TECHNOLOGY AND THE ENVIRONMENT: AN EVOLUTIONARY APPROACH TO SUSTAINABLE TECHNOLOGICAL CHANGE

IE Working Paper WP 02 / 04 19 / 01 / 2004

Dr. Javier Carrillo-Hermosilla

Instituto de Empresa
Centre for Environmental & Energy Studies
Castellón de la Plana, 8
28006 - Madrid
Spain
Javier.Carrillo@ie.edu

Abstract
Can the individual actions of agents spontaneously move the system out of a state where it is locked in to an environmentally inferior technology, or is coordination from outside the system necessary in the form of public intervention? More importantly, even if the system were able to make the transition unaided, could market coordination mechanisms play an important role? The results of our model show that it would be advisable to undertake policies expressly *aimed at the process* of sustainable technological change –applying an *ex ante* (precautionary) approach– in a way that is complementary to the conventional *equilibrium oriented* environmental policies. The nature of these policies and how they might be implemented are questions we will address from this novel approach to the concept of sustainable development. In short, the main objectives of this paper are to understand more fully the dynamics of the process of technological change, its role in sustainable development, and to assess the implications of this dynamic approach to techno-environmental policy. To achieve these goals we have developed an agent based model (ABM), using distributed artificial intelligence (DAI) concepts drawn from the general methodology of social simulation.

Keywords
Technology diffusion; standardization; lock-in; sustainability; precautionary approach; evolutionary models; agent-based models

Depósito Legal: M-20073-2002 I. S. S. N.: 1579-4873

1. Introduction

The role of technological progress in sustainable development derives from the fact that the way in which energy and raw materials are transformed in the economy depends primarily on the state of technological know-how (Mulder et al., 1999). This implies that the diffusion of technological innovations can change the material basis of the economic process. Thus, the technologies used can be perceived as being simultaneously both the cause and possible solution to environmental problems (Gray, 1989). However, the literature has paid greater attention to the extent to which technological change can enable sustainable development to be achieved (Ausubel and Langford, 1997; Ausubel and Sladovich, 1989).

The conflict between defenders of the weak and strong forms of sustainability to a large extent stems from the difference of opinion between the two camps as to the potential of technological change (Faucheux, 1997). Both viewpoints ascribe a crucial role to technological change in their concept of sustainability. However, neither perspective offers the basis for a detailed analysis of the *processes* involved in technological change. The reason for this limitation is in the similarity of the concept of technological change underlying both approaches. Both schools reduce technological change to an aggregate, unidimensional level, by assuming an exogenously determined *rate* of technological change. The value assigned to this rate is what, to some extent, differentiates the two schools. However, sustainable development is a dynamic *process*, and as such, any description of it should include not only quantitative aspects, in terms of rates of technological progress, but also the *qualitative* aspects of that change (Saviotti, 1996). When studying technological change it is necessary to take into account the multiple dimensions of today's major techno-environmental issues, such as the depletion of the ozone layer, the loss of biodiversity, soil erosion and degeneration, water pollution, etc. These problems are characterized by their global nature, high degree of uncertainty, irreversibility and the high complexity of their consequences and probabilities of occurrence (Faucheux and Froger, 1995). The broadening spectrum of environmental problems, in conjunction with the uncertainty regarding their scale and duration, and their possible irreversibility, added to the growing social preference for environmental quality, make it necessary to undertake an *ex ante* (precautionary) approach to the link between productive activity and environmental quality, namely technology. We firmly believe that the right approach to sustainable development involves understanding the *process* of technological change that leads towards sustainability, and that the way to achieve this understanding is to use an evolutionary approach, such as that incorporated in the model put forward in this paper[1].

[1] The main differences between the conventional or neoclassical approach to the analysis of technological change and the evolutionary approach adopted here basically arise from the objections of evolutionary economists to the way in which the (aggregate) production function is used by neoclassical economists and their apparent inability to explain the *processes* of technological innovation (Nelson and Winter, 1974, 1977 and 1982; Dosi, 1982; Dosi *et al*., 1988). Thus, while the neoclassical approach portrays technological change as a simple change in the information available on the relationship between the economy's *inputs* and *outputs* (Stoneman, 1983; Gomulka, 1990), the evolutionary approach considers technological change to be the result of a self-referential process of evolution influenced by the prevailing economic, social and political institutions. According to this approach, technological development should be understood as a process of evolution in which alternative technologies compete with one another and with the dominant technology, with a subsequent selection determining the winners and losers, but considerable initial uncertainty about who these winners will be (Nelson and Winter, 1982). Given that uncertainty is intrinsic to the process of technological change, the assumption of rational maximizing behaviour is replaced by a search for profit "in the dark" (e.g. using heuristic search routines); as a result, there is no single welfare maximizing equilibrium, but rather a plurality of possible equilibria: historical accidents thus determine which equilibrium is reached or approached at any given time; the structure, including the institutions, is often made explicit in evolutionary models, so that its place in the process of technological change can be studied (Lipsey and Carlaw, 1998).

It seems self-evident that in order to achieve greater environmental quality without limiting productive activity, an effort needs to be made to promote *innovation* in clean technologies[2]. In fact, environmental innovation has been recognized as being crucial to tackling the thorny issue of the timing of climate policy (Wigley et al., 1996; Schneider and Goulder, 1997). Nevertheless, there is a growing consensus on the potential for environmental improvement that could be achieved through the *diffusion* of the clean technologies that *already exist*, in particular in terms of improved energy efficiency and the consequent reduction in the emissions associated with the use of fossil fuels (Bernow et al, 1998; Koomey et al., 1998; Krause, 1996; Lovins, 1991; Union of Concerned Scientists and Tellus Institute, 1998; Interlaboratory Working Group, 1997; Alliance to Save Energy, 1997). It is therefore worth asking what is holding back the diffusion of these existing technologies. The debate basically rests on the cost of transition to these new technologies. This is an issue which has been approached from two opposing perspectives: aggregate economic models (a top-down approach) and engineering studies (a bottom-up approach)[3]. According to various authors, both approaches rely on excessively simplistic assumptions about the *dynamic* of energy substitution and the *process* of technological change (Kemp, 1997; Carraro and Galeotti, 1997). In this paper we put forward a broader view of the *process* of technological change which allows us to show how an important barrier to the diffusion of clean technologies arises from the fact that the economic system is locked in to technology standards (Arthur, 1989, 1990, 1994; Cowan, 1990; David, 1985) which are potentially environmentally inferior. This lock-in is due to the existence of significant *increasing returns to adoption* of energy technologies, produced by economies of scale, learning (Arrow, 1962a; Sheshinsky, 1967) and networks (Katz and Shapiro, 1985 and 1986; Farrell and Saloner, 1986a and b; Economides, 1996), arising out of the integrated and systemic nature of these technologies (Schilling, 1998: 269; Kemp, 1996: 161). Under these conditions, the same distribution of technologies and user preferences can lead to different structures in the breakdown of the user market, depending on how things start out (Economides, 1996: 26). The system therefore has a multiplicity of equilibria which, when expressed in terms of market shares, can be interpreted as spontaneous or de facto standards (David and Greenstein, 1990). Spontaneous standards emerge as a result of internal market processes and not as the result of a coordinated action by its participants. Early superiority, however, is no guarantee of long-term suitability (David, 1989; Cowan, 1990; Nelson, 1994a). Thus, in the presence of increasing returns, apparently inferior designs can become locked in to the production system *indefinitely* in a historically dependent process in which circumstantial events determine the winning alternative (David, 1985, 1997). We would like to highlight the fact that the analysis of technological diffusion contained in the literature on the phenomenon of technological lock-in has devoted very little attention to issues concerning pre-existing alternatives or the conditions under which new technologies are able to displace old ones in a technological succession (Windrum and Birchenhall, 2000). As well as Arthur, many other authors have also portrayed the technology selection process as an "all or nothing" story (Abrahamson and Rosenkopf, 1997). This is a general shortcoming of the technology diffusion and

[2] Clean technologies or environmentally sound technologies (ESTs) are defined in chapter 34 of *Agenda 21* (United Nations, 1992b) as those technologies that "(...) protect the environment, are less polluting, use all resources in a more sustainable manner, recycle more of their wastes and products, and handle residual wastes in a more acceptable manner than the technologies for which they were substitutes (...) Environmentally sound technologies are not just individual technologies, but total systems which include know-how, procedures, goods and services, and equipment as well as organizational and managerial procedures." The minutes of the 2nd Plenary Meeting under the *Kyoto Protocol* (United Nations, 1997), requires that the Convention Secretariat " (...) continue its work on the synthesis and dissemination of information on environmentally sound technologies and know-how conducive to mitigating and adapting to climate change" and the parties are urged to "create an enabling environment to help further stimulate private-sector investment in, and transfer of, environmentally sound technologies".

[3] An overview of models representing each of these perspectives can be found in Böhringer (1998).

standardization models which has repeatedly been highlighted in various studies over the last decade (Schilling, 2002: 395; Jaffe et al., 2000: 41; Windrum and Birchenhall, 1998: 112; David, 1997: 36; Nelson, 1994b; David and Greenstein, 1990: 8). It seems clear that, rather than the deterministic view of conventional models of technology lock-in, it might be worth having an expanded formal view of the process of technology diffusion and standardization which bears in mind the possibility of a *technological succession*[4], understood as a series of replacements of old technologies by new technologies performing the same basic function (Grübler, 1991).

Various authors have flirted with the application of the concept of technology lock-in introduced by Arthur and his co-authors (Arthur, 1983, 1988, 1989; Arthur, Ermoliev and Kaniovski, 1987) in the environmental field (Kline, 2001; Mulder and Van den Bergh, 2001; Kallis, 2001; Jaffe et al., 2000; Van den Bergh and Gowdy, 2000; Peters et al, 1999; Kemp, 1997; Goodstein, 1995; England, 1994; Kemp and Soete, 1992; Ayres, 1991). However, most of these studies have been undertaken at the level of what Nelson and Winter (1982) refer to as *appreciative theory*[5]. Very few studies have formally applied the evolutionary concept of technological change to environmental policy and sustainability. Indeed, this is precisely one of the contributions this study aims to make.

Conventional environmental policy is mainly based on economic and regulatory instruments that aim to control the negative impacts of production on the environment *ex post*. In terms of technological change, these policies have mainly led to *incremental* changes in the established technologies, and to the development and use of "end-of-pipe" (EOP) technologies[6]. The results obtained may be acceptable in some cases, but in view of the progressive deterioration of the environment we are witnessing, they are clearly not sufficient. The reorientation of the current economic system towards sustainability requires not only incremental improvements in existing technologies and systems, but more fundamental changes in the technology regime in those sectors with the greatest environmental impact (Mulder et al., 1999: 8; Freeman, 1996: 37; Arentsen et al., 1999: 3). A number of authors admit that it is relatively unlikely that conventional environmental policy measures, not necessarily focused on technological change, may alone be able to bring about this *radical* change in technologies and practices (Kline, 2001: 97; Smith, 2000: 94; Kuper and Van Soest, 1999; Mulder et al., 1999: 26; Kemp, 1996: 162; Carraro and Siniscalco, 1994: 546; Ayres, 1991: 265). This raises the following questions: can the individual actions of agents spontaneously move the system out of a state where it is locked in to an inferior technology or is coordination from outside the system necessary in the form of public intervention? More importantly, for the purposes of the hypothesis under examination here: even if the system were able to make the transition unaided, could market coordination mechanisms play an important role? The results of our

[4] As will be seen below, our methodological approach to the problem being examined does not follow the few formal mathematical models that have attempted to tackle the process in which a technology is replaced by multiple alternatives (Peterka and Fleck, 1978; Marchetti and Nakicenovic, 1979) and, obviously, it also departs from binary models of technology replacement (Fisher and Pry, 1971). For this reason, in order to ensure a clearer and more direct exposition of our approach, we have not explained them at length. For more information on these models see, for example, Kwasnicky (1999b).

[5] Identification and evaluation of the main facts that characterize an empirical phenomenon, so as to provide a broad conceptual base and theoretical elements necessary for subsequent formal models.

[6] A distinction is usually drawn between cleaning technologies, such as EOP and other technologies to treat environmental problems downstream from the production process and clean technologies, which are those being discussed here. Clean technologies involve identifying the environmental problem upstream of the production process and using clean product. Clean technology is preventive, whereas cleaning technology is only curative (Kemp, 1997: 12). At present, most investments in pollution control equipment in industrialized countries (around 80%) is spent on EOP technologies (OIG, 2000).

model show that it would be advisable to undertake policies expressly *aimed at the process* of sustainable technological change –applying an *ex ante* (precautionary) approach– in a way that is complementary to the conventional *equilibrium oriented* environmental policies. The nature of these policies and how they might be implemented are questions we will address from this novel approach to the concept of sustainable development.

In short, the main objectives of this paper are to understand more fully the dynamics of the process of technological change, its role in sustainable development, and to assess the implications of this dynamic approach to techno-environmental policy. To achieve these goals we have developed an agent based model[7] (ABM), using distributed artificial intelligence (DAI) concepts drawn from the general methodology of social simulation.

2. Techno-environmental policies

The process of technological change is commonly described in terms of the so-called "Schumpeterian trilogy" of invention, innovation and diffusion (Schumpeter, 1942). However, technology policy in developed countries has traditionally tended to focus on the initial phases, invention and innovation, in the form of science and R&D (Limpese *et al.*, 1992). Although it is generally recognized that the productive potential and competitiveness of technologies is achieved through the process of diffusion, policy initiatives have overlooked numerous opportunities to improve the process of technology diffusion (Hahn and Yu, 1999). Nevertheless, over the last decade there seems to have been a gradual reorientation of technology policy towards diffusion (Stoneman and Diederen, 1994). The subject we are dealing with here highlights the importance –indeed the need– for this reorientation; at the same time, it seems to call for a new perspective in the justifications and focus of technology diffusion policy.

The neoclassical approach to technology policy is built on Arrow's (1962b) analysis of market failure. According to this analysis, a completely competitive and decentralized market will provide a sub-optimal level of knowledge. This justifies public intervention either to create knowledge or to establish intellectual property rights. In neoclassical microeconomics a state with a welfare maximizing goal (under conditions of unbounded rationality) and perfect information on its environment and the consequences of its decisions, should be able to correct market failures efficiently and bring the economic system to a Pareto optimal equilibrium. The role assigned to the State is therefore *corrective* in nature (Moreau, 1999: 5). The evolutionary approach to technological change suggests taking a broader view of technology policy than that put forward by the neoclassical approach. The fundamental difference lies in the fact that evolutionary economics departs from the assumption of a single stable equilibrium for the economic system. The existence of multiple alternative equilibria gives a new rationale to the State's intervention in the economy, in that *coordination*[8] of the

[7] Other commonly used names for this discipline include: *Agent-Based Simulation*, *Agent-Based Computational Economics* (ACE) or *Multi-Agent Systems*(MAS).

[8] Within Neo Keynesian economics a whole sub-field has grown up dedicated to coordination failures based on the work of Bryant (1983), Diamond (1982), Hart (1982) and Weitzman (1982). According to this literature, in numerous socio-economic situations coordination problems (failures) appear, which can arise from a situation in which there are multiple equilibria (Cooper and John, 1988; Ball and Romer, 1991). These situations include the presence of increasing returns (Weitzman, 1982; Manning, 1990; Bohn and Gorton, 1993). These failures are the result of the inability of the agents to coordinate their actions successfully in a decentralized economy (Cooper and John, 1988: 442). Coordination failure models generate outcomes that are inferior in terms of welfare, due to the fact that the agents have no incentive to change their behaviour and

decisions by individual agents may be necessary in order to seek convergence between the particular and general interests (Moreau, 1997: 6). In the evolutionary approach the main question is not optimization and equilibrium, but endogenous change, evolution and economic development (Llerena and Matt, 1999: 4). The focus of attention has ceased to be on the market failure *per se* and has moved to the improvement in competitive performance and the promotion of structural change (Mowery and Rosenberg, 1989). Thus, the role assigned to the State ceases to be corrective and becomes *adaptive*, insofar as it is more concerned with influencing the process than imposing a particular result (Metcalfe, 1995: 31).

The model put forward here eschews the irrevocable determinism of conventional technology lock-in models and shows how endogenous changes in industry, on both the technology supply and demand sides, allow transitions between equilibria to arise within the system itself, without the need for public intervention. However, the timing of this spontaneous transition may fail to be the socially most appropriate (David and Greenstein, 1990: 12). From this view point, our main justification for public intervention in the process of technology diffusion where there are increasing returns to adoption, which may result in a succession of socially sub-optimal technology standards, lies in the greater ability of the State to *coordinate* technology choices (Metcalfe, 1995: 31) and achieve a socially superior timing. In order to pursue this goal, the State should cautiously take on what David and Greenstein (1990: 12) and Moreau (1999: 8) call a *pilot role* as the coordinator of a market process, guiding it through multiple point attractors. On this view, a State with bounded rationality and imperfect information about the respective social merits of the various attractors discovers and learns the characteristics of the competing products (technologies) as it goes along. This learning process takes place *simultaneously* with the process of competition. According to the approach proposed by Moreau, a timely intervention is enough to create a sufficient stimulus to guide the system towards the (socially) desired attractor, as once a given user base has been acquired, cumulative endogenous phenomena come into play (economies of scale and learning) and can replace the exogenous public intervention. According to Moreau, when the existence of multiple point attractors is considered, public intervention becomes "richer" in the evolutionary perspective than the neoclassical. The State does not have to limit itself to correcting market failures, but can guide and fine tune the economic system.

