Technological Diffusion and Preference Learning in the World of *Homo sustinens*: The Challenges for Politics

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Abstract

This article relates agents' learning of a preference for a technology, competition of technologies, and their relative diffusion among potential adopters. Competitive interactions between two technologies are captured by an extended Lotka-Volterra model. To also incorporate preference learning on the part of potential adopters of these technologies, we combine it with a model of cultural learning based on role model, conformist, and hedonistic learning. Our theoretical analysis is illustrated by a concrete example: the competition between electric mobility and conventional forms of individual mobility. The model enables an evaluation of specific policy instruments as to the promotion of sustainable technology.

Keywords: Consumer Behavior – Cultural Evolution – Learning – Sustainability – Diffusion

JEL Classifications: D11, D83, Q01, C61

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1. Introduction

This article relates individual and social learning of preferences for a technology, competition of technologies, and their relative diffusion in a population of potential adopters. To capture the interplay of two technologies we propose a dynamic competition theory using an extended Lotka-Volterra model. In addition, to incorporate preference learning on the part of potential adopters of these technologies, we combine it with a model of cultural learning based on role model, conformist, and hedonistic learning. By doing so, we offer insights concerning the desirable mix of innovation policies intended to stimulate the diffusion of sustainable technology. The model enables an evaluation of specific policy instruments as to their effectiveness and efficiency in promoting environmental innovation. We argue that a combination of formal methods, in our case models from population ecology and cultural evolution theory, is more suited to address aspects of complex, innovative systems (also Norgaard, 1989). Moreover, we offer a model of adopter learning and technological diffusion for environmental policy theory that is based on behavioral assumptions that deviate from the economic standard model, while being rooted in behavioral reality (see also Røpke, 1999; Janssen and Jager, 2002; Jackson, 2002).

Key attributes of humans are individual and social learning (e.g., Leibenstein, 1950; Bandura, 1977; Witt, 2001; Richerson and Boyd, 2005) and these should be at the core of a behaviorally-grounded socio-ecological research agenda (see Luks and Siebenhüner, 2007; Pahl-Wostl et al., 2008; Garmendia and Stagl, 2010). We show how individual and social preference learning processes and their coevolution with technological features potentially lead to the dissemination of green preferences and respective technologies. The acquisition of preferences is endogenized in order to identify crucial determinants of the diffusion of environmentally-friendly technologies. The often conflicting interplay of cost motives with (socially acquired) “green preferences” takes center stage in this context. Individual preferences for technologies, it is shown, are relevant for a change toward sustainability. Understanding these dynamics is an important prerequisite for removing hindrances of a widespread adoption of sustainable technology (see Brennan, 2006). In a next step, we combine these preference learning dynamics with an extended Lotka-Volterra competition model – originally stemming from ecology – that is well-suited to capture competition between technologies also in economic contexts (see Richerson and Boyd, 1998). It accounts for interactions between and differential diffusion of technologies in more informative ways as compared to the economic standard model on competition and diffusion (see, as starting points, Rogers, 1983; Geroski, 2000). Policy recommendations are directly flowing from this combined model.

The broad qualitative results of our formal analysis have a number of potential applications to research problems in the field of ecological economics. Siebenhüner (2000), for instance, suggested *Homo sustinens* as a new – behavioral – conception of humans for the science of sustainability. Our model of cultural learning accounts for some of the social, behavioral, and evolutionary facets of such an agent. For example, the behavior of peers and observable preferences of reference persons or organizations are crucial triggers to purchase a green technology (e.g., Welsch and Kühling, 2009; Woersdorfer and Kaus, 2011). Role models, such as opinion leaders, agents of collective action, or the media contribute to the dissemination of information on – and preferences for – technologies, an observation accounted for by our formal model below. We also show how the interplay of cost differences, the potential existence of niche markets, the timing of policy intervention, and a technology's supporting infrastructure affect the relative diffusion rates of competing technologies. Our approach, therefore, increases the breadth of the methodological base of ecological economics by incorporating insights from anthropology on cultural learning and from ecology on competition in an environment endowed with scarce resources.

