agent itself is the predominant actor, in evolutionary theories the population(s) of individuals play a role too (e.g. Witt, 1991). Let's try to make the difference also clear by sticking to the environmental economic oriented research theme of this thesis. Kemp (1997) investigates the diffusion of energy-saving technologies by adopting a neo-Schumpeterian framework in combination with neoclassical theory and shows how a synergy can be established. He gives the following distinction between the two approaches:

> Central to economic evolutionary theory is that optimal behaviors and technologies cannot be determined ex ante on the basis of economic calculus but are selected ex post in the selection environment - they are selected ex post by the evolution of social needs, the actions of other firms and organizations, new discoveries in technology and science, and government interventions, much more than they are selected by the choices of economic actors that look into the future (Kemp, 1997, p.3).

Seminal is the evolutionary contribution of Nelson and Winter (1982) who study economic growth based on organizational decision making guided by 'rules of thumb' rather than optimization. Since the appearing of their work evolutionary studies on the innovation and diffusion of technology have expanded and found their way up. Main contributions are e.g. Dosi (1982, 1988a, 1988b, 1991), Dosi *et al.* (1988), Freeman and Soete (1990, 1997), Freeman (1982, 1988, 1991), Metcalfe (1988, 1994a, 1994b) and Silverberg (1991). In the light of the environmental economics theme of this thesis, the work of Kemp (1997) and Kemp and Soete (1990, 1992) are applications of the evolutionary paradigm to the analysis of environmentally benign technological change. Kemp (1997) examines the problem of technological regime shifts and is mainly demand oriented. He investigates how the system may develop into new directions due to changes in the selection environment, i.e., changes in the institutional setting and changes in the technological relationships. In short, changes in the technology-economy relationship. We do not focus on radical technological regime shifts in this thesis and stick to the general definition of evolution, which implies any gradual change (see chapter 2). Other studies exploring and surveying the usefulness of evolutionary theories for sustainable development are Kemp *et al.* (1999) and Mulder and Van den Bergh (2001).

The evolutionary perspective is broad in the sense that it allows economic, political and social institutions to play all their interdependent roles. Selection is active at all these different levels (e.g. Freeman, 1991). On the one hand such a framework enriches the neoclassical approach but at the same time the quantitative modelling of the behaviors of all these economic subjects becomes much more difficult. Therefore, evolutionary studies are often *qualitative* in nature. However, one might recognize a turning point in recent neo-Schumpeterian diffusion studies that overstep the confinements of such a qualitative framework and step into formal quantitative modelling (see e.g. Winter *et al.* 2000). In this thesis, we explicitly combine the qualitative and quantitative evolutionary approach and as a preliminary introduction the central ideas shall now be sketched.

According to Geroski, evolutionary models of technology diffusion assume, alike probit models, a heterogeneous population of technology users. Furthermore, the driver of dynamics in evolutionary models is a selection mechanism and the impact of this mechanism on technology adoption and diffusion is the central subject of study. The selection dynamic can take any specific form as long as it features monotonicity (see chapter 2). The basic idea behind frequency-dependent growth models is that 'contagion' affects the adoption decision of the members in the population through the impact the degree of diffusion has on the individual expected benefits and costs of adopting, or not adopting the new technology respectively. For example, if more and more members of the population make use of the new diffusion item, the individual net benefits (or utility) to all adopters may decrease (increase), and for non-adopters the net benefits of sticking to the old item may increase (decrease). If such developments have not been foreseen, for instance due to 'short sightedness' of agents facing a largely unknown future, the observed spreading of the diffusion item will affect today's decision on (non)adoption. We will illustrate the frequency-dependency effect based on an example presented by Witt (1991).

Assume that an individual has a bimodel choice between adopting y or not adopting z a particular diffusion item[3]. Assume that at time t the relative frequency of adopters in the population (that is, the share of the total population that has adopted the diffusion item) is stated as $F_y(t)$. The net benefit u_y for an individual choosing y over z is dependent on $F_y(t)$, i.e.,

$$u_y = u_y(F_y(t)).$$

Assume $u_y(0) > 0$ and $u_y' < 0$. This could, for example, represent the case of a new product market. When more and more firms enter this new market domain, the benefit per firm will become lower.