From the arguments above, which will be considered in the model proposed below, it may be deduced that faced with the possibility and/or fact of a situation of sub-optimal technology lock-in, the technology diffusion policy should (and can) go beyond establishing ad hoc economic incentives to consider new types of instruments –markedly evolutionary in nature– which we have defined as techno-environmental prevention policies and techno-environmental transition policies.

2.1. Techno-environmental prevention policy

The essence of this precautionary approach in the environmental field derives from Principle 15 of the *Rio Declaration on Environment and Development* (United Nations, 1992), which states that: "Where there are threats of serious or irreversible damage, lack of full scientific

reach a more preferred state of welfare (Allen and Stone, 2001). If the coordination problems reflect the inability of the agents to select the Pareto optimal equilibrium, then the State can take steps to achieve the desired outcome by eliminating some undesirable equilibria as it converts the strategies that support them into dominated strategies (Cooper, 1999: 126).

certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation." Thus when there is a real possibility of a sub-optimal technology lock-in, a "technology prevention" policy needs to be considered. Obviously, there is no generally applicable algorithm allowing policy-makers to identify in advance with absolute certainty what technologies are environmentally superior (Kline, 2001). Rather, our view lends support to the role of policy-makers who act as a coordinator of the market process through the multiple point attractors, with bounded rationality and imperfect information about their respective environmental merits, who discover and learn the characteristics and risks of the competing technologies as they go. It is important to note that this learning process takes place *simultaneously* with the competition process, so it could be considered vigilance rather than prediction. We believe that in practice policy-makers have a series of precautionary tools that, from the perspective of technological change, can complement traditional environmental policy instruments as a means of achieving sustainable development. The results of this research support the greater development and use of such tools, which include:

– Environmental Technology Assessment (EnTA), which focuses on the preliminary assessment and evaluation of the environmental consequences of specific technology options. This is a qualitative multidisciplinary tool that is based on dialogue. Its aim is to aid the selection of the most sustainable technology option at the start of its development. EnTA can be a win-win process for governments, users and other social agents, as well as for the environment (UNEP, 2000).
– Pollution Prevention Strategies (PPS) force a broadening of view, inquiring what alternatives can reduce emissions *ex ante* rather than what alternatives can mitigate emissions *ex post*. This therefore constitutes a way of evaluating options independently of the dominant solution (Sinsheimer et al., 2002; EPA, 1996; Becker and Ashford, 1995).
– Other tools, which are perhaps more technical than political in scope, and which although they are not focused strictly on technological choice, nevertheless share this preventive feature, include: Environmental Impact Assessment, Environmental Risk Assessment and Life Cycle Assessment.

2.2. Techno-environmental transition policy

In a case of existing sub-optimal environmental technology lock-in, a policy of "technology transition" is required, which builds on the cumulative, feedback character of technological change. Once again the policymaker adopts the role of a guide for the market, highlighting and creating incentives for the socially desirably technology option until, once a given user base has been achieved –which would have been difficult to reach without an intervention, due to the lock-in of the dominant technology– cumulative endogenous phenomena come into play (economies of scale and learning) and are able to replace the exogenous public intervention. The tools available in policy-making practice –the greater use of which is supported by the findings of this study– include the following in particular:

– Strategic Niche Management (SNM), which is a process oriented towards modulating the dynamics of socio-technological change by creating and managing spaces in which a new technology can be used (Weber et al., 1999; Schot et al., 1994; Rip, 1992). Through this limited temporary protection SNM aims to create a space that is protected from the selective pressures of the market. This strategy is particularly useful in the case of "clean" technologies, in which the social benefits are undervalued by the market, and systemic technologies, such as energy technologies.

– Market Transformation Programmes (MTPs). These have the policy objective of creating incentives or inducing social, technological and economic change in a way that leads towards greater energy efficiency (Almeida et al., 2003; Blumstein et al., 2000). The main question is how market agents can apply guided actions to enable, facilitate or accelerate the diffusion of technological innovations, and thus bring about environmental benefits (Weber et al., 2002: 288).
– Demand Side Management (DSM) concentrates on stimulating demand and promoting the early commercialization of clean energy technologies which show substantial learning-by-doing potential (Levine and Sonnenblick, 1994).
– Environmental Voluntary Agreements (EVA) are cooperation agreements between industries and/or firms and the agencies responsible for environmental regulation. Under such agreements the industry undertakes to carry out a series of actions voluntarily reducing the impact of its activity on the environment and/or facilitating its progressive compliance with the environmental legislation in force (EEA, 1999). This may constitute a relatively effective instrument with which to stimulate technological innovation, compared with other instruments such as taxes, standards or trading permits (Menanteau, 2002; Carraro and Leveque, 1999). Delmas and Terlaak (2001a, b and c) offer numerous examples of EVA being applied successfully in the international business community.

3. An Evolutionary Model of Sustainable Technological Change

In the last few years simulation has become a popular means of discovering and exploring complex natural and social systems (Hannerman and Patrick, 1997). The recognition that social and economic phenomena frequently exhibit characteristics typical of complex systems –significant non-linearity among them– is a challenge to traditional research methods (Holland, 1998; Epstein and Axtell, 1996; Latané, 1996; Gilbert, 1995). Thus, simulation has been put forward as a new way of conducting research, a "third scientific discipline" (Ilgen and Hulin, 2000; Axelrod, 1997) that complements and is built on the traditional methods of induction and deduction. An important branch of simulation in the social sciences is agent based modelling (ABM), which is a form of modelling characterized by a number of autonomous agents which interact with one another and with their environment, with little or no central coordination (Conte et al., 1997; Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999; Weiss, 1999). Thus, the emergent properties of an ABM (i.e. the system's macro-behaviour) are the results of bottom-up processes (arising from micro-level interactions between agents in the system) rather than of top-down processes. According to Wooldridge and Jennins (1995), in an ABM the agents are computational processes that are characterized by: i. their autonomy, in that they control their own actions; ii. social abilities, i.e. the agents interact with one another by means of some kind of "language"; iii. reactivity, in that the agents can perceive their environment and respond to it; and iv. proactivity, in that they are able to carry out actions in order to achieve an objective. Clearly, to a large extent, agents in the business world exhibit these characteristics, a fact making ABM seem an appropriate methodology for studying emergent phenomena in markets. It should be highlighted that although ABM uses simulation its goal is not necessarily to represent a specific empirical application precisely, but rather to give us a more detailed understanding of the fundamental processes that may emerge in various applications. If this is the aim, what is important is the simplicity of the assumptions and not a detailed representation of a particular reality (Axelrod, 1997).

Building on the ABM research methodology, this section describes the model put forward to achieve the aims and compare the hypotheses of the investigation. Its calibration, verification and validation are also discussed.

3.1. Assumptions of the model

We assume an indefinite time horizon of t periods in which time evolves discretely ($t \in \mathbb{N}$) and the dynamic is asynchronous. We assume a single good or service X, which may be produced using multiple alternative technologies $T_j\left(j=1,...,J_t,...,J\right)$, the characteristics of which are defined below. In each period t the free entry of one or more new individual producers $P_i\left(i=1,...,I_t,...,I\right)$[9] of X takes place in a Poisson-type[10] random process with an average rate of appearance of new producers in a given period $l_P > 0$, which for simplicity we assume to be constant over time. Thus the probability that I_t new producers emerge in the period *t* will be given by the probability function

$$f\left(I_t\right)=\frac{\left(e^{-l_p} \cdot l_p^{I_t}\right)}{I_t!}, \quad I_t = 1,2,\dots I \qquad [1]$$

Each P_i has an intrinsic survival parameter s_i associated with it (>0). For simplicity this parameter is assumed to remain constant over time. In this simulation it is distributed independently at random between the different P_i in a way that follows a normal distribution $N\left(\bar{s}, s_s\right)$. Thus, in each t there is also the *free exit* of producers whose survival period has expired, with the rest remaining in the following period as old producers.

We assume that in each period t one or more new alternative technologies appear on the market $T_j\left(j=1,...,J_t,...,J\right)$ in a way that cannot be anticipated by the agents producing the good X. These process innovations are provided by multiple technology suppliers[11], who act motivated by the pursuit of a patent which grants them a certain degree of monopoly power,

---

[9] Assuming a finite number of agents in the industry responds to one of the criticisms of Arthur's model, such as that raised by Dalle (1995) who questions the validity of "(...) assuming the existence of an infinite number of agents, as unanimity is not found except at the limit, making the time and therefore the number of agents tend to infinity. It seems to us that economic systems are constructed rather of a finite number of agents, who comprise a network and make use of local channels of information to enable them to make their decisions."

[10] The assumption of a Poisson distribution is realistic and is well established in the literature for situations in which numerous successive events (in this case, the entry of firms in the sector) have independent sources (Mayer and Chappell, 1992: 772; Loch and Hubberman, 1999: 6)

[11] According to Kemp (1997: 221) process innovations are generally developed by specialist suppliers, research institutions other than the producer firms, whereas product innovations are usually developed by the firms themselves. The model presented here deals with the diffusion of the first of these types of innovation: new technologies which substantially modify production processes.

albeit temporarily. We will suppose that these technologies arise following a Poisson-type[12] random process, with $l_T > 0$ constant over time[13].

$$f\left(J_t\right) = \frac{\left(e^{-l_T} \cdot l_T^{J_t}\right)}{J_t!}, \quad J_t = 1,2,\ldots J \qquad [2]$$

It is assumed that any technology T_j which has not been adopted at any time t by at least $P_T\left(>0\right)$ producers –in accordance with the mechanisms described below– after $t_T\left(>0\right)$ periods have passed, is considered to have been "rejected" by the productive system and as of that point in time is no longer available.[14] We also assume that each T_j can be characterized according to a set of criteria or characteristics C_k^j which allow their performance[15] to be measured from K different dimensions. Following Rogers (1995)[16], we propose the following technology characterization, adding one additional of criterion of social choice to his 5 individual adoptability criteria ($K = 6$), although the number of criteria and their definition does not affect the main results of this model, the multi-dimensionality of the evaluation being the only genuinely important assumption[17]:

[12] As done, for example, by Silverberg and Lehnert (1993), (1994).

[13] In this way the model overcomes another of the habitual criticisms of Arthur's model: "(...) a poorly convincing hypothesis is usually adopted in technological competition models. In Arthur's model, for instance, competing technologies appear simultaneously on a virgin market. It seems much more realistic to consider a new technology entering a market held by one or several well-established technologies" (Moreau, 1999: 8).

[14] "Those technologies that are not pre-selected or fail to be accommodated in the system (...) are bound to fail and will not survive" (Arentsen et al., 1999: 9). This assumption could easily be relaxed if we accept that the new technologies that emerge in each period are "improved versions" of technologies which have been rejected by the market. This could give rise to the introduction into the model of the issue of learning by doing and learning by using in R&D (Jaffe et al., 2000: 44) and the "quality ladders" models (Sala-i-Martin, 1994: 113).

[15] According to David and Greenstein (1990: 30), performance-oriented specifications are generally preferable to design-oriented specifications, especially in the development of anticipatory standards.

[16] Following the main reference in the literature on this topic, Rogers (1995: 206), the *attributes* of an innovation *perceived* by its potential users explain to a large extent the rate of adoption of that innovation. According to this author, between 49 and 87 per cent of the variation in the adoption rate is explained by just five attributes: the *relative advantage* is the extent to which an innovation is perceived as being better than the idea that preceded it (the perception of the relative advantage of an innovation is positively related to its adoption rate); the *compatibility* is the extent to which an innovation is perceived as being consistent with existing values, past experience and the needs of potential adopters (this perception is positively related to the rate of adoption); the *complexity* is the extent to which an innovation is perceived as being relatively difficult to understand and use (this perception is negatively related to the adoption rate); the *trialability* is the extent to which an innovation can be tried on a limited basis (a perception that is positively related to the adoption rate); the *observability* is the extent to which the results of an innovation are visible to others (positively related to the adoption rate).

[17] The traditional approach to the decision to invest in a technology (adoption) has focused on the evaluation by the adopter of a single criterion, usually the expected return on investment. However, it is widely accepted that the performance of a technology is a multi-dimensional construct (Anderson and Tushman, 1990: 627; Foray and Grübler, 1990; Suárez and Utterback, 1995: 418; Rogers, 1995: 206; Kemp, 1997: 88; Christensen, 1997; Windrum and Birchenhall, 1998: 114; Nelson, 2000: 70; Cantner and Hanusch, 2001: 229). Therefore, it would seem to be reasonable to asume that business people make their technology adoption decisions bearing in mind multiple dimensions or attributes of a technology, evaluating their (albeit imperfect) perceptions of them according to their (heterogeneous) preferences regarding each dimension or attribute.

C_{Ak} : Adoptability criteria
- C_{A1} – Relative advantage
- C_{A2} – Compatibility
- C_{A3} – Complexity
- C_{A4} – Trialability
- C_{A5} – Observability

C_{Sk} : Social choice criterion
- C_{S6} – Sustainability

Thus, each T_j can be characterized by a performance vector

$$\overrightarrow{P_j}\left(C^j_{A1}, C^j_{A2}, C^j_{A3}, C^j_{A4}, C^j_{A5}, C^j_{S6}\right) \qquad [3]$$

with elements $C_k \in [0,1]$, where the values 0 and 1 represent the extremes of a "bad" or "good" evaluation of its performance, respectively, within this continuous range. In this way the proposed classification system allows a virtually unlimited number of alternative technologies T_j for the production of the good X to be characterized. Obviously, in reality this would be beyond the cognitive limits, and indeed the physical limits, of technological development[18]. However, it demonstrates the flexibility of the proposed model compared with those[19] that centre their analysis on only two alternative technologies. In the simulation we also establish that, due to the presence of increasing returns to adoption (deriving from learning by doing and learning by using, network effects, economies of scale, increasing returns to information and technology interrelations) the real value of each C_k (*actual performance)* for each T_j evolves as a function of the degree of adoption by P_i producers (*installed user base*). Where C^j_{kt} is the value of the actual performance of T_j in C_k in t. As, in fact, the five individual selection criteria proposed are met, in the proposed range of values (range [0-bad,1-good]), we assume that C^j_{Ikt} is an increasing function of the number of agents P_i that adopt the technology T_j in each t, $I^j_t = \sum_t P^j_i$:

$$C^j_{Akt} = f\left(I^j_t\right) = \frac{\widehat{C}^j_{Ak}}{1+\left(\left[\widehat{C}^j_{Ak} - C^j_{Ak_0}\right]\Big/ C^j_{Ak_0}\right)\cdot e^{-r_j \cdot I^j_t}} \qquad [4]$$

---

[18] Although Kemp (1996: 158) states optimistically that the number of technology options for improvement of climate change is almost infinite.

[19] See, for example, Arthur (1983, 1988, 1989); Laffond et al. (1999); Farrell and Saloner (1986); Shy (1996); Cowan (1988).

This is an increasing logistic function[20] (Figure 1) with an upper asymptote at the maximum level of performance $\widehat{C}^j_{Ak}$ or "frontier of improvement" which cannot be exceeded by each criterion of a technology, despite the accumulation of new adopters. $C^j_{Ak_0}$ represents the starting level of performance ($I^j_t = 0$) of T_j in C^j_{Ak}. In the simulation, $\widehat{C}^j_{Ak} > C^j_{Ak_0}$ is always fulfilled, both variables being distributed randomly and independently between the different technologies arising in the same period t following a $N(0,1)$ within a range of possible values $[0,1]$. Also, an upper limit of $\widehat{C}^j_{Ak_0}$ is set for $C^j_{Ak_0}$, which should be closer to 0 than 1 in this continuous range.[21]

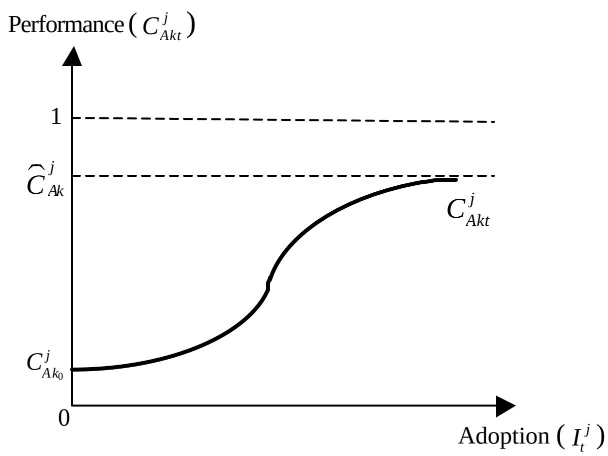


Fig. 1. Function showing the evolution of the performance of a technology as its adoption grows

The variable $r_j\,(>0)$ represents the rate at which T_j improves as a result of the presence of increasing returns to adoption[22]. For simplicity, we will assume that the value of this rate of improvement r_j is common to all the criteria of a given technology, although it is probable that in reality some technologies will improve more rapidly than others as the number of users increases. However, the model does incorporate the fact that the various alternative technologies will enjoy different degrees of increasing returns to adoption. Thus, in the

[20] According to Foster (1986: 96), an S-shaped curve shows precisely how the performance of a technology improves in comparison with the effort used to develop it. In practice, much of this development is the result of economies of learning, which in turn depend on the level of adoption and the experience of users. Many authors use similar functions: Loch and Huberman (1999: 12); Windrum and Birchenhall (2000: 12); Frenken and Verbart (1998).

[21] According to Kemp (1997: 273), "Many historical studies show that, at the time of their introduction, new technologies were often ill-developed in terms of performance characteristics and offered only few advantages over existing technologies. They needed to be improved, in terms of both prices and technical characteristics, in order to be diffused more widely." According to Rosenberg and Frischtak (1983: 147), new inventions are typically very primitive at the time of their emergence. Their performance is generally poor compared with the (alternative) technologies that exist and with their future performance.