The article is organized as follows. The next Section lays out the model of individual and social preference learning and relates this to the competitive process between two technologies. Our theoretical analysis is illustrated by a concrete example: the competition between electric mobility and conventional forms of individual mobility. Section 3 presents several diffusion scenarios emanating from the model, discusses them, and derives political implications and predictions as to green technology's diffusion prospects. Section 4 concludes.

2. A model of individual and social learning of preferences and two competing technologies

The first two parts of our model capture the individual and social learning processes underlying the acquisition of preferences toward one out of two competing technologies, A and B. We assume agents to develop these preferences through two channels: via direct hedonistic experiences made individually and via cultural transmission processes, i.e., social learning. To motivate our theoretical analysis, we will discuss its implications with the help of a concrete example: the competition between electric mobility and conventional forms of individual mobility. Let technology A represent "electric mobility" and a the preference for this kind of mobility service. B denotes "conventional mobility" and b the preference for this technological variant. In this context, the agents' preferences represent a general positive attitude toward the respective technology and a willingness to adopt it if other factors such as cost differences or network externalities do not prevent agents from doing so. Hence, as will be shown below, we observe situations in which a share of consumers develops a preference for a certain technology without actually revealing it by also adopting the corresponding choice option. This phenomenon reflects conflicting motives on the part of adopters and adds behavioral realism to the model.

The state of the population of N users is determined by the frequency of agents that prefer technology A, i.e., those holding preference a, labeled p. Accordingly, the frequency of potential B adopters, endowed with preference b, is given by $1 - p$. Below, we define recursion equations in discrete time that allow us to predict the frequency of p in the next stage of the individual and social preference learning processes, p' and p'' respectively, given its frequency in the stage before. The general structure of these models of cultural evolution is

$$p' = p + \ cultural\ evolutionary\ forces\ (biases).$$

Specifically, we will focus on three cultural evolutionary forces that bias preference learning: a hedonistic, a role model, and a conformity bias. All can be traced back to evolved cognitive dispositions of human agents and are supported by evidence from disciplines such as social psychology, anthropology, cognitive sciences, among others. Finally, the third part of our model presents an extended Lotka-Volterra competition model that captures competition between technologies A and B and their relative diffusion in a population of adopters by integrating the preference acquisition dynamics described before.

2.1 A hedonistic bias in individual learning

We argue that technology B, representing “conventional mobility”, is hedonistically more rewarding than technology A, denoting “electric mobility”. The number of A- and B-users is given by N_A and N_B respectively. Technology B is more harmful to the environment but has more attractive characteristics otherwise. B’s hedonistic superiority emanates from its being the established technology in the market ($N_B \gg N_A$ in the beginning). This position entails a more convenient utilization because of an existing supporting infrastructure, prior experiences and learning with this technology, a perceived lower risk of usage, or sensory pleasures due to perfected performance. In this case, a *direct learning bias* favoring the “hedonistic” variant results from this superiority (see Boyd and Richerson, 1980; Richerson and Boyd, 2005). Suppose that users encounter and experiment with the alternative technologies and then, based on their individual experience, develop a preference, a or b, for one of these technologies (also Ruprecht, 2005; Buenstorf and Cordes, 2008). Such a process may also be based on an individual’s imagined or anticipated hedonistic experiences. This biased individual learning implies that agents who have acquired a preference for the green technology beforehand, for example, via social learning (see below), might switch back to conventional mobility on account of its hedonistic benefits.

To formally capture the hedonistic superiority of technology B in individual learning, we assume that each preference a holder has a certain chance of learning to favor the hedonistically more attractive technology B, measured by μ_{ab}. Moreover, we assume the hedonistic difference and thus the switching probability μ_{ab} to depend on the number of adopters of technology A, N_A, relative to the total population of adopters, N, that includes users of B ($N = N_A + N_B$). In the initial setting, N_A, is low relative to N. However, the higher the number of technology A-users in proportion to N, the lower is its hedonistic disadvantage as compared to B. Preference acquisition, therefore, also depends on how widespread a technology is: for instance, the more adopters use “electric mobility”, the better is the infrastructure supporting this technological choice, the more mature are its products and services, the lower is the hedonistic distance to the “conventional mobility” option, and the lower is the number of agents switching to preference b. The individual learning bias function is thus defined as