[3] In this thesis the diffusion item is the clean technology.

The probability f_y of choosing y over z is defined as the probability that a member of the (total) population (including those who have adopted y as well as those who have not) will take up the diffusion item. The probability f_y can be interpreted as the willingness to adopt y[4]. Let's assume a monotonic increasing relationship between the probability f_y of choosing y over z and the net benefit, i.e., as the net benefit increases the probability f_y increases too: $f_y = f_y(u_y)$ with $df_y/du_y > 0$. Subsequently, the frequency-dependency effect of the net benefit associated with adoption y of the diffusing item can be expressed by a function $f_y = \varphi(F_y(t))$. From $df_y/du_y > 0$ and $du_y/dF_y < 0$ it follows that $df_y/dF_y < 0$. The relation $f_y = \varphi(F_y(t))$ is shown in figure 3.3a and illustrates that as the number of adopters increases the willingness or probability to adopt the new item decreases.

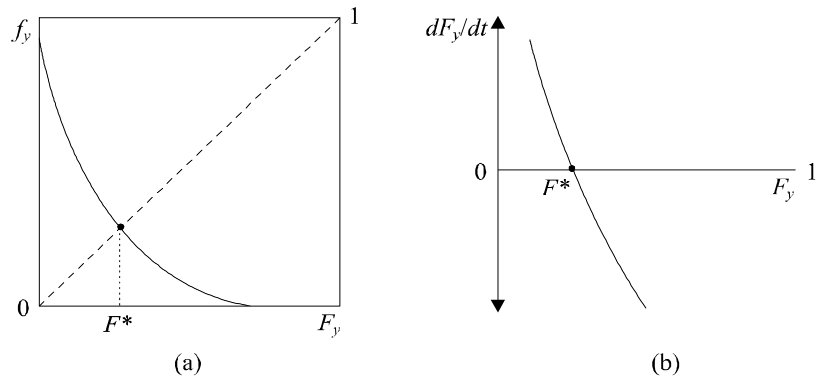

Figure 3.3: *Frequency dependency and uniqueness of equilibrium (source: Witt, 1991).*

In order to determine the diffusion process over time based on the above results and illustrated in figure 3.3a, we introduce the notion that the degree of adoption, that is the change in the share of the population that has adopted the new diffusion item, depends on the gap between the willingness (probability) to adopt the item f_y and the actual adoption F_y. It is plausible to assume that the larger the gap is (either positive or negative), the bigger the rate of change in the frequency of adoption will be. The function $dF_y/dt = \psi(f_y - F_y)$

[4] For instance, $f_y = 0.1$ means that 10 percent of the total population is willing to choose y rather than z.

expresses this. It determines how the relative frequency of adopters changes over time. Figure 3.3b shows this functional relationship. F^* represents the state where the willingness to adopt f_y and actual adoption F_y are equal. At a lower value of F_y we have $f_y > F_y$ and $dF_y/dt > 0$ and for $F_y > F^*$ it is $f_y < F_y$ with $dF_y/dt < 0$. Here we see that the diffusion process evolves towards the single interior state F^*, representing a state where both types of technology users, i.e., those who have adopted and those who have not adopted the diffusion item, coexist in the long-run.

Figure 3.3 shows a non-linear dependent relationship between the probability of adoption f_y and the relative frequency F_y with f_y strictly decreasing in F_y. Different behavior is also possible. Following the same intuition behind adopting y or not adopting z, figure 3.4 represents the case where f_y is increasing in F_y. Such a situation would occur when the utility adoption y increases for a member of the population if the number of adopters increases. This is different from the previous case in figure 3.3, where the net benefit from adoption was decreasing in the relative frequency of adopters. The willingness to have the new item increases if the actual relative frequency rises. As illustrated in 3.4a, an example of the positive relationship between f_y and F_y could be due to e.g. the diffusion of two competing technologies, where each technology is characterized by external economies of scale; for example, because of positive network effects. By definition such positive externalities increase in the relative frequency of adopters.