[22] It should be highlighted that despite the fact that the increasing returns are different (deriving from learning by using and learning by doing, economies of scale, increasing returns to information and technological interrelations), they are usually handled together mathematically (Nelson, 1995: 74; David and Greenstein, 1990: 6; Cabral, 1987; Metcalfe, 1994: 937)

simulation $r_j\left(>0\right)$[23] is distributed randomly and independently between the various different T_j emerging in the same t following an $N\left(\bar{r}, s_r\right)$. With regards to C_S^j, we assume its evolution randomly increases or decreases with respect to the number of each technology users I_t^j, incorporating the uncertainty and complexity which surround techno-environmental links into the model[24]. Thus r_j in expression [4] for C_S^j will take the same value as in the rest of characteristics of T_j, but with a positive or negative value according to a Bernoulli distribution of probability a between the different technologies arising in the same period.

We assume the information in this technology market to be imperfect, such that each potential adopter has a different *perceived performance* of each technology in terms of his own individual selection criteria[25]. C_{Akt}^{ij} is the perceived value of the performance of technology T_j by agent P_i according to the criterion C_{Ak} at time t. In the simulation we assume that C_{Akt}^{ij} is distributed between the different agents, within the range of possible values $\left[0,1\right]$, according to a normal distribution[26] with its average at the actual value C_{Akt}^{j} and a standard deviation of s_{Akt}^{j}: $C_{Akt}^{ij} \sim N\left(C_{Akt}^{j}, s_{Akt}^{j}\right)$, where s_{Akt}^{j} is a decreasing function of the number of agents adopting technology T_j at a given moment t, $I_t^j = \sum_t P_i^j$:

$$s_{Akt}^{j} = g\left(I_t^j\right) = \frac{1}{1 + c \cdot I_t^j} \qquad [5]$$

The parameter $c > 0$ represents the rate of communication between users. The function $g\left(I_t^j\right)$ incorporates in the model the fact that as the number of users increases, so the uncertainty and information search costs decrease, and agents' knowledge[27] of the actual performance of a technology, and their expectations of it increase[28]. This characterization of the process of diffusion of knowledge, which depends on the number of users[29], acts as a self-

[23] Also, in the simulation, a value of $\bar{r} < 0$, for all T_j, would allow us to represent a situation characterized by decreasing returns to adoption, whereas with $\bar{r} = 0$ (and $s_r = 0$), for all T_i, we would be in a situation of constant returns to adoption.

[24] "New technologies may be able to solve some problems, but they may also introduce new ones" (Kemp *et al.*, 1998: 180). "Climate change researchers are regularly confronted with new surprises" (Janssen y de Vries, 1998: 62).

[25] Rogers (1995: 206) argues that the *perceived attributes* of an innovation, as seen by its potential users, to a large extent explain the rate of adoption of the innovation. Frenken and Verbart (1998) point out that the return on the adoption of a technology probably depends on its *perceived* utility when a certain task is performed or a particular problem solved.

[26] Abrahamson and Rosenkopf (1993).

[27] We argued above that as the number of people adopting a given technology grows, so the uncertainty is reduced and both the users and producers perceive reduced risk. Their confidence in the quality and performance of the technology and perception of its likelihood of continuing to be available in the future therefore increases (Arthur, 1991). At the same time, the increase in the number of users reduces information search costs (Blackman, 1999).

[28] Before deciding whether or not to adopt a technology alternative, the potential users have limited and imperfect information about its actual performance. It is a generally accepted fact that agents' expectations regarding the diffusion of a technology affect their decision to acquire it or invest in it (Katz and Shapiro, 1985: 426; Farrell and Saloner, 1986: 941; David and Greenstein, S., 1990: 7; Loch and Huberman, 1999; Mulder et al., 1999: 9). Despite this consensus, most models of technological change use the change in actual performance of the technologies in question as a fundamental axis of their dynamic (unless they consider it constant). The model proposed here takes an alternative and more realistic approach by focusing on the changing *perceptions* potential users have of the real performance of the technological alternatives. As happens in the real world, in the model these perceptions of a technology improve with market experience, and come closer to the actual performance as the number of users grows.

[29] Responding to Dalle's (1995) criticism of Arthur's model, the model suggested here does not require that the potential adopter know the *exact number* of users of each technology, but rather it incorporates the advantage of the technology with

reinforcing factor in the interest of agents P_i in the technology T_j, whose actual performance benefits from the number of users I_t^j itself, is an accurate representation of the bandwagon effect defined earlier.

In random time intervals, following a stochastic process of replacement of obsolete technologies[30], each of the (new and old) producers P_i active in the market in period t decides individually. This means that, as will be discussed below, each producer can either decide to continue with the last technology he decided to install or adopt a new one from the T_j available in the period concerned. For this purpose, in the simulation each active agent P_i at each time $t(>0)$ is assigned a replacement parameter rp_t^i which takes a value of 1 (replacement) or 0 (continuation) according to a Bernoulli probability distribution b within the group of agents active in that same period. The greater or lesser magnitude of the parameter b allows the model to represent industries with a greater or lesser tendency to technological obsolescence and/or industries in which technological change involves higher or lower costs.

We assume that agents P_i are not aware of the aggregate environmental output of their individual decisions, that is to say, they do not take C_{Sk} into account in their technological choices[31]. We measure the ecological impact of technological choices by means of a function of environmental damage $DA_t \in [0,1]$, 0 and 1 being the extremes of a minimum and maximum environmental damage respectively, within a continuous range:

$$DA_t = 1 - C_{Skt}^{total}, \qquad \text{where } C_{Skt}^{total} = \frac{\sum_j I_t^j \cdot C_{Skt}^j}{I_t} \qquad [6]$$

In this way, we are saying that, environmental damage resulting from business activity at each t, is symmetrically proportional to the average performance of the technological system in terms of sustainability. Let $\widehat{DA}$ be the maximum damage or waste assimilation and natural resources regeneration capability of the ecosystem affected by business activity, over which environmental damage become irreversible if their source remains active for more than $\hat{t}_{DA}$. Finally, we define the accumulated environmental damage at time t as $\sum_t DA_t$.

We assume the presence of a collective decider (from now on the "Agency") which represents the interests of both companies and the rest of society. Apart from taking into account the

---

the greater number of users by means of a function reflecting its better actual performance [4] and a function incorporating the lesser uncertainty [5] surrounding this performance in the performance perceived by the producers.

[30] David and Greenstein, 1990:6.

[31] In this respect, several studies show that, apart from being unaware of the ecological damage resulting from their business activities, firms often do not know which cleaner technologies are available (Kemp, 1997: 224). According to Kemp and Soete (1992: 450), "Although companies might increasingly feel responsible for the damage caused to environment, cleaner production does not represent an objective per se within companies. As a consequence, the decision to adopt these technologies depends heavily on government regulation".

performance of technologies relevant to individual choice[32], the Agency looks after technologies sustainability[33]. In this sense, we assume that the Agency is aware that there are increasing returns to adoption and is conscious of its accumulative consequences in individual adoptability criteria. The Agency counts on the above when it comes to direct market evolution through prevention and transition policies, as have been previously described. Moreover, it is able to assess the aggregate (social) consequences of individual decisions. Nevertheless, under the imperfect information assumption, this assessment is possible only during the course of events, and not prior to them. This is due to the uncertainty and complexity of socio-techno-ecological links. We assume furthermore that, aware of its bounded rationality to cope with the complexity of the problem, the Agency aims at satisfying its objectives and not optimising its decisions.[34] The Agency can influence individual decisions, trying to guide the market through a competition process (transition policy). We represent this influence by means of a dynamic and generic[35] support $\Delta_t^j \in [0,1]$ which can be assigned by the Agency, to a most preferred technology T_j as shown below. In the simulation, starting from a tentative Δ_0^j, intensity of the support increases or decreases exponentially over time $(t > 0)$ at a rate $t \in [0,1]$, depending on current environmental damage level (DA_t); on the intensity of the support the last time that damage evolution changed its course (Δ_c^j) and depending on time elapsed since that change took place ($t - t_c$). We can thereby state that the Agency "learns" and acts according the following decision algorithm (see Appendix 1 for a deeper explanation):

i. If $DA_t \begin{cases} < \widehat{DA} \\ < DA_{t-1} \end{cases}$ then $\Delta_t^j = \Delta_c^j \cdot e^{-t(t-t_c)}$ [7]

ii. If $DA_t \begin{cases} < \widehat{DA} \\ > DA_{t-1} \end{cases}$ then $\Delta_t^j = 1 - \left(1 - \Delta_c^j\right) \cdot e^{-t(t-t_c)}$ [8]

iii. If $DA_t > \widehat{DA}$ then $\Delta_t = 1 - \left(1 - \Delta_c^j\right) \cdot e^{-z \cdot t(t-t_c)}$ [9]

where $z = \dfrac{\hat{t}_{DA}}{\hat{t}_{DA} - t_{\widehat{DA}}}$, being $t_{\widehat{DA}}$ the time elapsed since $DA_t > \widehat{DA}$.

---

[32] "Policy should take such aspects into consideration [*performance characteristics*] in designing environmental policies in order to prevent cost inefficiencies, obstruction from industry and non-compliance" (Kemp, 1997: 240).

[33] "It is also important that policy makers take into account the technological opportunities to develop substitutes for environmentally hazardous technologies, together with firms´ capabilities and willigness to use them" (*op. cit.*: 241).

[34] All these assumptions have been sufficiently justified before.

[35] This support Δ_t^j does not necessarily intend to represent an economic subsidy, but all those signs (information, formation, demonstration, voluntary agreements, etc.) which show the official interest with regard to a certain technology to industry: "(...) Knowing that the government is giving priority to a particular externality (…) makes it more rational for a firm to adopt environmental protection measures than if it were acting alone" (DeCanio, 1993: 912).

An agent can be considered to have bounded rationality regarding various aspects of the problem, such as his ability to calculate or access to all the information he needs to make a decision. In this model it is possible to argue that despite his imperfect information, the individual agent may *try* to optimize the problem of individual choice. In other words, we assume that each P_i has bounded rationality in terms of access to information, but that given the decision scale he acts *as if* he were optimizing his private decisions[36]. Let us also suppose that P_i agents have heterogeneous preferences regarding the adoption characteristics C^j_{Ak} of the productive technologies. Thus, in each t, each P_i adopts[37] the T_j that offers the greatest value in terms of the linear decision[38] function $U^i_t\,(>0)$:

$$Max \qquad U^i_t = w^i_1 \cdot C^{ij}_{\mathrm{A1t}} + w^i_2 \cdot C^{ij}_{\mathrm{A2t}} + w^i_3 \cdot C^{ij}_{\mathrm{A3t}} + w^i_4 \cdot C^{ij}_{\mathrm{A4t}} + w^i_5 \cdot C^{ij}_{\mathrm{A5t}} + w^i_{\Delta} \cdot \Delta^j_t \qquad [10]$$

where the parameters $w^i\,(0 < w^i < 1)$ are the weightings the agent P_i attributes to the various criteria involved in his decision. In the simulation we assume that for each P_i the weightings are normalized, i.e. the condition $\sum w^i = 1$ is met; additionally, we assume that the values of each of the weightings w^i that each P_i attributes to each criterion is distributed independently and randomly between the different producers P_i following a $N(0,1)$ distribution within the range of possible values $[0,1]$. In this way, apart from contemplating the assumption of heterogeneous preferences of agents with regard to adoptability criteria, we reflect the fact that different agents react unevenly to a same public stimulus. We assume that the value of these weightings, which constitute the preference profile of *each agent* P_i, do not change over the course of the agent's active life. Nevertheless, the average weightings assigned by the *group* of active agents in each t do change, given that the group changes (quantitatively and qualitatively) as agents enter and leave the market.

Through a participative process[39] which considers the preferences of all relevant stakeholders, the Agency sets, both initially ($t = 0$) and subsequently in each period (as shown below), a satisfaction threshold[40] C^*_{St} with regard to the social choice criteria valued in a technology that is compatible with its collective aims of sustainability. In the simulation, C^*_{St} value is set arbitrarily at $t = 0$[41] within this range $[0,1]$.

---

[36] According to Nelson (1995: 50), "there is no real difference between saying that companies literally maximize and saying that their behaviour has been learned through trial and error, and in some cases they have been selected by the competitive process. In this way, agents act 'as if' they were maximizing." Using this approximation, for example, Loch and Huberman (1999: 5) assume that "(...) agents are governed by profits but are unable to optimize due to their bounded rationality. [On this assumption] agents simply choose the 'best' of the technologies available, without being able to conduct a full evaluation or anticipate the equilibrium of the system."

[37] In other words, each agent adheres to a "technology population" in Saviotti's sense (2001: 200), which evolves in quantitative terms (size) and qualitative terms (composition).

[38] We apply a simple method of weighted (linear) summation (see, for example, Pomerol and Barba-Romero, 2000: 76).

[39] For a practical approach see, for example, Linares and Romero (2002) or Feinberg and Smith (1989).

[40] See Pomerol and Barba -Romero (2000: 71).

Each term t the Agency valuates each available, old and new[42] technology performance in terms of sustainability C_{St} (techno-environmental prevention policy). It therefore takes the satisfaction threshold C^*_{St} and the first technology in t in order of availability T^1 and compares C^*_{St} to the corresponding value of C^1_{St} in $\overrightarrow{D^1_t}$. If C^1_{St} were below threshold C^*_{St}, then technology T^1 would be valued in the next period (if it is still available and within sight of its evolution); the following technology in order of availability T^2 would be compared to the threshold. If C^1_{St} were equal or higher than C^*_{St}, T^1 would remain until performance valuation of the following technology T^2. This process would last until all[50] technologies available in t had been evaluated. If no available technology in t exceeded the satisfaction threshold, this would remain invariable in next period $t+1$ and the Agency would keep supporting the last chosen technology T^{j*}_t. If only one technology rose above the threshold, it, rather than the other alternatives, would receive the Agency´s support Δ^j_t. If more than one technology remained, the one whose performance in criterion C_S strictly dominated the remainder would be chosen and supported with Δ^j_t, and these technologies would valued in the next period (if they are still available and within sight of their evolution)[43].

Each time t, the performance of C_S of chosen and supported technology T^{j*}_t, plus an improvement differential $d^*_t\left(>0\right)$, automatically determines the new satisfaction threshold C^*_{St+1}, which more demanding by definition than the previous one. This new threshold will be faced by the new alternative technologies emerging during the next period.

$$C^*_{St+1} = C^*_{St} + d^*_t \qquad [11]$$

Building upon Simon´s ideas[44], this threshold evolution should depend on the previously obtained results and the ease with which they are obtained. If the threshold were static, the search could end prematurely (low-demanding) or, in the opposite case, never finalize (high-demanding)[45]. We therefore assume that the threshold moves gradually: the Agency's satisfaction threshold will rise to the same extent that it finds easily satisfactory alternatives; in the opposite case, the threshold will remain stable[46]. So, we propose that d^*_t be a direct

[41] The underlying assumption here is that technological development in $t=0$ is not very advanced. Therefore, following Simon´s (1964, 1972) assertions concerning pragmatism when setting a satisfaction threshold, it seems reasonable to establish at the outset a value nearest to 0 than to 1, within the performance range.

[42] As shown in Appendix 4, in the base scenario technology population stabilizes around a dozen alternatives, constantly changing and renewed in its composition.

[43] We want to emphasize that in no case are we suggesting the Agency optimises, given that we assume its bounded rationality. We propose a dynamic approach to Simon´s satisfaction model (static). Optimization implies future evaluation of today's available alternatives, choosing the one that maximices an objective function within a determined horizon, assuming some probabilities. On the contrary, dynamic satisfaction implies actual evaluation of currently available technologies and choosing the one which better satisfies a threshold today. In Laville (1998) a wider discussion can be found about divergence among optimization and bounded rationality and satisfaction under adaptation mechanisms.

[44] See Barba-Romero and Pomerol (1997: 290).

[45] Laville (1998).

[46] In Kemp (1997: 230) we find a real example of increasingly demanding threshold effectiveness: "The regulation of CFC use is even unique in one respect: the regulations have been tightened several times instead of being softened, to give industry more time to comply with regulations (...) On the whole, government policy seem to have been a success in making a relative quick and smooth transition away from CFCs."

function of the gap between C^*_{St} and C^*_{St-1}, and an inverse function of the number J^E_t of alternatives needed to be evaluated between T^{j*}_{t-1} and T^{j*}_t:

$$d^*_t = \frac{\left(C^*_{St} - C^*_{St-1}\right)}{J^E_t} \qquad [12]$$

with d^*_t as a number within range $[0,1]$.[47]

Thus the Agency, sets a shifting and affordable threshold on the basis of its past experiences (expressions [11] and [12]) and modifies its incentives to achieve it (expressions [7], [8] and [9]). In other words, the Agency learns and responds flexibly according to events, following prevention and transition policies.

Lastly, we define as the standard or dominant technology in t that T^{jST}_t which achieves a market share $\sum_j I^j_t > I^{ST}\%$, for $J_t > 2$ technologies[48], for at least t^{ST} periods. We define as a "challenging technology" in t that T^{jCH}_t which first exceeds the market share of T^{jST}_t, once the latter has ceased to be the standard. Here, t_{rp} (replacement time) is the moment at which T^{jCH}_t replaces T^{jST}_t (by exceeding its market share). F^j_t is the actual fitness[49] of technology j at time t, defined as $\sum_{Ak} C^j_{Akt} \big/ Ak$. F^{ij}_t is the perceived fitness of technology j (i.e. the average perception of the i users of this technology) at time t, defined as $\left(\sum_i \left[\sum_{Ak} C^{ij}_{Akt} \big/ Ak\right]\right) \big/ I^j_t$.

Table 1 recaps the (independent) variables used in the model to characterize the industry represented and the attributes of the technology standardization process (dependent variables), the relationship of which with the independent variables we aim to identify and evaluate.