$$\mu_{ab}(N, N_A) = \lambda\left(1 - \frac{N_A^2}{N^2}\right). \tag{1}$$

Here, λ measures the strength of hedonistic learning. Figure 1 shows the shape of this function for a representative parameter constellation. According to this nonlinear expression, the hedonic disadvantage of technology A is high when the number of A-users is low. However, if technology A reaches a certain – potentially critical, as shown below – number of adopters, its hedonic disadvantage as compared to technology B decreases and may vanish in the limit.

The evolution of the general willingness to adopt a certain technology in a population of potential users due to hedonistic learning is reflected by changes in the relative frequencies of the preferences concerning alternative technologies, a and b, over time. These are derived from a first partial recursion equation in discrete time that determines p in the next time step, p', given the value of p in this period and given that a fraction $\mu_{ab}(N, N_A)$ of technology A adherents switches its preference to technology B, and so are subtracted each learning step. Hence, the partial recursion for the individual, hedonistically biased learning phase is

$$p' = p - p\mu_{ab}(N, N_A). \tag{2}$$

2.2 Biases taking effect in social learning: a role model and a conformity bias

Potential adopters of different technologies are normally not capable of sensorily experiencing the environmental impact of their choice – in contrast to the directly rewarding hedonistic experiences in the case of, for example, driving a perfected conventional car (see Buenstorf and Cordes, 2008). Therefore, the diffusion of preferences for environmentally benign technology choices, such as electric cars, is mainly subject to consciously controlled learning of relevant information, which in turn is strongly affected by social learning (e.g., Luks and Siebenhüner, 2007; Welsch and Kühling, 2009). Reflecting humans' evolved psychology, social learning is biased; adopters tend to socially acquire some cultural traits – in our case: different preferences for technologies that provide mobility services – rather than others. To understand how cognition directs social learning, we take account of two further biases, a model-based bias and a conformity bias.

Evidence from social psychology and anthropology suggests that human agents are prone to adopt cultural traits that are shown by role models in their social environment (e.g., Bandura, 1977; Harrington Jr., 1999; Henrich and Gil-White, 2001; Labov, 2001). A cognitive disposition to imitate successful or prestigious agents takes effect in cultural transmission, i.e., there is a *model-based bias* in social learning. To allow the relevance of different models to differ, for example, for individuals in different social roles in an agent's cultural environment, activist groups, science, or the media, we assign different weights to them. The influence of the ith model in social learning depends on her basic weight α_i ($\sum_i \alpha_i = 1$), which varies with an individual's or medium's social role, charisma, or prestige. Moreover, ith influence also depends on the set of models i belongs to. Below, we specify the probability that a particular set of role models makes a potential user to develop a preference for technology A or B.

Another social learning bias important to understand an individual's learning of preferences is the *conformity bias*: agents are more likely to pick the behavioral variant that is modeled by the majority of persons in their social environment. They discriminate against behaviors that are rare in the group. Again, anthropological and psychological evidence indicates the existence of such a heuristic in social learning (e.g., Aronson et al., 2002; Kameda and Diasuke, 2002; Cialdini and Goldstein, 2004; Henrich, 2004). A role model's influence in cultural transmission, therefore, also depends on the commonness of her exhibited preference in an individual's set of models. We look at a set of three models, the smallest set in which conformity bias is feasible (Boyd and Richerson, 1985, ch. 7). The frequency-dependent component of the models' impact is expressed by a conformity bias parameter η. We assume $0 \leq \eta \leq 1$, which implies that cultural transmission creates a force increasing the weight of the more common preference in the set of models. If $\eta = 0$, no conformity bias is present, while if $\eta = 1$, its influence is maximized.