This is an example where so-called technological 'lock-in' appears (*cf.* Witt, 1991). The idea of (technological) lock-in has originally been developed by David (1985), Arthur *et al.* (1987) and Arthur (1988, 1989). The essential aspect of technological lock-in is that one of the competing technologies, even though it is not superior to the other, wins in the long-run and completely wipes out the other technology. The famous example is the diffusion of the QWERTY-keyboard. The more users had adopted and learned to type on this particular format, the larger the general willingness to adopt it.

Lock-in is narrowly related to path-dependency. This is described using figure 3.4b. Assume that initially the equilibrium state is F_0. Now a small perturbation could make the state to be situated in the basin of attraction left of F_0 or in the basin of attraction right of F_0. Since F_0 is unstable, once a certain direction has been set in one will never return to point F_0 and eventually will end up in either one of the corner states F^* or F^{**}. There is path-dependency since only one of the corner states will eventually become selected depending on the history, i.e., initial conditions.

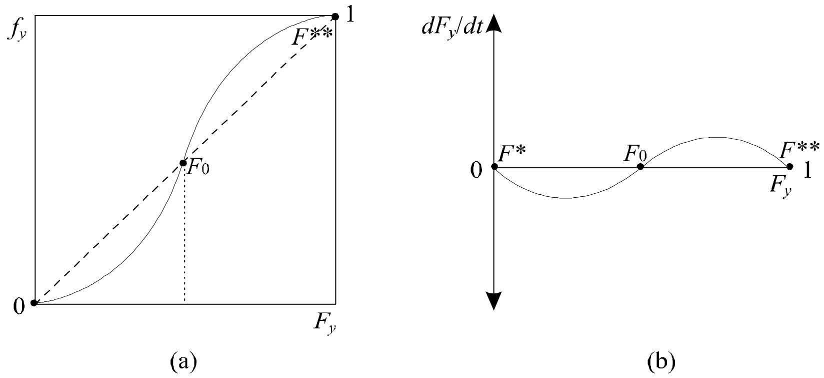

Figure 3.4: *Frequency dependency and multiple equilibria (source: Witt, 1991).*

From the above graphical illustration, it appears that frequency or density dependence is the hallmark of an evolutionary framework. The qualitative behavior of the diffusion process is contingent on the current distribution of diffusion. Looking back at the epidemic model from this perspective, we can observe that it has the characteristic of frequency dependency and, in that respect, it has an evolutionary flavor. However, as pointed out earlier, it is not so clear what the explicit economic driver of diffusion in the epidemic model is, i.e., it lacks a microeconomic underpinning of decision making. Recall, for instance, the logistic equation (3.1). The level of contagiousness (in equation (3.1) expressed by the adjustment speed ξ) is exogenous and the model does not incorporate any economic variable at all. Therefore, the economic decision to adopt or not to adopt is not included. Since behavior of (non)adopters is not modelled, it is impossible to relate the decisions to the frequency of adoption. In other words, there is no such thing as strategic interaction between economic agents showing how the adoption decision of members of the population affect the (non)adoption decision. In this section we have shown how economic considerations and interaction could be introduced. It turned out out that in such a model the ultimate state of saturation is endogenous and not exogenous as in the epidemic model.

In contrast to neoclassical economic theory, the neo-Schumpeterian approach illustrates the relevancy of interaction between technology and the economy and emphasizes the complex relationships between various populations of economic agents. And as already argued above, by doing so it remains, however, rather qualitative in nature. The example of Witt (1991) on the bimodel choice between adopting or not adopting a particular diffusion item outlined above, lacked any formal underlying economic decision making rationale. What it showed was the importance of the population in the individual's adoption decision. In this respect, it is only a subdivision of the neo-Schumpeterian approach, which emphasizes the *whole* complex technology-economy interaction. We argue that by adopting evolutionary game theory as a tool to capture the technology-economy relationship, the neo-Schumpeterian approach can be captured in formal economic models and become more quantitative in nature.