[47] In the simulation, the addition of d^*_t to C^*_{St} is necessarily always less than 1.

[48] In the simulation, this condition (*for* $J_t > 2$ *technologies*) will only apply in the initial moments after the emergence of the industry given that with a small number of technologies (<2) the fact that one of them obtains more than 50% of adopters may be the result of chance (*first mover advantage*) rather than its merit. However, if later on while one technology is dominant the others reduced their share or disappeared altogether, it would not make sense to say that the non-fulfilment of the condition (*for* $J_t > 2$ *technologies*) caused the technology in question to lose its recognition as the standard, given that it had obtained it by its own merits.

[49] Nelson (1995: 64) defines the 'fitness' of a technology as its ability to resolve a specific technology problem better; Saviotti (2001: 207) defines it as the technology's ability to adapt to the environment in which it operates.

Table 1. Recap of the variables and parameters of the model
Characteristics of the industry (independent variables used in the model)

Parameter	Definition and interpretation
l_T	Average rate at which new available technologies appear during the period in the industry ("average rate of innovation").
P_T	Minimum number of adopters the technology needs to obtain within time t_T in order to survive ("scale of network" necessary).
t_T	Maximum time in which a technology needs to obtain P_T adopters in order to survive ("competitiveness of the technology market")
$\bar{r}$	Average rate of improvement with the adoption of technologies T_j emerging within the same period t ("degree of increasing returns to adoption")
s_r	Dispersion of the average rate of improvement with the adoption of technologies T_j emerging within the same period t ("degree of differentiation in the capabilities of the technology providers")
l_P	Average rate at which new active producers appear in each period ("barriers to entry").
$\bar{s}$	"Average survival of firms"
s_s	Dispersion of the average survival of firms ("competitiveness of the industry")
c	"Rate of communication" between users
b	Probability that an agent i replaces his technology j at time t ("tendency to technological obsolescence in the industry"; "cost of technological change in the industry").
$I^{ST}\%$	Minimum market share –in terms of the relative number of adopters– that a technology needs to achieve during t^{ST} periods in order to be considered the industry's "standard" technology.
t^{ST}	Minimum time a technology needs to maintain the minimum market share $I^{ST}\%$ in order to be considered the industry's "standard" technology.

Attributes of the technology standardization process (dependent variables)

Variable	Definition and interpretation
t_0^{ST}	*Emergence:* for each simulation, the initial moment t in which a technology exceeds a share $I^{ST}\%$ of the active users (for $J_t > 2$) for at least t^{ST} periods, thus becoming the standard.
fr^{ST}	*Frequency:* the number of times the above event occurs over the course of each simulation.
v^{jST}	*Speed:* for each standard, the time elapsing in the experiment between the entry of a technology in the market and its acceptance as a standard.
d^{jST}	*Duration:* for each standard, the time elapsed (greater than t^{ST} periods) during which a technology's share of users remains above $I^{ST}\%$ (for $J_t > 2$).

p^{jST}	*Depth:* for each standard, the maximum share achieved by the technology during the time it remains the standard.
scs^{jST}	*Susceptibility to changes in supply:* for each standard, the magnitude of improvement necessary in the perceived performance of an alternative technology to break its dominance (percentage variation between F_t^{ijR} and F_t^{ijST} at replacement time t_r).
scd^{jST}	*Susceptibility to changes in demand:* for each standard, the magnitude of the change in preferences of the users needed to break the dominance of a standard technology. Defined as $scd^{jST} = \vec{a} \cdot \vec{b} = \sum_k a_{Ak} \cdot b_{Ak}$ at time t_{rp} being $\vec{a} = \left\| \vec{w}_{Ak}^{I^{jCH}} - \vec{w}_{Ak}^{I^{jST}} \right\|$, $\vec{b} = \frac{\vec{w}_{Ak}^{I^{jCH}} + \vec{w}_{Ak}^{I^{jST}}}{2}$, and $\forall i \in I^{jCH}$, $\vec{w}_{Ak}^{i} = (w_{A1}^i,...,w_{Ak}^i)$, $\vec{w}_{Ak}^{I^{jCH}} = \frac{\sum_i \vec{w}_{Ak}^{i}}{I_t^{jR}}$ $\forall i \in I^{jST}$, $\vec{w}_{Ak}^{i} = (w_{A1}^i,...,w_{Ak}^i)$, $\vec{w}_{Ak}^{I^{jST}} = \frac{\sum_i \vec{w}_{Ak}^{i}}{I_t^{jST}}$

Other model dependent variables

Variable	Definition and interpretation
$F_{t_{ST}}^{jST}$	Actual fitness of the technology standard j at the time t_{ST} when it becomes the standard. Defined as $\sum_{Akt_{ST}} C_{Akt}^{jST} \big/ Ak$.
$F_{t_{ST}}^{jBAT}$	Actual fitness of the technology that would have been the best alternative technology j, (simultaneously or beforehand) a standard in the t_{ST} moment at which it becomes the standard as such and is adopted by an equivalent number of users. Defined as $\sum_{AktST} C_{Akt}^{jBAT} \big/ Ak$.
ced	Cumulative environmental damage ($\sum_t DA_t$) at the horizon of each simulation in the experiment without the intervention of the Agency.
ceda	Cumulative environmental damage ($\sum_t DA_t$) at the horizon of each simulation in the same experiment with the intervention of the Agency.

3.2. Calibration of the model

Given our interest in its dynamic properties and the difficulty of its mathematical treatment, the agent based model (ABM) described has been developed to run in MATLAB™, a specific mathematics-oriented programming language, recognized for its capabilities and versatility.[50] In keeping with the philosophy of ABM, we have sought to use this flexibility to provide a research methodology to enhance our understanding of the basic processes which might appear in various applications, and not represent or make specific predictions regarding a particular empirical application. Thus, when calibrating the model (base scenario) we opted for a set of theoretically acceptable parameters obtained from the literature, but which are not intended to represent precisely any particular situation or industry. The subsequent sensitivity analysis will make it possible to evaluate statistically the effect of modifications on this base scenario.

As regards $I^{ST}\%$, Anderson and Tushman (1990) consider a dominant design (standard) to have emerged when a new architecture obtains 50% or more of the installed processes[51] and maintains this market share for at least 3 consecutive years[52]. Various studies of different industries in a number of countries (Klepper and Simons, 1997; Gort and Klepper, 1982) confirm that a value of 15 for the parameter l_P may be theoretically acceptable for the base scenario. As regards the parameters $\bar{s}$ and s_s, studies such as those by Klepper and Simons (1997), Mata and Portugal (1994) or Tegarden et al. (2000) suggest that values in the base scenario for $\bar{s}$ and s_s of 5 and 2 years, respectively, are of a theoretically acceptable order of magnitude. Klepper and Simons (1997) also offer guidance as to an approximate magnitude for l_T. In the base scenario we have opted for a value of 1.

Unlike the previous parameters, which are populational, and whose magnitudes can be justified from empirical studies, the way the underlying assumptions were decided for the remainder of the initial parameters in the model was more *ad hoc*. Where possible, we have sought to justify the values used on the basis of the preceding values. In this way, given the magnitude (justified) of the entry and exit of firms to and from the industry, which leads the industry to stabilize in the base scenario with a population of almost 80 firms which are constantly being renewed, we believe it reasonable that a technology should be adopted by at least 5 firms (P_T) within 2 years (t_T) in the base scenario in order for it not to be considered "rejected" by the productive system and for network economies to come into play, allowing it to compete with the other technologies. Given this value of P_T, if we ascribe a value of 0.2 to the maximum dispersion s^{j}_{Akt} of the perceived performances C^{ij}_{Akt} around the actual

[50] Our model has been designed to make it straightforward for the analyst to enter the starting-point conditions of the experiment. It is possible to modify the magnitudes of the initial parameters describing the industry (rate of innovation, barriers to entry, rate of increasing returns, etc.) and the general conditions of the experiment (number of dimensions of the technology, number of iterations per simulation and number of simulations per experiment). It also allows a random seed to be saved and reused under different conditions. As well as experimenting with a "base scenario", it is possible to perform multiple sensitivity analyses on the various parameters of the model. Finally, this model generates a wide range of graphics and numerical tables recording the paths taken and giving details of the different perspectives of the process of technological change we are interested in studying. The source code of the model can, of course, be requested from the author, together with the technical details of the modular structure of the program, the names and descriptions of the model's variables, and the routines it contains.

[51] This condition can obviously only be obtained by one technology at any time .

[52] In their various studies Anderson and Tushman vary this figure between 3 and 4 years.

performance of a technology C^j_{Akt} $(\in[0,1])$, according to expression [5] the rate of communication c should have a value of 0.8. In the same way, if the maximum values that can be achieved by $\widehat{C}^j_{Ak}$ and $C^j_{Ak_0}$ are 1 and 0.5, respectively, from expression [4] we can deduce that a rate $\bar{r}$ of around 0.5 places the "frontier of technological improvement" at approximately 50% in an industry of 80 firms. In other words, we are assuming that only one technology standard can reach its full performance potential, which, at all events, is limited (<1). We also establish a deviation s_r = 0.2 to ensure a certain degree of diversity between the technological alternatives. With regard to the initial parameters that define the Agency´s behaviour, it was argued earlier that, following Simon´s (1964, 1972) assertions concerning pragmatism when setting a satisfaction threshold, it seems reasonable to establish initially a value nearer to 0 than to 1, within the performance range. So, we ascribe in $t=0$ a value of 0.1 to $C^*_{St}\in[0,1]$. Additionally, we establish a tentative initial support $\Delta^j_0\in[0,1]$ at a minimum level of 0.1, and ascribe a value of 0.8 to the rate $t\in[0,1]$ at which support intensity grows and decreases exponentially.

The maximum capacity for damage or waste assimilation and natural resources regeneration of the ecosystem affected by business activity $\widehat{DA}\in[0,1]$ is established at 0.7, a level over which environmental damages become irreversible if their source remains active for more than $\hat{t}_{DA}$ = 10 periods.

Lastly, the value of 0.2 assigned to b (probability that agent i replaces his technology j at time t) in the model is justified by the relative tendency to technological obsolescence and the considerable costs of technological change in the industry.

3.3. Numerical simulations

In order to fulfil the aims of the investigation and check the hypotheses set out below, we ran an experiment using the base scenario, involving 150 simulations of 50 iterations each, using different random seeds in each simulation[53]. As a sample, and for reasons of space, Appendix 2 presents only the first 10 simulations of all the standards recorded in each simulation. The table in the appendix shows the different characteristics of each of the standards, and the

---

[53] To decide on the appropriate number of simulations in the main experiment we first ran a pilot in which 15 simulations were run on the base scenario with different random seeds. This pilot experiment yield standard deviations of s for the variables F^{jST}_{tsr}, F^{jBAT}_{tsr}, scs^{jST}, scd^{jST}, ced and $ceda$, involved in the hypotheses H1, H2, H3 and H4. When a confidence of 95% was required (z_a = 1.96), for reasonable amplitude intervals of d, the variable requiring the largest sample n was scs^{jST}, which required a sample of around 70 cases of at least one standard (see the following note), an objective that in our base scenario required approximately 150 simulations:

$$P(\bar{x}-\frac{s\cdot z_a}{\sqrt{n}}\leq m\leq \bar{x}+\frac{s\cdot z_a}{\sqrt{n}})=1-a \qquad \rightarrow \qquad d=\frac{s\cdot z_a}{\sqrt{n}} \qquad \rightarrow \qquad n=\frac{s^2\cdot z_a^2}{d^2}$$

As regards the choice of 50 iterations per simulation, this number was selected because it was considered a sufficiently distant horizon to enable the phenomenon of a series of successive standards to be studied. A remoter horizon did not yield different conclusions, but required more computation time in the experiments.

complete standardization process, recorded in each "history" (simulation) of this industry, according to the attributes described above (time, frequency, speed, duration, depth, susceptibility to changes in supply and in changes in demand). Appendix 3 shows the data for the first standard recorded in each simulation, filtered out from the general results of the 150 simulations. The characteristics of these standards will be examined in more detail below [54].

The set of graphs included in Appendix 4 shows the results of a typical model simulation using the base scenario. The first graph shows the time course of the adoption (market shares as a unit proportion) of the technologies by the various producers present in each moment in the industry producing good X. Following Anderson and Tushman (1990), technologies that exceed a 50% share for at least 3 periods are identified as technology standards[55]. It is worth highlighting the striking visual isomorphism between the results of the model and the patterns of the phenomenon observed in real industries as, according to Marney and Tarbert (2000), this may be considered an indicator of the validity of the model. In a test of *external validity*, as understood by Kleijnen (1998), in Appendix 5 it is possible to see that our model offers a representation of the phenomenon of technological succession consistent with the empirical evidence on the diffusion of technologies in industries as diverse as RAM chips, steel manufacturing or power generation.

Unlike conventional models of technology diffusion and standardization, which focus on the *rate* at which *one* new technology diffuses until it is fully adopted, our model enables a broader approximation to the *process* of technological change to be obtained, from the perspective of the *extension* of the diffusion of *multiple* alternative technologies and the related phenomenon of standardization. Previously, we pointed out that in addition to Arthur, many other authors have portrayed the technology selection process as an "all or nothing" story (Abrahamson and Rosenkopf, 1997). This is a general shortcoming of diffusion and standardization models that has been pointed out repeatedly in various studies over the last decade (Schilling, 2002: 395; Jaffe et al., 2000: 41; Windrum and Birchenhall, 1998: 112; David, 1997: 36; Nelson, 1994b; David and Greenstein, 1990: 8). Despite the various forces (*positive feedbacks*) that help reinforce the dominant position of a technology standard, experience shows that no standard remains in place in an industry indefinitely (Abrahamson and Rosenkopf, 1997; Ruttan, 1997; Witt, 1997; Grübler, 1990; Ausubel, 1989). On the contrary, in reality, if a long enough horizon is taken, one sees a succession of standards, a dynamic of transition between unstable equilibria, which this model is able to represent and characterize.

It is rare for a technology standard to achieve absolute diffusion in an industry, where this is understood to mean a 100% market share. By contrast, one often observes how different degrees of standard coexist with less successful technological alternatives, which may survive for a variable length of time in market niches (Grübler, 1990; Dalle, 1995; Freeman, 1996). The existence of these niches is explained both by the emergence of new alternatives, which start to build their own installed user base, and by the heterogeneity of users' preferences,

[54] We consider the first standard to be representative of the characteristics of the rest of the standards in the same simulation, and given that it is the one produced in the greatest number of simulations, its choice ensures the greatest number of data. Those standards that emerge at the start of the experiment and continue to dominate through to the end are considered outliers and discarded.

[55] The number next to the word "standard" (simulator otputs in Spanish: "estándar") identifies the technology in question and represents its order of appearance in the history of the industry shown.

which may circumstantially maintain different groups apart from the dominant standard. Again, the proposed model makes it possible to show in greater detail than conventional "all-or-nothing" models (which, moreover, usually focus on the competition between just two alternatives) the reality of an industry divided at all times between multiple available alternatives, all with different levels of adoption at each moment in time.

The second graph of the first line of Appendix 4, equivalent to that described, shows the results of a parallel experiment under identical conditions, but with the presence of an Agency in the terms defined in the model's assumptions. The third graph shows the time course of the environmental damage without the intervention of the Agency (red) and with the intervention of the Agency (blue). We will return to this graph later. The first graph on the second line shows the time course of the environmental damage with the intervention of the Agency, and the intensity of the effort needed to avoid the system's becoming locked in to environmentally inferior technology standards, thus orienting technological change towards a sustainable path. The last two graphs show the evolution of the population of firms and the population of technologies, respectively.

4. Examination of hypotheses

It was argued above that in the presence of increasing returns to adoption the market may become locked-in in favour of one of the competing alternatives due to historical circumstances. It is a recurring statement in the literature on this issue that under these conditions there is no guarantee that there are no alternatives to the winning technology that would have had lower unit costs if they had achieved an equivalent position of market dominance (Arthur, 1989; David, 1989; Cowan, 1990; Metcalfe, 1994). Moreover, throughout this paper we have maintained that the technology path followed by an industry is shaped by chance historical events (*path dependency*). Thus we can state that the distribution of market shares between the different technological alternatives at any given time, and the succession of possible technological standards, will depend on the one hand on the chance order in which these alternatives are available for adoption and that in which the potential adopters enter and exit the industry. It will also depend on the characteristics of each of these heterogeneous "populations" (technologies and firms) at each time (performances and preferences, respectively).

> **Hypothesis 1.** *In an industry characterized by increasing returns to technology adoption, over a sufficiently long time horizon, we will witness a succession of multiple alternative equilibria (standards), which cannot be anticipated and are not necessarily Pareto-optimal.*

Proof. In the table of general results in Appendix 2 it is possible to see how the different "histories" of the industry represented by the various simulations do indeed show alternative technological paths which cannot be anticipated in advance. The data in column 2 of the table (ID_ST, identifier of standard j) show that in the various simulations (SIM is the number of the simulation) different standards emerge, each of them characterized by a different initial performance vector $\overline{P}_{t_0}^{j}$ (columns 5 to 9). Under the same initial conditions, with an identical base scenario, the element of chance in the evolution of the populations of technologies and adopters (order of entry and exit, characteristics, preferences, etc.) leads the different simulations ("histories" of the industry) to different standard technologies in each case. Clearly, these paths of technological change cannot be anticipated by the agents participating in the industry, as their course depends on unpredictable events. In this respect the model presented here overcomes the determinism to which the traditional assumptions leads and allows this theoretical exercise to be performed in a way which shows how different sequences of events in the same industry can lead to different technology paths.