Moreover, we assume that one of the cultural role models, M1, always shows an adoption preference for technology A, i.e., this user or medium is exclusively exhibiting the environmentally benign technological preference, a.[1] One rationale for this is the existence of media, politicians, or environmental interest groups that are willing to become "agents of collective action" to promote the diffusion of green technology (e.g., Witt, 1992). Investigating into the effects of such dedicated cultural role models introduces an important aspect of social learning, especially when it comes to explain the influence of the media. Furthermore, this setting also enables us to focus on the potentially conflicting effects of (hedonic) individual and social learning in preference acquisition. The weight of the sustainable role model, M1, in cultural transmission is allowed to vary in the following and may reach zero in the limit. Moreover, the other role models, M2 and M3, may show either preference of technological choice and may also have varying weights in cultural transmission. With these assumptions, the cultural transmission table (see Boyd and Richerson, 1985, p. 209) showing the probability of agents adopting a preference for technology A or B given a particular set of cultural role models (M1, M2, M3) with different weights yields:[2]

Table 1 The probability of users acquiring a preference for technology A or B, denoted a and b, given a particular set of models (M1, M2, M3) that have different intrinsic weights (α_1, α_2, α_3) and frequency-dependent cultural transmission (bias parameter η).

[1] M1 might be a "live model" or act through "symbolic modeling", for example, via publications on sustainability issues (e.g., Bandura, 1977).

[2] We are grateful to Jeroen van den Bergh for making us aware of this straightforward formal description of role models' influence in cultural transmission.

Preference of			Probability That Agent Acquires Preference	
M1	M2	M3	a	b
a	a	a	1	0
a	a	b	$(\alpha_1+\alpha_2)+\eta(1-\alpha_1-\alpha_2)$	$\alpha_3(1-\eta)$
a	b	a	$(\alpha_1+\alpha_3)+\eta(1-\alpha_1-\alpha_3)$	$\alpha_2(1-\eta)$
a	b	b	$\alpha_1(1-\eta)$	$(\alpha_2+\alpha_3)+\eta(1-\alpha_2-\alpha_3)$

Then, from this table, the frequency of a after transmission, p'', given that it was p' before transmission, is

$$p'' = p'^2 + p'(1-p')\{(\alpha_1+\alpha_2)+\eta(1-\alpha_1-\alpha_2)+(\alpha_1+\alpha_3)+\eta(1-\alpha_1-\alpha_3)\}$$
$$+ (1-p')^2\{\alpha_1(1-\eta)\}$$

$$= p' - (p'-1)\big(\alpha_1+\eta(p'-\alpha_1)\big), \tag{3}$$

which constitutes our second partial recursion for the social learning phase. This term computes the frequency of each set of cultural models, multiplies this by the probability that a particular set of models results in an individual user adopting preference a, and then sums over all possible sets of cultural models. M1 shows technological a with probability 1. The conformity parameter η always favors the technological preference that is more common within the set of models.

The complete recursion for p, obtained by substituting the partial recursion for the individual learning phase (2) into (3) is expressed as

$$p'' = p\big(1-\mu_{ab}(\bullet)\big) - \Big(\big(p\big(1-\mu_{ab}(\bullet)\big)\big) - 1\Big)\Bigg(\alpha_1 + \eta\Big(\big(p\big(1-\mu_{ab}(\bullet)\big)\big) - \alpha_1\Big)\Bigg)$$

$$= p\big(1-\mu_{ab}(\bullet)\big) - \big(1 + p(\mu_{ab}(\bullet) - 1)\big)\Big(\alpha_1(\eta - 1) + \eta p\big(1-\mu_{ab}(\bullet)\big)\Big). \tag{4}$$