3.4 Concluding remarks

Up to now, we have discussed the epidemic model, the probit model, the classic game theoretic model and the evolutionary model. Like probit models, game theoretic models put value on the economic factors in the decision whether or not to adopt a technology. Contrary to probit models, game theoretic models go a step further in terms of the strategic setting in which these decisions take place. That is, they bring the strategic environment into picture, which is ignored by both epidemic models and probit models. On the other hand, game theoretic models ignore the information spreading factors, which epidemic diffusion models explicitly take into account. Neo-Schumpeterian diffusion models allow room for the complex network of interactions between technology on the one hand and economy on the other. Due to this, the modelling framework is rather qualitative. But in contrast to neoclassical theory, it provides an explicit interdependent relationship between the individual and the population of which the individual agent is a member.

Given these different modelling features, we will introduce an evolutionary game diffusion model in chapter 6, which synthesizes all three approaches: the epidemic model, the probit model, classic game theory and the evolutionary approach. By combining these main approaches, we obtain a mix of these features which could make the diffusion framework more valuable. Such an approach should not be regarded as a substitute but as complementary to the above mentioned approaches. We will argue that an economic evolutionary game approach brings together: (a) strategic interaction, (b) economic orientation and (c) endogeneity of 'contagiousness'. We shall briefly sketch the main ingredients and show to what particular diffusion model it is attached and in what respect it complements the previous approaches.

We start from definition 4 given in chapter two, which includes the elements of an evolutionary game. The definition confines the evolutionary game to any model of *strategic interaction over time* with the features of *monotonicity*, *inertia* and *Game Against Nature*. So first of all the evolutionary game approach to study diffusion should embody strategic interaction. In our approach, the interaction consists of two parts. First, the technology choice between a new 'clean' and an old 'dirty' technology, where a number of adopters will imitate the example that is set by the most successful firm. Second, the clean and dirty firms interact with each other in an oligopolistic market and compete in outputs[5].

Strategic interaction occurs over time, implying that the game is played repeatedly. In this sense, the evolutionary game approach complements the static one-shot game approach of Reinganum (1981a, 1981b, 1983). An essential ingredient of the dynamics of diffusion at the strategic level in an evolutionary game is the monotonicity principle. Recall that monotonicity implies that, in the long-run, lower payoff strategies are wiped out by the higher payoff strategies. This type of adjustment dynamics thus represents the diffusion of a technology item. Hence the dynamics refers to the strategy level and also to the repeated interacting nature between players.

Contrary to static classic game theory, by explicitly defining and incorporating an adjustment dynamic, evolutionary game diffusion models can gain insight into how the equilibrium degree of diffusion becomes established. The adjustment dynamic is attached to the Game Against Nature element which means that players do not systematically attempt to influence other players' future behavior. In our model, the firm's choice for a clean or dirty technology will be based on following the example of the most successful firm and firms do not make plans to change other firms' decisions systematically. Another explicitly modelled part of the diffusion model is the output market in terms of a Cournot oligopoly. Also on such markets, players do not try to influence the quantities set by competitors, but accept them as given.

Finally, the inertia element is automatically fulfilled since diffusion of technology is a slow process and often reflected by a gradual change in the population of adopters. With the inertia assumption, we rule out radical technological regime shifts as in e.g. Kemp (1997).

[5] To some extent this approach resembles the so-called 'market selection diffusion models' (e.g. Metcalfe, 1988), which initiate the availability of multiple technologies and shows that diffusion takes place given the pressure of competitive market selection forces. Adeoti (2001, p.38) summarizes the assumptions of the market selection diffusion models: heterogeneous firms produce a homogeneous good; uniform unit costs of inputs; a constant capital-output ratio (constant returns to scale); and the firm's growth depends on the propensity to accumulate rather than on its efficiency.