With regard to the second part of Hypothesis 1, the possible non-Pareto-optimal nature of the equilibria (standards) arrived at implies that as a result of the presence of increasing returns to adoption, uncoordinated adoption decisions by mutually influenced producers may lead the industry, in a dynamic conditioned by the way events unfold, to an inferior technology standard than that which could have been achieved had they chosen one of the available alternatives in a coordinated way (Arthur, 1989; Cowan, 1990; David, 1993). Obviously, *ex post* it is impossible to confirm or refute this statement empirically (Nelson, 1994: 141). Under certain reasonable assumptions the model presented allows a counter-factual exercise comparing the performance of a dominant technology at the time when it becomes the standard and the hypothetical performance that the other alternatives coexisting with it or preceding it would have achieved if they had been adopted by an equal number of users. Column 10 (FIT_ST, $F_{t_{ST}}^{jST}$) of Appendix 3 shows the actual fitness of the technological standard (column 2, ID_ST) at the moment (column 3, TST) at which it becomes the standard. Column 11 (FIT_BAT, $F_{t_{ST}}^{jBAT}$) shows the actual fitness the best alternative technology from among those coexisting with or preceding the technology when it became the standard would have achieved (column 12, ID_BAT) had it been adopted by an equal number of users. It can be seen that in a significant[56] number of cases FIT_BAT exceeds FIT_ST, which leads us also to accept the second part of Hypothesis 1.

As described earlier, on Anderson and Tushman's (1990) view of the technology cycle, the transition between two standards is usually presented as the result of a technological discontinuity. In Foster's terms (1986), there needs to be a "jump" of a certain order of magnitude between two S-shaped technology performance curves. Other authors have also suggested that it is necessary for there to be a significant improvement in the performance of an alternative to the standard in order to overcome the inertia of the system and initiate the transition from a locked-in technology to a new one (Grove, 1996; Drucker, 1993). A number of empirical studies have tried to quantify this order of magnitude in specific industries and historical circumstances. One frequently cited example is that of David (1985), who concluded that 20-30% savings were insufficient to cause a transition from the QWERTY system to the Dvorak keyboard. However, we do not have a formal generalizable observation of this fact in technology transitions. This model enables us to examine statistically whether this is the case. It also makes it possible to measure, as will be shown below, the relationship between the magnitude of the improvement necessary to produce a technology transition and

[56] It is not, however, a *statistically* significant number of cases. In column 8 of Appendix 2 the dichotomous variable FST_FB1 = 1 when FIT_BAT > FIT_ST and = 0 otherwise. According to the results of a non-parametric (binomial) analysis of proportionality on FST_FBI which does not allow us to state that the proportion of zeroes is different from that of ones for any reasons other than chance (bilateral asymptotic significance = 0.644). Given that FIT_BAT and FIT_ST are distributed normally, we also performed a T-test for independent samples (for this purpose the variable FST_FB2 was created, with values 1 and 2 for each group) throwing up an equivalent result as that in the previous comparison (t=-1.408; bil. sig.=0.161). At all events, to accept this second part of H1 it is enough to demand that FIT_BAT is greater than FIT_ST on at least one occasion, as in fact happens.

the different characteristics of the various industries in which a transition of this kind takes place (rates of innovation, barriers to entry, etc.)

> **Hypothesis 2.** *The emergence of an alternative to the locked-in technology (standard) that offers a sufficient improvement in its characteristics (technology supply side), can lead the cumulative endogenous phenomena in the industry, which derive from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry.*

Proof. Column 15 of the table of results in Appendix 3 shows, for each standard, its susceptibility to changes in supply (scs^{jST}), previously defined as the magnitude of the necessary improvement in performance for an alternative technology to break its dominance (percentage variation in F_t^{ijCH} and F_t^{ijST} at time t_{rp}). In an interval of confidence of 95% for the average between 17.07 and 32.78, the variable scs^{jST} takes an average value of 24.93% in the base scenario, with a standard error of 3.94. According to results of a T-test (t=6.330; bilateral significance < 0.01) the average of the sample is statistically non-zero and the value 0 is outside the confidence interval. In other words, the model confirms Hypothesis 2: the emergence of an alternative technology to the locked-in technology (standard) which presents a sufficient improvement in its characteristics (in this base scenario, of the order of 25%) can cause the system to escape the lock-in endogenously (technology supply side).

However, the evidence (Kemp, 1997: 281; Cowan and Hulten, 1996) reveals that a technology standard's loss of the dominant position is not always solely due to the emergence of an alternative offering significantly better performance. To obtain a more realistic view of the internal processes explaining the dynamics of diffusion and the succession of standards, the proposed model also incorporates the importance of possible changes on the *demand side*, which it represents as changes in the preferences of the possible adopters.

> **Hypothesis 3.** *A sufficient change in the average preferences of potential adopters regarding the features of technologies (technology demand side), can lead the cumulative endogenous phenomena in the industry, which derives from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry..*

Proof. Column 16 of the table of results in Appendix 3 shows, for each standard, its susceptibility to changes in demand (scd^{jST}), defined above as the magnitude of the necessary change in user preferences to break its dominance (see *table 1*). Within an interval of confidence of 95% for the average between 2.84 and 3.95, the variable scd^{jST} takes an average value of 3.40%, with a standard error of 0.28. According to results of a T-test (t=12.261; bilateral significance < 0.01) the average of the sample is statistically non-zero and the value zero is outside the confidence interval. In other words, the results of the model confirm H3: a sufficiently large change in the average preferences of potential adopters regarding technology features (in this base scenario, of the order of 3.5%) can cause the system to escape the lock-in endogenously (technology demand side).

As argued on the preceding pages, the broadening spectrum of environmental problems, the uncertainty regarding their scale and duration, and their possible irreversibility, in the context of the growing social preference for environmental quality, make it necessary to undertake an *ex ante* (precautionary) approach to the link between productive activity and environmental quality. As we have sought to show in this paper, this link lies in technology, and the right approach is to understand how the process of technological change can lead towards sustainability. The added value of Evolutionary Economics in the context of environmental policy resides mainly in the fact that it warns that certain inferior environmental technologies may be locked in to the economic system. As we have seen, this model shows that endogenous changes within the industry, on either the supply side (i.e. the emergence of new technologies that are notably superior to the locked-in technology) or the demand side (i.e. changes in the average preferences of potential adopters) can enable a transition between equilibria to take place within the system without the need for public intervention. However, the timing of this spontaneous transition may not be the socially most appropriate. The main justification we offer for public intervention in the process of technology diffusion in the presence of increasing returns to adoption, and hence which may result in a succession of environmentally sub-optimal technology standards, lies in the greater ability of the State to coordinate technology choices and achieve a environmentally superior timing.

> **Hypothesis 4.** *If we accept the global nature, uncertainty, complexity and irreversibility of environmental problems, the intervention of a coordinator acting in accordance with sustainability criteria in the technological choices of adopters, exploiting the cumulative phenomena arising from increasing returns to adoption, could guide technological change onto a better path in environmental terms and reduce the risk of irreversible damage to the environment.*

Proof. Columns 17 and 19 of Appendix 3 show the cumulative environmental damage ($\sum_t DA_t$) at the horizon of each simulation in the experiment without the intervention of the Agency (ced) and the cumulative environmental damage at the horizon of each simulation in the experiment with the intervention of the Agency ($ceda$)[57]. The fact that in the results of this experiment only the variable $ceda$ has a normal distribution, as shown by a Kolmogorov-Smirnov test (ced: 0.142, sig. 0.001; $ceda$: 0.071, sig. 0.200), rules out the possibility of a T-test to confirm the hypothesis that the averages of each of the variables are the same. Instead, we ran a non-parametric (binomial) proportionality test, the results of which confirm that the proportion of cases[58] in which dac is less than das is statistically different from that which might have arisen by chance (50%) (bilateral asymptotic significance < 0.01). The hypothesis H4 is therefore accepted. Obviously, the proven effectiveness of a coordination mechanism

[57] As mentioned a few pages back, our model has been developed in such a way as to allow the simultaneous execution of two parallel experiments using the same scenario and the same random seed, the first without the intervention of the Agency ($\Delta_t^j = 0$, i.e. the agents decide on the technologies based only on their individual adoption criteria C_{Akt}^j), and the second with the intervention of the Agency ($\Delta_t^j \neq 0$, i.e. the same agents decide on the same technologies on the basis of C_{Akt}^j and Δ_t^j). The results of the two experiments are therefore fully comparable and make it possible to observe the technological path of the industry and its environmental consequences without any coordination of the technology adoption decisions and what the technology path would have been with coordination guided by sustainability criteria.

[58] For this purpose, the dichotomous variable CED_CEDA was created. This variable takes the value 1 when CEDA is less than CED and 0 otherwise.

such as that modelled depends on the starting point hypotheses, in particular the flexibility and rapidity of the response of the Agency. Although it is debatable whether this mechanism could be put in practice with this degree of flexibility and rapidity of response, we consider the model and the confirmation of hypothesis H4 to at least support the desirability of an approach to the problem like that proposed[59].

The model allows us to show graphically the positive influence of the Agency's intervention on the environmental performance of industry. Figure 2 shows the typical results of our model, showing the time course of the environmental damage (and the existence of irreversible damage, as defined in the model), with and without the intervention of the Agency, starting from the same base scenario and identical random seeds.

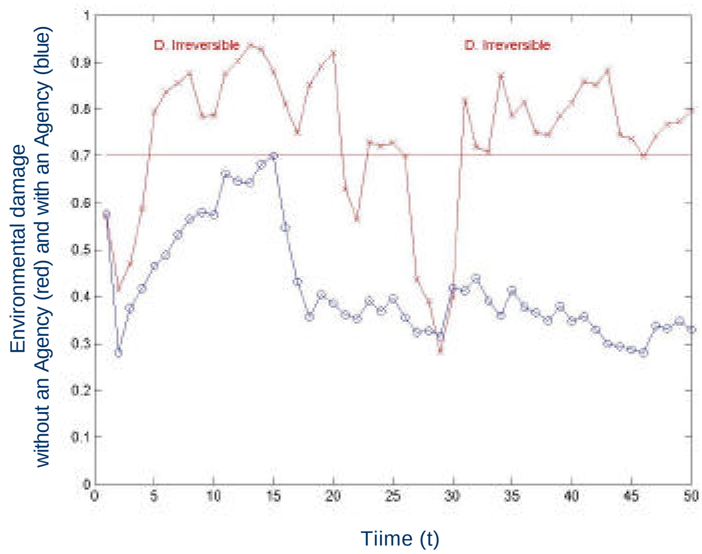


Fig 2. Results of a typical simulation with the model
(time course of environmental damage)

5. Conclusions

Unlike conventional models of technology diffusion and standardization, which focus on the rate at which one new technology diffuses until reaching full adoption, the model presented here enables a broader approximation to the process of technological change to be obtained, encompassing the diffusion of multiple alternative technologies and the phenomenon of a succession of standards, as has been observed empirically. Experience shows that no standard remains in place in an industry indefinitely, and it is unusual for a technology standard to achieve total diffusion. By contrast, in reality, over a sufficient horizon it is possible to observe a succession of standards of differing degrees that coexist with less successful

[59] In this regard we second the words of the Nobel prizewinner for Economics, Amartya K. Sen, who in his book *Choice of Techniques*, after arguing for an elaborate model of technology choice for developing economies which was highly demanding of the capabilities of its Planning Commission, justified the value of his proposal in the following terms (Sen, 1960: 80): "(...) Can we really work all this out? The answer is of course, NO. What then is the justification for what we have been saying so far? That will become clear if we try to see what is the alternative approach. There hardly seems to be any alternative approach that can be considered satisfactory (…) If the approach is complicated it is because the real world is not simple. In practice it might not be possible to obtain a perfect solution. This does not, however, that the problem is hopeless. The approach outlined in the preceding pages shows *in what lines we have to proceed.* How far we can go that line will of course depend upon particular circumstances." (emphasis added).

alternative technologies, which may survive for varying lengths of time in niche markets. The proposed model makes it possible to show with greater detail than conventional "all-or-nothing" models (which, moreover, usually focus on the competition between just two alternatives) the reality of the dynamics of transition between unstable equilibria in an industry divided at all times between multiple available alternatives, all with different levels of adoption at each moment in time. Our model overcomes the determinism of conventional models of technology lock-in by representing the process of standardization and technological succession dynamically and allowing for the renewal and heterogeneity of technology supply and demand.

It is a recurring theme in the literature on technology diffusion that in the presence of increasing returns to adoption the market may become locked-in in favour of one of the competing alternatives due to historical circumstances. There is no guarantee that there are no alternatives to the winning technology that would have had lower unit costs if they had achieved an equivalent position of market domination. This model makes it possible to confirm the path dependence and possible non-optimality of uncoordinated adoption, which is frequently argued for in the literature but rarely formalized.

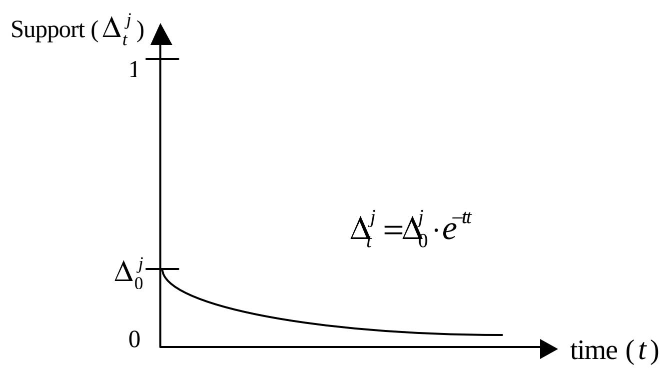
Various authors have also suggested that it is necessary for there to be a significant improvement in the performance of an alternative to the standard to overcome the inertia of the of the system and initiate the transition from a locked-in technology to a new one (*supply side*). Although a number of empirical studies have attempted to quantify this order of magnitude in specific industries and historical moments, there is no formal or generalizable confirmation of this fact in technology transitions. The evidence also shows that the loss of dominant position by a technology standard is not always *solely* due to the emergence of an alternative offering significantly better performance. It may also be due to changes on the technology *demand side*. The proposed model has also allowed us to examine the hypothesis that either a *sufficient improvement in the features* of alternative technologies or a *sufficient change in the preferences* of potential adopters regarding a technology's features can cause cumulative endogenous industry phenomena, deriving from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry.

The problem of technology lock-in is potentially significant when the impact of technology choices on the natural environment is considered. From this perspective, the quest for sustainable technological change implies that policy-makers face the challenge of preventing and escaping from technology lock-in in environmentally unsustainable practices and systems. As we have seen, this model shows that endogenous changes within the industry, on either the supply side or the demand side, can enable a transition between equilibria to take place within the system without the need for public intervention. However, the timing of this spontaneous transition may not be the socially most appropriate. The main justification we offer for public intervention in the process of technology diffusion where there are increasing returns to adoption, which may result in a succession of environmentally sub-optimal technology standards, lies in the greater ability of the State to *coordinate* technology choices and achieve environmentally superior timing. Based on a number of plausible assumptions, our model has made it possible to evaluate the frequently argued-for, but again rarely demonstrated, desirability of a coordination mechanism to guide the process of technological change towards the path of sustainability.

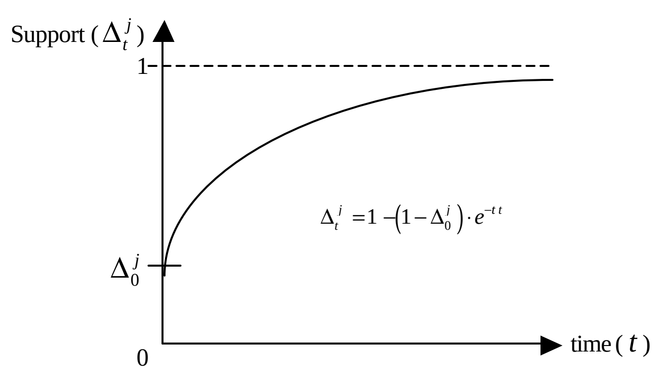
By incorporating an evolutionary view of technological change and sustainable development, in this study we have proposed a novel taxonomy of techo-environmental policies (prevention and transition), complementary to conventional environmental polices, which permits a more formal justification of the appropriateness to new sustainability problems of the various instruments available in practice, and to which previously little attention had been paid by governments.