This recursion models the change of the frequency of the technological preference a, measured by p, in the population of users over one individual and one social learning step. By setting the parameters of this system, we analyze its long run behavior by conceptually iterating Equation (4) recursively for many learning steps. Moreover, we can calculate the equilibrium frequency of p implied by the set of coupled recursions in (4) if we assume $\mu_{ab}(\bullet)$ to be constant. At equilibrium the population does not change so $p'' - p = 0$. After subtracting p from both sides of (4), the equilibrium frequency of preference a denoted by $\hat{p}$ is given by:[3]

$$\hat{p} = \frac{\eta - \mu_{ab}^{const.}(1+\eta) + \alpha_1\Big(\mu_{ab}^{const.} - 1 + \eta\big(1 - \mu_{ab}^{const.}\big)\Big) + \sqrt{-4\alpha_1\big(\mu_{ab}^{const.} - 1\big)^2(\eta^2 - \eta) + \Big(\alpha_1 + \mu_{ab}^{const.}(1-\alpha_1) + \eta(1+\alpha_1)\big(\mu_{ab}^{const.} - 1\big)\Big)^2}}{2\eta\big(\mu_{ab}^{const.} - 1\big)^2}. \tag{5}$$

2.3 The competitive process between two technologies

In a third step, we use a *Lotka-Volterra competition model* to capture competition between two technologies, A and B, and modify this population ecology theory by integrating the preference learning dynamics described above. As shown, individual and social learning processes endow agents with different technological preferences interpreted as a general

[3] There is a second solution for $\hat{p}$ that yields negative values and is therefore ignored in this context. The equilibria denoted by $\hat{p}$ and given by equation (5) are stable.

willingness to adopt a certain technology if, for example, cost conditions do not hinder agents to follow this preference. We assume a dynamic system that has two populations of adopters, one opting for technology A, the other choosing technology B. The corresponding Lotka-Volterra model we examine takes the form

$$N_A' = N_A + \delta N_A \left(1 - \frac{N_A}{Kp} - \frac{\beta_{AB} N_B}{Kp}\right) \quad (6)$$

and

$$N_B' = N_B + \delta N_B \left(1 - \frac{N_B}{K(1-p)} - \frac{\beta_{BA} N_A}{K(1-p)}\right). \quad (7)$$

We let N_A in (6) be the number of adopters of technology A and N_B in (7) the number of users of technology B. $\mathrm{N_A'}$ and $\mathrm{N_B'}$ denote the respective numbers of adopters in the next time step. The growth rates of the numbers of a technology's users are determined by the expressions in the brackets on the right hand sides of (6) and (7). These include K as a measure of total market capacity, i.e., the total number of potential adopters for which the two technologies compete.[4] Accordingly, the term Kp in (6) represents that share of total market potential that can be exploited by technology A. The size of this submarket, labeled K_A, depends on the frequency of agents with an a preference, as measured by p, in the total population of potential adopters times the total number of potential adopters, K. The same logic applies for the term $K(1-p)$ in (7) that denotes technology B's market capacity, K_B. Moreover, the further the number of a technology's adopters, N_A or N_B, approaches market saturation, K_A or K_B, the lower is its growth rate. Hence, the growth rate in the number of adopters of a technology depends on how much of its submarket capacity has already been exhausted; the greater the unexhausted submarket

[4] While $N = N_A + N_B$, K represents total market capacity that may be exploited by a growing N.

capacity, the higher the rate of growth in the number of adopters of a technology. Consequently, the individual and social preference learning dynamics described above have a direct bearing on the respective technology's market potential and its corresponding growth rate.

Finally, β_{AB} and β_{BA} capture inter-technological competition effects. Two technologies compete if the addition of one adopter of either decreases the rate of growth of the other. There are, therefore, interdependencies or externalities in adopters' choices (see David, 1985; Arthur, 1989). To capture this effect, we define β_{AB} and β_{BA} as positive variables that represent inter-technological competition based upon differences in technologies' utilization or purchase cost: we interpret β_{AB} as the competitive impact of a single B-adopter's technological choice on an A-adopter's decision situation due to changes in relative costs. The term $\beta_{AB}N_B$ then denotes the total competitive effect of technology B-adopters on technology A's market capacity and corresponding growth rate. β_{BA} and $\beta_{BA}N_A$ are interpreted analogously. We define these cost-related competition coefficients as (see, for a similar application in evolutionary theory, Rice, 2004, p. 286):

$$\beta_{AB} = e^{-(-c_d+1)^2} - e^{-1} \tag{8}$$

and

$$\beta_{BA} = e^{-(c_d+1)^2} - e^{-1}. \tag{9}$$

These expressions contain a difference in purchase or utilization cost of the two competing technologies, c_d. A technology's competitive impact, therefore, depends on the costs connected to its acquisition or utilization. This cost difference is defined as $c_d = \frac{N_B - N_A}{N_A + N_B}$ and ranges from -1 to 1. If $c_d < 0$, then technology A has a competitive cost advantage that is due to its higher number of adopters, N_A ($\beta_{BA} > 0$; $\beta_{AB} = 0$). For instance, producers of this technology may enjoy a competitive advantage that rests on economies of scale, which tend to lower unit costs (Pratten, 1971; Jovanovic and MacDonald, 1994).[5] Each individual's adoption choice would then confer a relative advantage to the chosen technology emanating from size-related economies of scale accruing to its producers.[6] If $c_d > 0$, then B enjoys a relative cost advantage in the competition with the other technological choice because more agents opted for this alternative ($\beta_{AB} > 0$; $\beta_{BA} = 0$).

Figure 2 shows the shapes of the competition functions in Equations (8) and (9). The less costly adoption choice yields the respective technology a competitive advantage: the inter-technological competition coefficients, β_{AB} and β_{BA}, capture the purchase or utilization cost-based effects a technology has on the competing technology's market potential and growth rate. They denote the magnitude of the effect of increases in the number of adopters of one technology on the growth rate of the other mediated by c_d. If these coefficients are larger than zero, then a technology reduces the competing technology's market capacity, as measured by K_A or K_B respectively, by making this technological choice relatively less attractive. For instance, some agents holding an a preference and constituting technology A's submarket may nevertheless decide to adopt technology B for its relative cost advantages, as measured by β_{AB}. Cost motives would dominate ecological motives in these agents. On the other hand, a relative cost advantage of A would confer this technology competitive superiority attracting some b preference holders ($\beta_{BA} > 0$). Therefore, a technology can gain a comparative competitive advantage by reducing

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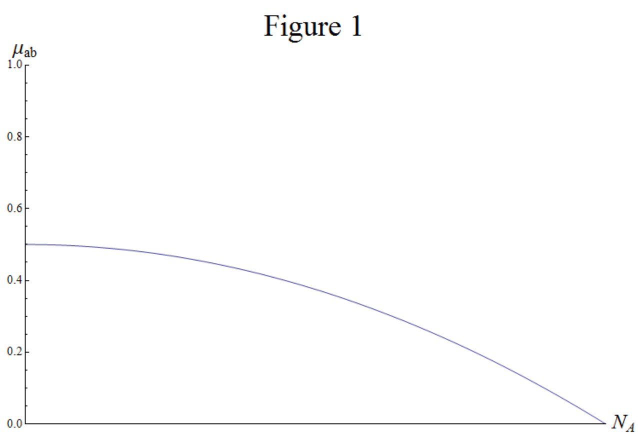
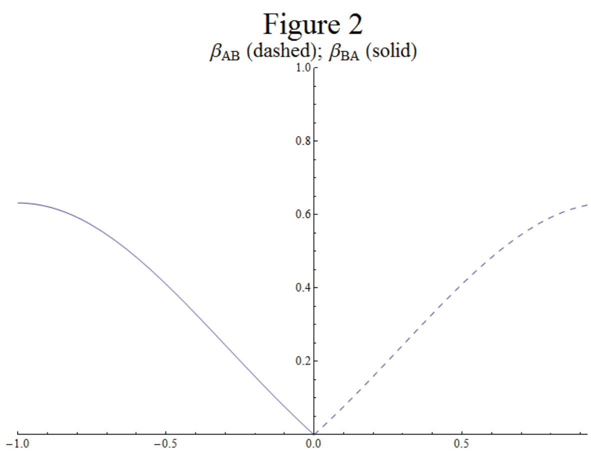
[5] Moreover, the pricing and servicing activities of suppliers have a direct bearing on technological acquisition, for the learning process they undergo is also likely to lead to a decrease in purchasing cost.