Appendix 1. Algorithm for support by the Agency

We start out by assuming that the notion of dynamic and reactive support can be represented by an exponential function. First of all, we represent the three "pure" cases in which the tendency of the support (*i.* decreasing, *ii.* increasing proportionally, and *iii.* increasing more than proportionally) set by the decision criterion (relationship between DA_t, $\widehat{DA}$ and DA_{t-1}) is constant over time. In case (*i*) where the environmental damage in the current period DA_t is below the maximum damage $\widehat{DA}$ and the damage in the previous period DA_{t-1}, it is clear that the intensity of the support $\Delta_t^j \in [0,1]$, which starts from a tentative initial level Δ_0^j, should be decreasing (we assume a rate of $t \in [0,1]$). It may even disappear (asymptote at 0) if the damage in t relative to the damage in $t-1$ continues decreasing uninterruptedly over time:

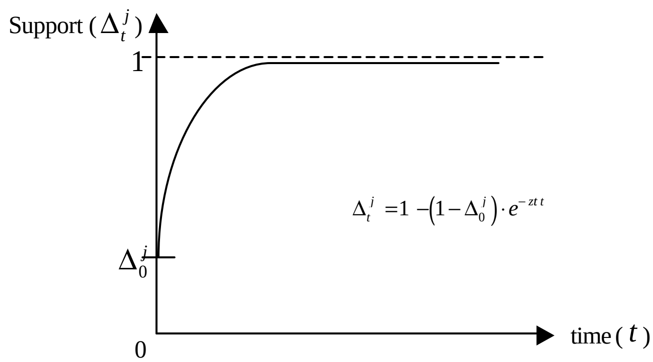


In case (*ii*) where the environmental damage in the current period DA_t is below the maximum damage $\widehat{DA}$ but exceeds the damage in the previous period DA_{t-1}, the intensity of the support Δ_t^j, which starts from a tentative initial level Δ_0^j, should increase proportionally (we assume a rate of $t \in [0,1]$). It may even reach a maximum (asymptote at 1) if the damage in t relative to the damage in $t-1$ continues increasing uninterruptedly over time:

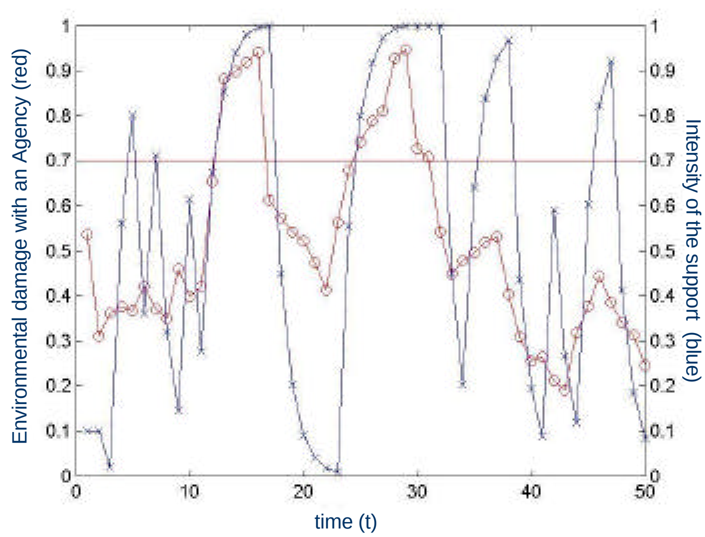


Lastly, in case (*iii*) where the environmental damage in the current period DA_t is above the maximum damage $\widehat{DA}$, the intensity of the support Δ_t^j, that starts from a tentative initial level Δ_0^j, should increase more than proportionally (we assume that the rate of $t \in [0,1]$ is multiplied by a factor $z = \dfrac{\hat{t}_{DA}}{\hat{t}_{DA} - t_{\widehat{DA}}}$, which grows with the time elapsed from the time when

$DA_t > \widehat{DA}$ approaches the period of irreversible damage $\hat{t}_{DA}$). Thus, the intensity of the support Δ_t^j rapidly reaches it maximum level (asymptote at 1) if the damage in t remains above $\widehat{DA}$ uninterruptedly over time.



Given the way the environmental damage function [6] has been defined, we cannot expect the relationship between DA_t, $\widehat{DA}$ and DA_{t-1} to remain constant over time as in previous representations. The decision algorithm of the Agency will respond at each time t with one of these functions Δ_t^j depending on the aggregate environmental result of the individual adoption decisions. On the first occasion, the dynamic support Δ_t^j will start from a tentative initial level Δ_0^j (which can be modified in the simulation). However, on successive occasions, obviously the intensity of the support Δ_t^j will start from the intensity on the last occasion t_c on which the evolution of the damage changed direction (Δ_c^j), i.e. change of case (*i*, *ii*, *iii*). In this mode, the proposed functions [7], [8] and [9] are identical to those represented above, with the difference that in each t they start from Δ_c^j and "set the counter to 0" in t_c:



Results of a typical simulation
(time course of environmental damage vs. support intensity; $\widehat{DA}$=0.7; Δ_o^j=0.1)

Appendix 2. Experiment using the base scenario, 150 simulations of 50 iterations each, using different random seeds in each simulation (sample of the first 10 simulations)

1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
SIM	**ID_ST**	**TST**	**TFST**	**CA01**	**CA02**	**CA03**	**CA04**	**CA05**	**FIT_ST**	**FIT_BAT**	**ID_BAT**	**FST**	**VST**	**DST**	**PST**	**ID_CHT**	**TRP**	**SCS**	**SCD**	**CED**	**F_ICED**	**CEDA**	**F_ICEDA**	**AC_SU**
1	1	3	50	0,254	0,451	0,101	0,157	0,329	0,650	0,692	3	1	0	47	0,988					48,240	1	41,111	1	45,100
2	1	2	50	0,058	0,422	0,478	0,366	0,269	0,716	0,576	2	1	0	48	0,989					49,261	1	44,127	1	46,759
3	2	2	11	0,469	0,390	0,272	0,370	0,397	0,722	0,674	3	3	1	9	0,847	9	12	-2,425	6,722	33,829	0	33,406	1	35,436
3	9	16	20	0,443	0,127	0,416	0,041	0,190	0,488	0,769	8	3	11	4	0,667	17	24	-2,425	3,307	33,829	0	33,406	1	35,436
3	9	47	50	0,443	0,127	0,416	0,041	0,190	0,508	0,866	28	3	40	3	0,688					33,829	0	33,406	1	35,436
4	3	4	10	0,191	0,410	0,134	0,350	0,292	0,746	0,723	5	2	3	6	0,667	12	9	1,980	4,213	37,247	1	35,617	0	32,484
4	14	16	19	0,464	0,412	0,155	0,082	0,178	0,679	0,746	3	2	4	3	0,730	20	20	1,980	2,228	37,247	1	35,617	0	32,484
6	1	28	34	0,244	0,264	0,440	0,185	0,208	0,499	0,781	14	2	27	6	0,713					27,022	0	33,155	0	26,886
6	1	35	43	0,244	0,264	0,440	0,185	0,208	0,499	0,781	14	2	34	8	0,713					27,022	0	33,155	0	26,886
7	13	15	18	0,188	0,282	0,405	0,418	0,486	0,579	0,699	2	1	4	3	0,667	20	24	56,295	6,936	37,010	2	27,140	0	23,272
8	2	2	6	0,497	0,248	0,201	0,147	0,476	0,766	0,731	4	1	1	4	0,907	6	5	-5,472	2,659	38,460	2	30,784	0	25,557
9	4	7	10	0,145	0,089	0,252	0,394	0,082	0,670	0,751	5	1	4	3	0,733	5	10	-2,368	5,021	37,743	1	37,765	2	43,684
10	1	21	32	0,261	0,144	0,388	0,124	0,333	0,538	0,782	8	2	20	11	0,737					43,239	1	35,459	1	34,106
10	1	44	50	0,261	0,144	0,388	0,124	0,333	0,538	0,782	8	2	41	6	0,737					43,239	1	35,459	1	34,106
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Equivalence between statistical abbreviations (SPSS) and model variables

SPSS	Model
SIM	Number of simulation
ID_ST	Identifier of standard technology
T ST	Standard emergence (t_0^{ST})
TFST	Standard end
CA01	Starting level of performance of T^{jST} in criteria 1 ($C_{Ak_0}^{jST}, k=1$)
CA02	ditto $k=2$
CA03	ditto $k=3$
CA04	ditto $k=4$
CA05	ditto $k=5$
FIT_ST	Actual fitness (F_t^j) of the technology standard at the time t_0^{ST}
FIT_BAT	ditto of the BAT at the time t_0^{ST}
ID_BAT	Identifier of best alternative technology
FST	Frequency (f^{ST})

SPSS	Model
VST	Speed (v^{jST})*
DST	Duration (d^{jST})
PST	Depth (p^{jST})
ID_CHT	Identifier of challenging technology
TRP	Replacement time (t_{rp})
SCS	Susceptibility to changes in supply (dco^{jST})*
SCD	Susceptibility to changes in demand (dcd^{jST})*
CED	Cumulative environmental damage without the intervention of the Agency (ced)
F_ICED	Frequency of irreversible damage without the Agency
CEDA	Cumulative environmental damage with the intervention of the Agency ($ceda$)
F_ICEDA	Frequency of irreversible damage with the Agency
AC_SU	Accumulated support ($\sum_t \Delta_t^j, \forall j$) at the end of simulation

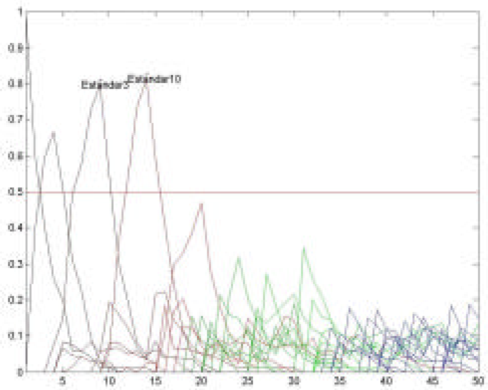
* Note: higher numbers indicate lower levels

Appendix 3. Data for the first standard recorded in each simulation, filtered out from the general results of the 150 simulations

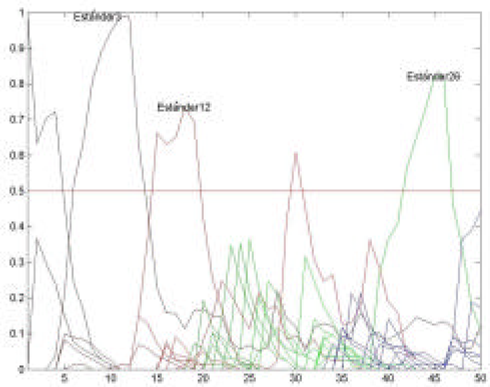
1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*
SIM	**ID_ST**	**TST**	**TFST**	**FIT_ST**	**FIT_BAT**	**ID_BAT**	**FST_FB1**	**FST**	**VST**	**DST**	**PST**	**ID_CHT**	**TRP**	**SCS**	**SCD**	**CED**	**F_ICED**	**CEDA**	**CED_CEDA**	**F_ICEDA**	**AC_SU**
3	2	2	11	0,722	0,674	3	0	3	1	9	0,847	9	12	-2,425	6,722	33,829	0	33,406	1	1	35,436
4	3	4	10	0,746	0,723	5	0	2	3	6	0,667	12	9	1,980	4,213	37,247	1	35,617	1	0	32,484
7	13	15	18	0,579	0,699	2	1	1	4	3	0,667	20	24	56,295	6,936	37,010	2	27,140	1	0	23,272
8	2	2	6	0,766	0,731	4	0	1	1	4	0,907	6	5	-5,472	2,659	38,460	2	30,784	1	0	25,557
9	4	7	10	0,670	0,751	5	1	1	4	3	0,733	5	10	-2,368	5,021	37,743	1	37,765	0	2	43,684
14	3	1	10	0,557	0,464	2	0	1	0	9	0,862	7	11	49,904	7,169	38,682	2	35,819	1	0	35,215
15	2	4	7	0,787	0,786	3	0	2	3	3	0,563	3	6	2,374	7,302	36,528	1	18,919	1	0	20,994
16	2	6	10	0,698	0,684	8	0	3	4	4	0,616	12	10	60,655	4,035	40,204	1	31,362	1	0	25,781
18	1	4	8	0,576	0,685	2	1	3	3	4	1,000	2	7	46,575	4,162	40,782	2	30,661	1	1	29,659
20	2	4	10	0,607	0,626	5	1	2	3	6	0,667	7	9	-3,865	2,202	41,211	2	48,123	0	1	47,674
22	4	5	12	0,717	0,616	5	0	1	3	7	0,925	13	13	69,454	2,959	39,304	1	39,093	1	2	43,622
25	3	9	12	0,635	0,721	7	1	2	7	3	0,638	10	12	-2,188	5,854	38,240	1	32,766	1	0	27,082
26	3	4	19	0,747	0,725	6	0	1	3	15	0,922	22	19	17,263	3,743	40,424	2	41,261	0	2	41,763
30	3	4	9	0,726	0,761	9	1	1	3	5	0,837	16	9	19,336	2,321	39,226	1	34,780	1	1	32,567
31	4	5	15	0,717	0,687	6	0	1	3	10	0,871	13	15	39,368	0,436	40,309	1	24,560	1	0	25,570
32	4	10	13	0,668	0,719	6	1	5	4	3	0,679	14	13	5,282	6,904	44,828	1	38,321	1	1	35,476
32	14	16	19	0,663	0,773	19	1	5	5	3	0,727	1	19	5,282	1,538	44,828	1	38,321	1	1	35,476
34	2	3	9	0,695	0,588	5	0	2	2	6	0,837	9	8	87,255	0,919	34,590	1	35,638	0	1	38,840
35	2	3	8	0,679	0,724	3	1	4	2	5	0,807	3	7	6,848	1,321	40,042	2	36,452	1	0	36,046
36	2	5	11	0,701	0,761	4	1	2	3	6	0,818	5	10	12,775	2,789	40,261	2	31,181	1	0	23,790
41	2	4	14	0,748	0,654	1	0	2	3	10	0,976	9	13	11,420	2,365	31,783	2	24,354	1	0	25,012
45	3	4	9	0,704	0,649	5	0	1	3	5	0,898	6	8	51,055	0,210	38,038	1	37,479	1	0	42,270
46	2	4	9	0,626	0,531	1	0	3	3	5	0,929	3	8	20,278	1,638	40,530	1	38,555	1	1	40,033
49	4	4	9	0,447	0,635	2	1	4	3	5	0,923	8	8	41,994	1,955	39,540	1	33,467	1	0	29,418
52	8	8	11	0,698	0,833	10	1	1	4	3	0,701	12	11	61,404	2,419	36,044	0	36,484	0	0	35,546
53	3	7	11	0,813	0,670	5	0	2	4	4	0,797	10	10	20,627	0,098	38,085	2	30,067	1	0	28,275
54	3	1	6	0,608	0,539	2	0	2	0	5	0,735	4	5	21,849	6,746	36,964	1	28,536	1	0	23,245
55	2	3	9	0,660	0,662	3	1	2	2	6	0,814	9	8	-19,459	2,747	37,020	0	33,188	1	0	32,249
58	9	8	12	0,672	0,691	11	1	1	4	4	0,737	12	12	26,455	0,806	37,226	2	36,403	1	1	35,919
60	2	5	16	0,786	0,754	3	0	1	3	11	0,905	13	17	5,424	1,533	35,341	1	30,345	1	0	28,980
62	4	7	12	0,622	0,547	3	0	1	5	5	0,659	8	12	0,819	4,425	39,429	2	47,526	0	1	47,674
65	4	3	6	0,628	0,677	2	1	2	2	3	0,617	6	7	6,033	3,715	30,669	0	33,426	0	0	27,494
66	2	4	7	0,846	0,786	3	0	3	3	3	0,986	4	6	13,720	0,602	33,503	1	32,400	1	1	33,068
68	3	15	22	0,651	0,682	16	1	1	11	7	0,847	21	21	12,689	4,994	37,679	2	33,150	1	0	25,969

SIM	ID_ST	TST	TFST	FIT_ST	FIT_BAT	ID_BAT	FST_FB1	FST	VST	DST	PST	ID_CHT	TRP	SCS	SCD	CED	F_ICED	CEDA	CED_CEDA	F_ICEDA	AC_SU
70	4	6	10	0,680	0,622	5	0	3	3	4	0,752	10	10	46,450	6,625	36,985	2	20,960	1	0	20,722
71	2	10	28	0,554	0,738	6	1	2	9	18	0,656	24	31	-23,571	2,387	41,201	1	35,088	1	1	33,136
72	2	4	11	0,657	0,695	4	1	2	3	7	0,928	6	10	40,860	2,030	38,938	2	34,848	1	1	32,102
74	2	4	13	0,751	0,641	4	0	2	3	9	0,945	7	13	8,857	5,524	33,946	1	34,427	0	0	33,062
75	3	4	11	0,819	0,764	6	0	2	3	7	0,917	13	10	130,657	3,408	36,892	1	27,291	1	0	23,025
76	3	3	7	0,566	0,522	1	0	1	2	4	0,574	6	7	-17,671	0,363	36,840	2	42,174	0	2	47,702
77	2	3	6	0,630	0,828	4	1	2	2	3	0,667	4	6	16,443	0,970	38,320	1	35,658	1	0	34,150
81	2	8	11	0,648	0,697	8	1	1	6	3	0,568	3	10	-8,824	8,004	42,270	1	37,106	1	1	37,074
85	1	4	8	0,623	0,537	2	0	2	3	4	0,745	4	7	5,982	2,645	46,149	1	25,454	1	0	23,231
87	2	4	15	0,655	0,489	1	0	2	2	11	0,883	8	15	10,751	3,546	41,896	2	37,013	1	1	40,176
88	5	7	10	0,657	0,682	3	1	1	6	3	0,853	8	10	4,455	5,038	34,947	0	29,650	1	0	28,623
90	2	2	25	0,753	0,735	1	0	2	1	23	0,647	1	25	-4,323	8,656	18,962	0	13,954	1	0	18,144
99	3	3	8	0,815	0,683	5	0	1	2	5	0,826	6	8	109,492	3,465	38,655	1	35,556	1	1	39,796
100	2	3	7	0,658	0,641	1	0	1	2	4	0,914	4	7	107,583	5,249	39,072	1	33,678	1	0	32,002
101	1	4	8	0,581	0,624	2	1	3	3	4	0,897	2	7	-0,567	1,866	33,853	1	35,509	0	0	33,056
102	2	4	11	0,736	0,745	3	1	1	3	7	0,928	8	12	84,478	0,966	37,641	1	36,122	1	1	35,220
105	4	8	12	0,734	0,741	9	1	1	4	4	0,699	12	12	31,504	3,319	34,555	0	22,429	1	0	21,606
106	1	4	7	0,680	0,752	2	1	2	3	3	0,833	2	6	2,380	2,418	49,164	1	49,103	1	1	47,674
109	9	10	13	0,580	0,622	4	1	1	4	3	0,707	11	13	46,684	2,310	36,787	1	33,037	1	0	24,031
114	11	10	13	0,638	0,735	10	1	1	4	3	0,575	16	19	-19,264	0,083	37,357	1	31,977	1	0	30,478
115	3	6	12	0,717	0,830	5	1	2	4	6	0,910	11	11	30,238	3,597	39,118	2	36,401	1	1	35,245
120	3	4	19	0,747	0,725	6	0	1	3	15	0,922	22	19	17,263	3,743	40,424	2	41,261	0	2	41,763
121	5	7	10	0,619	0,733	7	1	1	6	3	0,600	7	9	4,143	3,941	40,214	2	39,526	1	2	42,797
126	4	4	8	0,638	0,612	3	0	2	3	4	0,671	8	8	66,036	1,554	37,898	0	32,397	1	1	37,624
128	2	4	10	0,702	0,664	5	0	2	3	6	0,813	11	9	28,221	1,091	39,077	1	35,161	1	1	28,866
132	2	5	9	0,771	0,631	7	0	2	4	4	0,789	11	10	58,527	4,515	36,245	1	29,796	1	0	26,141
133	1	4	7	0,559	0,668	2	1	3	3	3	1,000	2	6	22,446	0,380	35,705	2	38,805	0	1	37,246
136	3	7	10	0,751	0,782	2	1	2	4	3	0,750	1	9	8,860	4,980	22,524	0	22,954	0	0	22,735
137	2	2	8	0,687	0,694	3	1	2	1	6	0,831	7	8	-7,965	2,964	41,250	2	31,725	1	0	33,407
140	2	5	10	0,676	0,733	5	1	1	4	5	0,679	4	10	69,611	8,182	36,446	2	27,215	1	0	25,174
141	2	7	11	0,756	0,669	3	0	2	6	4	0,753	3	11	35,131	1,998	32,478	1	31,667	1	0	27,800
142	3	5	8	0,756	0,743	7	0	3	4	3	0,651	6	7	3,273	0,394	31,298	0	29,268	1	0	24,248
144	1	4	8	0,590	0,921	5	1	1	3	4	0,844	2	26	-1,299	1,951	47,601	1	41,665	1	2	45,712
146	3	5	14	0,716	0,734	5	1	2	3	9	0,875	12	13	67,962	1,493	41,272	2	37,329	1	1	39,801
147	2	4	10	0,730	0,568	3	0	2	2	6	0,966	7	10	74,271	2,691	37,160	1	28,970	1	0	26,026
148	1	3	6	0,592	0,557	2	0	2	2	3	0,582	5	7	0,580	6,149	43,800	1	31,787	1	0	27,053
150	16	14	18	0,493	0,693	9	1	1	2	4	0,838	19	19	-18,174	9,669	36,520	2	26,440	1	0	27,795