[6] This argument bears some resemblance to the "random walk" model as suggested by Arthur (1989) that also includes increasing returns to a technology depending on its adoption numbers.

the competing technology's market potential and growth prospects, i.e., it can, *ceteris paribus*, realize a relative growth advantage. The strength of competition drops off as c_d increases and technologies serve increasingly different markets characterized by, for example, very different levels of willingness to pay on the part of consumers.





Figures 1 and 2. An exemplary function of the hedonistic difference between two technologies $\mu_{ab}(N, N_A)$ (1) and the shapes of the competition coefficient functions β_{AB} and β_{BA} (2)

The inter-technological competition coefficients also determine whether the two technologies compete for the same market or whether there are niches in which a technology is protected from competition. If one of these coefficients is equal or close to zero, then one technology's growth opportunities are unaffected or only slightly affected by the competing technology. Finally, δ is a parameter that measures the strength of market potential and inter-technological competition effects on the aggregate growth rate in the number of a technology's adopters in Equations (6) and (7). δ may vary between technologies.

3. Technological diffusion paths of green technology and some political implications

The model devised in the preceding section consist of three coupled recursions, describing the development of p in time (Equation 4) and the changing numbers of adopters of technologies A and B (Equations 6 and 7). By setting the parameters and iterating this dynamic system for many individual and social learning steps and changes in the adoption numbers of A and B, we can study its properties. In this context, iteration steps capture progressing time. We show that such a system of competing technologies and endogenous preference learning dynamics yields propositions that have immediate relevance for ecological economics and environmental policy making. Several scenarios that compare different constellations of learning dynamics, technological features, and resulting diffusion paths are helpful for this discussion.

Figures 3a and b show a situation in which a newly introduced product or service of the established technology B, “conventional mobility”, is hedonistically very attractive as compared to a new product or service of “electric mobility”, i.e., technology A. $\mu_{ab}(\bullet)$ in individual learning is high. This hedonistic inferiority of technology A may emanate from a more or less nonexistent supporting infrastructure or the relatively perfected performance of technology B, whose previous products and services have gained a high number of users. As Figure 3a illustrates, the new commodity of technology B spreads in the population of adopters and dominates the market. Diffusion follows a typical S-curve, as frequently identified in the diffusion of innovations theory (e.g., Geroski, 2000). For a low number of A-adopters, $\mu_{ab}(\bullet)$ tends to remain high (see Equation 1) and increases with the dissemination of B in the total population of adopters (see Figure 3b). Moreover, with a relatively more rapid increase in the number of adopters of B, the conventional technology has a strong competitive effect on technology A based on relative cost differences ($\beta_{\mathrm{AB}} > 0$ and $\beta_{\mathrm{BA}} = 0$ if $N_B > N_A$).[7] This is due

[7] Dominant, established technologies may also have created linkages with, for example, political organizations so as to increase their competitiveness.

to scale-induced cost advantages favoring the more frequent technological choice (as reflected by c_d in Equations 8 and 9). Technology A can gain a number of adopters for a certain time before declining again. Ultimately, the preexisting hedonistic disadvantages and the increasing cost difference prevent the green technology A from gaining significant and enduring market share. This happens although a certain share of agents in the population develops a preference for "electric mobility" (as measured by p and shown in Figure 3b). The latter fact can mainly be attributed to role model M1 ($\alpha_1 = 0.2$). Hence, a fraction of the population of users does not follow their "green preference" due to cost-based disadvantages of technology A.