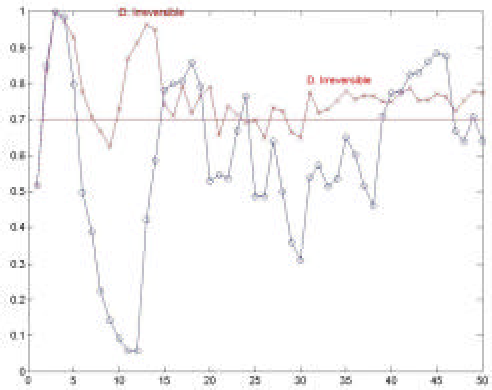
Appendix 4. Graphical results of a typical model simulation using the base scenario



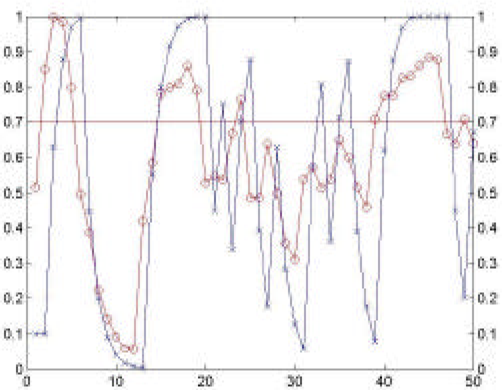
Evolution of technologies adoption (market share/ time) without the intervention of the Agency



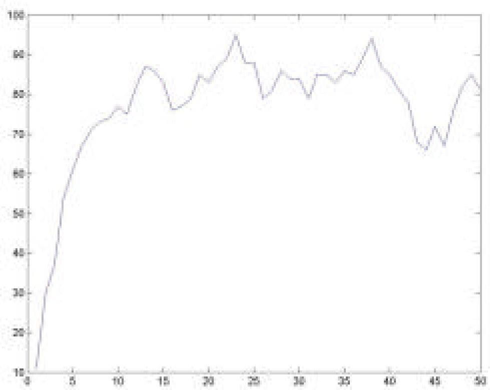
Evolution of technologies adoption (market share/ time) with the intervention of the Agency



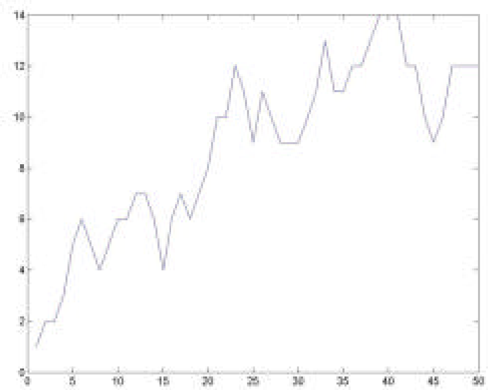
Evolution of the environmental damage (without the Agency: red; with the Agency: blue)



Evolution of the environmental damage with the Agency (red) and intensity of the support (blue)

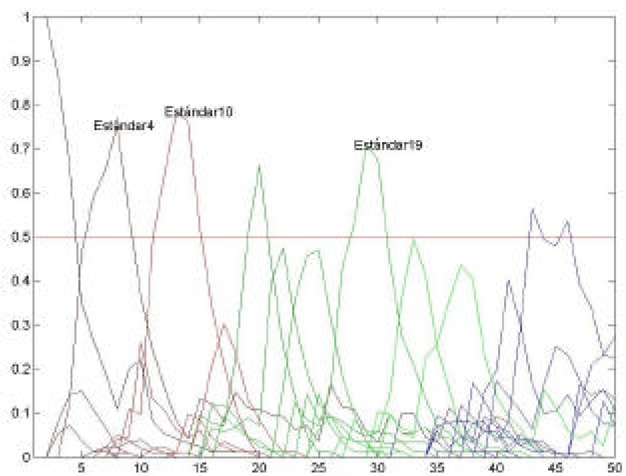


Evolution of the population of firms (number / time)

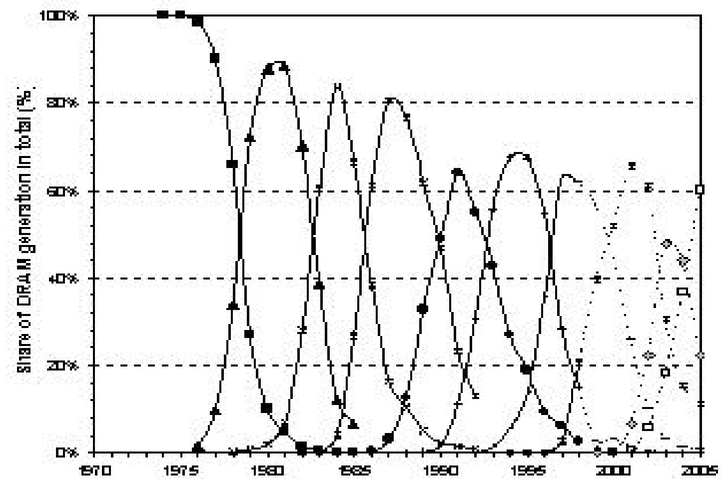


Evolution of the population of technologies (number / time)

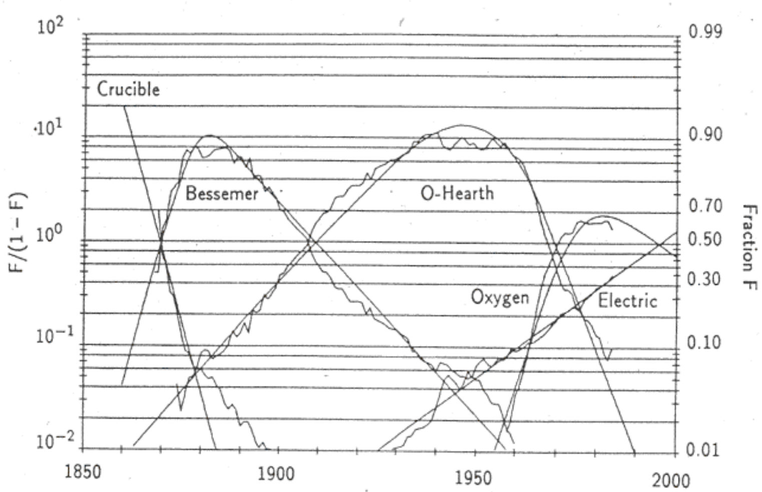
Appendix 5. Visual isomorphism between the results of the model and the patterns of the phenomenon observed in real industries



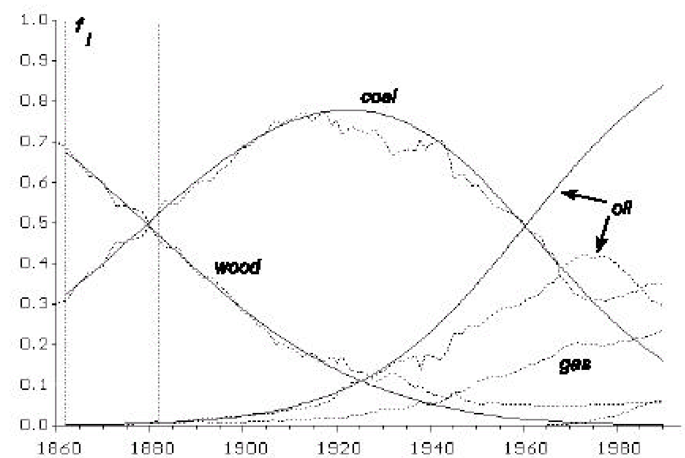
Typical results of the model (base scenario)



RAM technologies (Nadejda y Ausubel, 2002)



Steel manufacturing technologies (Grübler, 1991)



Power generation technologies (Kwasnicki, 1999)

References

Abrahamson, E. & Rosenkopf, L. 1997. Social network effects on the extent of innovation diffusion: A computer simulation, Organization Science, 8(3): 289-309

Allen, R.C. & Stone, J.H. 2001. Strategic behavior, real rigidities, and production coordination failures, Eastern Economic Journal, 27(3): 267-286

Alliance to Save Energy 1997. Energy Innovations: A Prosperous Path to a Clean Environment, ASE, Washington, D.C.

Almeida, A.T. de, Fonseca, P., Falkner, H. & Bertoldi, P. 2003. Market transformation of energy-efficient motor technologies in the EU, Energy Policy, 31: 563-575

Anderson, P. & Tushman, M.L. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change, Administrative Science Quarterly, 35: 604-633

Arentsen, M.J., Dinica, V. & Marquart, E. 1999. Innovating innovation policy: Rethinking green innovation policy in evolutionary perspective, Communication to the European Meeting on Applied Evolutionary Economics, 7-9 June, Grenoble, France

Arrow, K.J. 1962a. The economic implications of learning-by-doing, Review of Economic Studies, 29: 155-173

Arrow, K.J. 1962b. Economic welfare and the allocation of resources for invention, in: Nelson, R. (ed.), The Rate and Direction of Inventive Activity, Princeton University Press, Princeton: 609-625

Arthur, W.B. 1983. On competing technologies and historically small events: The dynamics of choice under increasing returns, Technology Innovation Project, Department of Economics, Stanford University (mimeo)

Arthur, W.B. 1988. Competing technologies: An overview, in: Dosi, G. *et al.* (eds.), Technical Change and Economic Theory, Pinter Publishers, London

Arthur, W.B. 1989. Competing technologies, increasing returns and lock-in by historical events, Economic Journal, 99: 116-131

Arthur, W.B. 1990. Positive feedbacks in the economy, Scientific American, February: 92-99

Arthur, W.B. 1991. Information constriction and information contagion, Working Paper, 91-05-026, Santa Fe Institute, Santa Fe

Arthur, W.B. 1994. Increasing Returns and Path Dependence in the Economy, The University of Michigan Press, Ann Arbor

Arthur, W.B., Ermoliev, Y. & Kaniovski, Y. 1987. Path-Dependent Processes and the Emergence of Macro-Structure, European Journal of Operational Research, 30 (1)

Ausubel, J.H. 1989. Regularities in technological development: An environmental view, in: Ausubel, J. and Sladovich, H. (eds.), Technology and Environment, National Academy Press,

Washington D.C.
Ausubel, J.H. & Langford, H.D. 1997. Technological Trajectories and the Human Environment, National Academy Press, Washington D.C.
Ausubel, J.H. & Sladowich, H.E. 1989. Technology and Environment, National Academy Press, Washington D.C.
Axelrod, R. 1997. Advancing the art of simulation in the social sciences, Complexity, 3(2): 16-22
Ayres, R.U. 1991. Evolutionary Economics and environmental imperatives, Structural Change and Economic Dynamics, 2: 255-273
Ball, L. & Romer, D. 1991. Sticky prices as coordination failure, American Economic Review, 81: 539-552
Barba-Romero, S. & Pomerol, J. C. 1997. Decisiones Multicriterio: Fundamentos Teóricos y Utilización Práctica, Servicio de Publicaciones de la Universidad de Alcalá
Becker, M. & Ashford, N. 1995. Exploiting opportunities for pollution prevention in EPA enforcement agreements, Environmental Science & Technology, 29: 220-226
Bergh, J.C.J.M. Van den and Gowdy, J.M. 2000. Evolutionary theories in environmental and resource economics: Approaches and applications, Environmental and Resource Economics, 17(1): 37-57
Bernow S., Dougherty W., Duckworth M. & Brower M. 1998. An integrated approach to climate policy in the US electric power sector, Energy Policy, 26(5): 375-393
Blackman, A. 1999. The economics of technology diffusion: Implications for climate policy in developing countries, Discussion Paper 99.42, Resources for the Future, Washington, D.C.
Blumstein, C., Goldstone, S. & Lutzenhiser, L. 2000. A theory-based approach to market transformation, Energy Policy, 28: 137-144
Bohn, H. & Gorton, G. 1993. Coordination failure, multiple equilibria and economic institutions, Economica, August: 257-280
Bryant, J. 1983. A simple rational-expectations Keynes-type model, The Quarterly Journal of Economics, August: 25-29
Cabral, L. 1987. On the adoption of innovations with ´network´ externalities, Center for Economic Policy Research, Technical Paper Number 97, Stanford University
Cantner, U. & Hanusch, H. 2001. Heterogeneity and evolutionary change: Empirical conception, findings and unresolved issues, in: Foster, J. and Metcalfe, J.S. (eds.), Frontiers of Evolutionary Economics, Edward Elgar, Cheltenham, UK, Northampton, MA, USA: 228-267
Carraro, C. & Galeotti, M. 1997. Economic growth, international competitiveness and environmental protection: R&D and innovation strategies with the WARM model", Energy

Economics, 19(1): 2-28

Carraro, C. & Leveque, F. (eds.). 1999. Voluntary Approaches in Environmental Policy, Fondazione Eni Enrico Mattei Series on Economics, Energy and Environment, vol. 14, Kluwer Academic, Dordrecht, Boston and London

Christensen, C.M. 1997. The Innovator´s Dilemma, HBS Press, Boston, MA

Conte, R., Hegeselman, R. & Terna, P. (eds.) 1997. Simulating Social Phenomena, in: Lecture Notes in Economics and Mathematical Systems, Springer, Berlin

Cooper, R. & John, A. 1988. Coordinating coordination failures in Keynesian models, The Quarterly Journal of Economics, Vol. CIII, Issue 3: 441-463

Cooper, R.W. 1999. Coordination Games: Complementarities and Macroeconomics, Cambridge University Press, Cambridge

Cowan, R. 1990. Nuclear power reactors: A study in technological lock-in, Journal of Economic History, 50: 541-567

Cowan, R. & Hulten, S. 1996. Escaping lock-in: The case of the electric vehicle, Technological Forecasting and Social Change, 53: 61-79

Dalle, J.M. 1995. Dynamiques d´adoption, coordination et diversité: la diffusion des standards technologiques, Revue économique, 46(4): 1081-1098

David, P.A. 1985. Clio and the economics of *QWERTY*, The American Economic Review, ´ 75(2): 332-337

David, P.A. 1989. Path dependence and predictability in dynamic systems with local network externalities: A paradigm for historical economics, High Technology Impact Program Working Paper, Center for Economic Policy Research, Standford University

David, P.A. 1997. Path Dependence and the Quest for Historical Economics: One More Chorus in the Ballad of QWERTY, Discussion Papers in the Economic and Social History, 20, University of Oxford

David, P.A. & Greenstein, S. 1990. The economics of compatibility standards: An introduction to recent research, Economics of Innovation and New Technology, 1: 3-41

Decanio, S.J. 1993. Barriers within firms to energy-efficient investments, Energy Policy, 21(9): 906-914

Delmas, M. & Terlaak, A. 2001a. A framework for analysing environmental voluntary agreements, California Management Review, Berkeley, 43(3): 44-63

Delmas, M. & Terlaak, A. 2001b. Voluntary Agreements for the Environment: Institutional constraints and potential for innovation, in: Deketelaere, K. and Eric, O. (eds.), Environmental Contracts: Comparative Approaches to Regulatory Innovation in the United States and Europe, Kluwer Law International, Boston, Dordrecht, London

Delmas, M. & Terlaak, A. 2001c. Institutional factors and Environmental Voluntary

Agreements: The cases of the United States, The Netherlands and France", Journal of Comparative Policy Analysis

Diamond, P. 1982. Aggregate demand management in search equilibrium, Journal of Political Economy, October: 881-894

Dosi, G. 1982. Technological paradigms and technological trajectories, Research Policy, 11: 147-162

Dosi, G., Freeman, C., Nelson, R., Silverberg, G. & Soete, L. (eds.) 1988. Technical Change and Economic Theory, Pinter, London

Drucker, P. 1993. Innovation and Entrepreneurship, HarperBusiness, New York

Economides, N. 1996. The economics of networks, International Journal of Industrial Organization, 14

EEA 1999. Environmental Agreements - Environmental Effectiveness, Environmental Environmental Issue Report nº 3, European Environment Agency, Copenhagen

EPA 1996. Partnerships in Preventing Pollution: A Catalogue of the Agency´s Partnerships Programs, Environmental Protection Agency, Washington D.C.

Epstein, J.M. & Axtell, R. 1996. Growing Artificial Societies: Social Science from the Bottom Up, MIT Press, Cambridge, MA

Farrell, J. & Saloner, G. 1986a. Installed base and compatibility: Innovation, product preannouncements, and predation, The American Economic Review, 76(5): 940-955

Farrell, J. & Saloner, G. 1986b. Standardization and Variety, Economic Letters, 20: 71-74

Faucheux, S. 1997. Technological change, ecological sustainability and industrial competitiveness, in: Dragun, A.K. and Jakobsson, K.M. (eds.), Sustainability and Global Environmental Policy, Edward Elgar, Cheltenham, UK. Lyme, US

Faucheux, S. & Froger, G. 1995. Decision-making under environmental uncertainty, Ecological Economics, 15: 29-42.

Feinberg, A. & Smith, J.H. 1989. Lessons from six applications of multi-criterion decision analysis to rank advanced technology alternatives, Proceedings of the International Conference on Multiple Criteria Decision Making: Applications in Industry and Service, Asian Institute of Technology, Bangkok: 661-675

Fisher, J.C. & Pry, R.H. 1971. A simple substitution model of technological change, Technological Forecasting and Social Change, 20: 199-213

Foray, D. & Grübler, A. 1990. Morphological analyses, diffusion and lock-out of technologies: Ferrous casting in France and FRG, Research Policy, 19: 535-550

Freeman, C. 1996. The greening of technology and models of innovation, Technological

Forecasting and Social Change, 53: 27-39

Gilbert, N. 1995. Computer simulation of social processes, Social Research Update, 6, University of Surrey

Gilbert, N. & Troitzsch, K.G. 1999. Simulation for the Social Scientist, Open University Press, London

Gomulka, S. 1990. The Theory of Technological Change and Economic Growth, Pinter Publishers, London

Goodstein, E. 1995. The economic roots of environmental decline: Property rights or path dependence, Journal of Economic Issues, 29(4): p. 1029

Gray, P.E. 1989. The paradox of technological development, in: Ausubel, J.H. and Sladowich, H.E. (eds.), Technology and Environment, National Academy Press, Washington D.C.

Grove, A. 1996. Only the Paranoid Survive, Doubleday, New York

Grübler, A. 1990. The Rise and Fall of Infrastructures, Springer, Heidelberg

Grübler, A. 1991. Diffusion: Long patterns and discontinuities, Technological Forecasting and Social Change, 39: 159-180

Hahn, Y-H & YU, P-I 1999. Towards a new technology policy: The integration of generation and diffusion, Technovation, 19: 177-186

Hannerman, R.A. & Patrick, S. 1997. On the uses of computer-assisted simulation modelling in the social sciences, Sociological Research Online, 2(2)

Hart, O. 1982. A model of imperfect competition with Keynesian features, Quarterly Journal of Economics, February: 109-138

Holland, J.H. 1998. Emergence: From Chaos to Order, Addison Wesley, MA

Ilgen, D.R. & Hulin, C.L. (eds.) 2000. Computational Modeling of Behavior Organizations: The Third Scientific Discipline, American Psychological Association, Washington D.C.

INTERLABORATORY WORKING GROUP 1997. Scenarios of US Carbon Reductions: Potencial Impacts of Energy Technologies by 2010 and Beyond, Lawrence Berkley National Laboratory, Berkley CA, an Oak Ridge National Laboratory, Oak Ridge, TN, LNLN-40533 and ORNL-444

Jaffe, A.B., Newell, R.G. & Stavins, R.N. 2000. Technological change and the environment, Discussion Paper 00-47, Resources for the Future, Washington D.C.

Janssen, M.A. & De Vries, B. 1998. The battle of perspectives: A multi-agent model with adaptive responses to climate change, Ecological Economics, 26: 43-65

Kallis, G. 2001. A co-evolutionary institutional approach to sustainable development: Theory and potential applications", Frontiers I Conference ESEE, Cambridge, UK, July 3-7

Katz, M.L. & Shapiro, C. 1985. Network externalities, competition and compatibility, The American Economic Review, 75(3): 424-440

Katz, M.L. & Shapiro, C. 1986. Technology adoption in the presence of network externalities, Journal of Political Economy, 94(4): 822-841

Kemp, R. 1996. The transition from hydrocarbons: The issues for policy, in: Facheux, S., Pearce, D. and Proops, J. (eds.), Models of Sustainable Development, Edward Elgar, Cheltenham, UK, Brookfield, US: 151-175

Kemp, R. 1997. Environmental Policy and Technical Change, Edward Elgar, Cheltenham, UK - Brookfield, US

Kemp, R. & Soete, L. 1992. The greening of technological progress: An evolutionary perspective, Futures, June: 437-455

Kleijnen, J.P.C. 1998. Validation of simulation, with and without real data, Department of Information Systems and Auditing (BIKA) / Center for Economic Research (CentER), Tilburg University

Klepper, S. & Simons, K.L. 1997. Technological extinctions of industrial firms: An inquiry into their nature and causes, Industrial and Corporate Change, 6(2): 379-460

Kline, D. 2001. Positive feedback, lock-in, and environmental policy, Policy Sciences, 34: 95-107

Koomey J.G., Martin N.C., Brown M., Price L.K. & Levine M.D. 1998. Costs of reducing carbon emissions: US building sector scenarios, Energy Policy, 26(5): 433

Krause, F. 1996. The cost of mitigating carbon emissions: A review of methods and findings from European studies, Energy Policy, 24 (10/11): 899-915

Kuper, G.H. & Van Soest, D.P. 1999. Asymmetric Adaptations to Energy Price Changes: An Analysis of Substitutability and Technological Progress in the Dutch Economy, Paper presented at PRET workshop, Maastricht, 18-19 March

Kwasnicki, W. 1999. Technological substitution processes: An evolutionary model, Institute of Industrial Engineering and Management, Wroclaw University of Technology

Latané, B. 1996. Dynamic social impact: Robust predictions from simple theory, in: Hegselmann, R., Mueller, U. and Troitzsch, K. (eds.), Modeling and Simulation in the Social Sciences from the Philosophy of Science Point of View, Kluwer, Dordrecht, The Netherlands

Laville, F. 1998. Modélisations de la rationalité limitée: De quels outils dispose-t-on?, Revue Économique, 49(2): 335-365

Levine, M.D. & Sonnenblick, R. 1994. On the assessment of utility demand-side management programs", Energy Policy, 22(10): 848-856

Limpese, I., Verspagen, B. & Beelen, E. 1992, Technology policy in eight European countries: A comparison, Report, MERIT, Maastricht

Linares, P. & Romero, C. 2002. Aggregation of preferences in an environmental economics context: A goal-programming approach, The International Journal of Management Science, 20: 89-95

Lipsey, R.G. & Carlaw, K. 1998. Technology policies in neo-classical and structuralist-evolutionary models, STI Review, 22: 31-73

Llerena, P. & Matt, M. 1999. Inter-organizational collaborations: The theories and their policy implications, in: A. Gambardella, F. Malerba (eds.), The Organization of Economic Innovation in Europe, Cambridge University Press: 179-201

Loch, C.H. & Huberman, B.A. 1999. A punctuated-equilibrium model of technology diffusion, Management Science, 45(2): 160-177

Lovins, A.L. 1991. Least cost climate stabilization, Annual Review of Energy and Environment, 16: 433-431

Manning, A. 1990. Imperfect competition, multiple equilibria and unemployment policy, Economic Journal, Conference: 151-162

Marchetti, C. & Nakicenovic, N. 1979. The dynamics of energy system and logistic substitution model, RR-79-13, IIASA, Laxenbug, Austria

Marney, J.P. & Tarbert, F.E. 2000. Why do simulation? Towards a working epistemology for practitioners of the dark arts, Journal of Artificial Societies and Social Simulation, 3(4)

Mata, J. & Portugal, P. 1994. Life duration of new firms, The Journal of Industrial Economics, XLII(3): 227-243

Mayer, W.J. & Chappell, W.F. 1992. Determinants of Entry and Exit: An Application of the Compounded Bivariate Poisson Distribution to U.S. Industries, 1972-1977, Southern Economic Journal, 58(3): 770-778

Menanteau, P. 2002. Can negotiated agreements replace efficiency standards as an instrument for transforming the electrical appliance market, Cahier de Recherche N° 28 BIS, Institut d´Economie et de Politique de l´Energie

Metcalfe, J.S. 1994. Evolutionary economics and technology policy, The Economic Journal, 104: 931-944

Metcalfe, J.S. 1995. Technology systems and technology policy in an evolutionary framework, Cambridge Journal of Economics, 19(1): 25-46

Moreau, F. 1997. Compétition technologique, development durable et théorie de l´auto-organisation", Working Paper du Laboratoire d´Econométrie, nº97-3, Conservatoire National des Arts et Métiers, Paris

Moreau, F. 1999. The role of the State in an Evolutionary Microeconomics, Working Paper du Laboratoire d´Econométrie, nº99-1, Conservatoire National des Arts et Métiers, Paris

Mowery, D. & Rosenberg, N. 1989. New developments in US technology policy: Implications for competitiveness and international trade policy, California Management Review, 32: 107-124

Mulder, P. & Bergh, J.C.J.M. Van den 2001. Evolutionary economic theories of sustainable development, Growth and Change, 32: 110-134

Mulder, P., Reschke, C.H. & Kemp, R. 1999. Evolutionary Theorising on Technological Change and Sustainable Development, European Meeting on Applied Evolutionary Economics, 7-9 June, Grenoble, France

Nadejda, M.V. & Ausubel, J.H. 2002. DRAM as model organisms for study of technological evolution, Technological Forecasting and Social Change, 69(3): 243-262

Nelson, R.R. 1994a. The coevolution of technologies and institutions, in: England, R.W. (ed), Evolutionary Concepts in Contemporary Economics, University of Michigan, Ann Arbor

Nelson, R.R. 1994b. Economic growth via the coevolution of technology and institutions, in: Leydesdorff, L. and Besselaar, P. (eds.), Evolutionary Economics and Chaos Theory, Pinter, London

Nelson, R.R. 2000. Selection criteria and selection processes in cultural evolution theories, in: Ziman, J. (ed.) Technological Innovation as an Evolutionary Process, Cambridge University Press: 66-74

Nelson, R.R. & Winter, S.G. 1974. Neo-classical vs. Evolutionary theories of economic growth, Economic Journal, 84: 886-905

Nelson, R.R. & Winter, S.G. 1977. In search of useful theory of innovation, Research Policy, 6: 36-37

Nelson, R.R. & Winter, S.G. 1982. An Evolutionary Theory of Economic Change, Harvard University Press, Cambridge, MA

OIG 2000. Environmental Technology Focus 2005, OneStone Intelligence GmbH, Germany

Peterka, V. & Fleck, F. 1978. The dynamics of energy systems and logistic substitution model, Volume 2: Theoretical part, Administrative Report AR-78-1C, International Institute for Applied Systems Analysis, Laxenburg, Austria

Peters, I., Ackerman, F. & Bernow, S. 1999. Economic theory and climate change policy, Energy Policy, 27(9): 501-504

Pomerol, J.C. & Barba-Romero, S. 2000. Multicriterion Decision in Management: Principles and Practice, Kluwer Academic Publishers, Boston/Dordrecht/London

Rip, A. 1992. A quasi-evolutionary model of technological development and a cognitive approach to technology policy", Revista di Studi, Epistemologici e Sociali sulla Scienza e la Tecnologia, 2: 60-103

Rogers, E.M. 1995. Diffusion of Innovations (4th Ed.), The Free Press, NY

Rosenberg, N. & Frischtak, C. 1983. Long waves and economic growth: A critical appraisal, The American Economic Review – Paper and Proceedings (May)

Ruttan, V.W. 1997. Induced innovation, Evolutionary Theory and path dependence: Sources of technical change, Economic Journal, 107: 1520-1529

SALA-I-MARTÍN, X. 1994. Apuntes de Crecimiento Económico, Antoni Bosch, Barcelona

Saviotti, P.P. 1996. Technological Evolution, Variety and the Economy, Edward Elgar, Cheltenham, UK

Saviotti, P.P. 2001. Considerations about a production system with qualitative change, in: Foster, J. and Metcalfe, J.S. (eds.), Frontiers of Evolutionary Economics, Edward Elgar, Cheltenham, UK, Northampton, MA, USA

Schilling, M.A. 1998. Technology lockout: An integrative model of the economic and strategic factors driving technology success and failure, Academy of Management Review, 23(2): 267-284

Schilling, M.A. 2002. Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities, Academy of Management Review, 45(2): 387-398

Schneider, S.H. & Goulder, L.H. 1997. Achieving low-cost emissions targets, Nature, 389, 13-14

Schot, J., Hoogma, R. & Elzen, B. 1994. Strategies for shifting technological systems: The case of the automobile system, Futures, 26(10): 1060-1077

Schumpeter, J. 1942. Capitalism, Socialism and Democracy, Harper, New York

Sen, A.K. 1960. Choice of Techniques, Basil Blackwell, Oxford

Sheshinski, E. 1967. Optimal accumulation with learning by doing, in: Shell, K. (ed.), Essays on the Theory of Optimal Economic Growth, MIT Press, Cambridge MA: 31-52

Silverberg, G. & Lehnert, D. 1993. Long waves and ´evolutionary chaos´ in a simple Schumpeterian model of embodied technical change", Structural Change and Economic Dynamics, 4: 9-37

Simon, H.A. 1964. "Rationality", in: Gould, J. and Kolb, W.L. (eds.), A Dictionary of the Social Sciences, The Free Press, Glencoe, IL

Simon, H.A. 1972. Theories of bounded rationality, in: Radner, C.B. and Radner, R. (eds.), Decision and Organization, North Holland Publishing Company, Amsterdam

Sinsheimer, P. 2002. Integrating pollution prevention technology into public policy: The case of professional wet cleaning", Environmental Science & Technology, 36(8): 1649-1655

Smith, K. 2000. Innovation as a systemic phenomenon: Rethinking the role of policy, Enterprise & Innovation Management Studies, 1(1): 73-102

Stoneman, P. 1983. The Economic Analysis of Technological Change, Oxford University Press, New York

Stoneman, P. & Diederen, P. 1994. Technology diffusion and public policy, The Economic Journal, 104: 918-930

Suárez, F.F. & Utterback, J.M. 1995. Dominant Designs and the Survival of Firms, Strategic Management Journal, Vol. 16: 415-430

Tegarden, L.F., Echols, A.E., & Hatfield, D.E. 2000. The value of patients and start-up firms: A re-examination of entry timing for emerging markets, Entrepreneurship Theory and Practice, 24(4): 41-58

UNEP 2000. Anticipating the environmental effects of technology: A manual for decision-makers, planners and other technology stakeholders, United Nations Environment Programme, International Environmental Technology Centre

Union of Concerned Scientists and Tellus Institute 1998 A Small Price to Pay: US Actions to Curb Global Warming Is Feasible and Affordable, UCS Publications, Cambridge, MA

United Nations 1992. Rio Declaration on Environment and Development, United Nations Conference on Environment and Development, Rio de Janerio, Brazil, 3-14 June

United Nations 1997. Kyoto Protocol, United Nations Framework Convention on Climate Change, Kyoto, Japan, 1-10 December

Weber, C., Gebhardt, B. & Fahl, U. 2002. Market transformation for energy efficient technologies: Success factors and empirical evidence for gas condensing boilers, *Energy*, 27: 287-315

Weber, M., Hoogma, R., Lane, B. & Schot, J. 1999. Experimenting with sustainable transport innovations: A workbook for strategic niche management, IPTS Report, ISBN 9036512751

Weiss, G. (ed.) 1999. Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence, MIT Press, Cambridge, MA

Weitzman, M.L. 1982. Increasing returns and the foundations of Unemployment Theory, Economic Journal, December: 782-804

Wigley, T.M.L., Richels, R. & Edmonds, J.A. 1996. Economic and environmental choices in the stabilization of atmospheric CO_2 concentrations, Nature, 379: 240-243

Windrum, P. & Birchenhall, C. 1998. Is product life cycle theory a special case? Dominant designs and the emergence of market niches through coevolutionary-learning", Structural

Change and Economic Dynamics, 9: 109-134

Windrum, P. & Birchenhall, C. 2000. Modelling technological successions in E-Commerce, MERIT/Infonomics, University of Maastricht

Witt, U. 1997. Lock-in´ vs. ´critical masses´: Industrial change under network externalities, International Journal of Industrial Organization, 15: 757-773

Wooldridge, S. & Jennings, N.R. 1995. Intelligent agents: Theory and practice, Knowledge Engineering Review, 10(2): 115-152

NOTAS

NOTAS

NOTAS