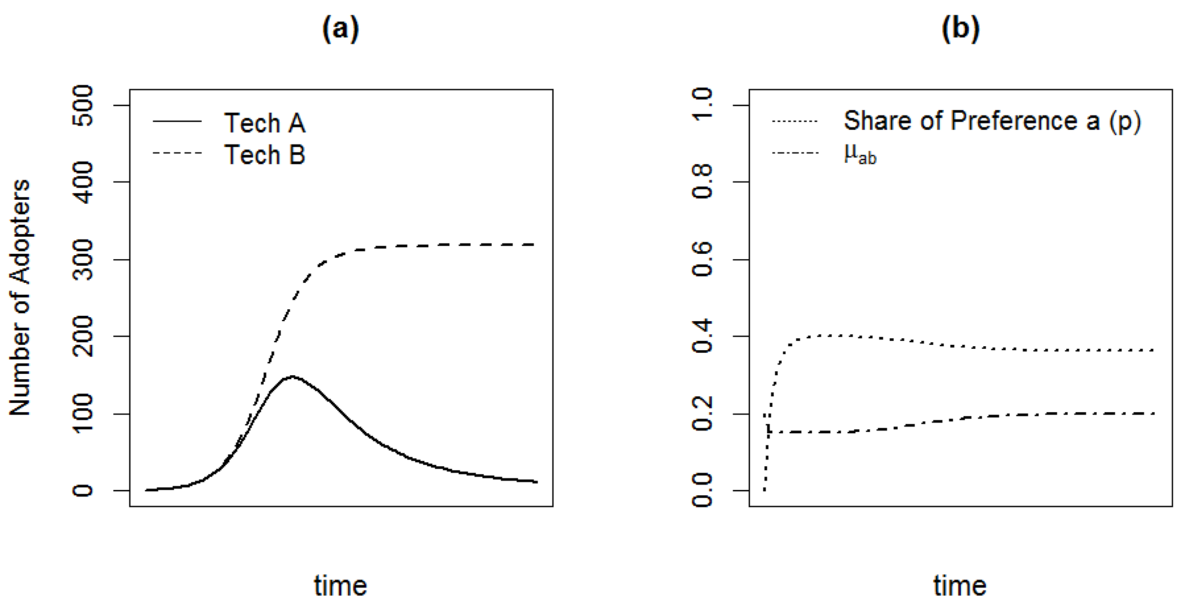


Figure 3. A dominant technology B
($\lambda = 0.2$, $\alpha_1 = 0.2$, $\mathrm{K} = 500$, $\eta = 0.2$, $\delta = 0.2$)

It is only when aspects of the institutional, social, or economic setting are changed that the alternative choice A has a chance to diffuse: if, for example, a prominent role model M1 (politicians, the media, or another "agent of collective action") takes strong influence in cultural transmission ($\alpha_1 = 0.5$), social preference learning can prepare the ground for diffusion of the green technology by spreading preference a in the population. M1 could, for example, make technology A a status good or provide information (potentially via eco-labeling) to foster consumers' motivation for adopting green cars (e.g., Coad et al., 2009). The resulting instance of structural change is depicted in Figures 4a and b. Starting point is a situation in which technology B is predominant, potentially brought about by a constellation as described in the first scenario and captured by the fact that the initial number of B-users is high relative to total market size ($\mathrm{N_B}(0) = 200$). Driven by the influential role model M1 and the conformity bias measured by η, p grows in the course of social preference learning on the part of potential users (see Figure 4b). In this context, conformity is an important aspect of social learning-based preference acquisition: beyond a certain point, which may be interpreted as a critical mass, M1 together with a growing number of a preference holders among M2 and M3 lead to an increasing number of sets of models where a is the more frequently exhibited preference, i.e., conformity then spurs the dissemination of preference a in the population.

Alongside with this, A's submarket, $\mathrm{K_A}$, increases and raises its growth prospects: the higher the number of potential adopters holding an a preference, the higher the number of agents that actually follow their acquired preference for the green technology despite momentary cost differences ($\beta_{\mathrm{AB}} > 0$). These pioneers are endowed with a relatively higher willingness to pay and follow their ecological motives (see Brennan, 2006). Then, technology A starts to diffuse within the population and can crowd out the dominant technology B in the longer run (see Figure 4a). This happens although B initially enjoys relative advantages in terms of individual hedonistic learning (as reflected by high values of $\mu_{ab}(\bullet)$ in Equation 1 and shown in Figure 4b) and purchase or utilization cost ($\beta_{\mathrm{AB}} > 0$ in the beginning). For an approximately constant $\mu_{ab}(\bullet)$, $\mu_{ab}^{const.}$, we can analytically determine the equilibrium frequency of p, $\hat{p}$, by using Equation (5) derived above.

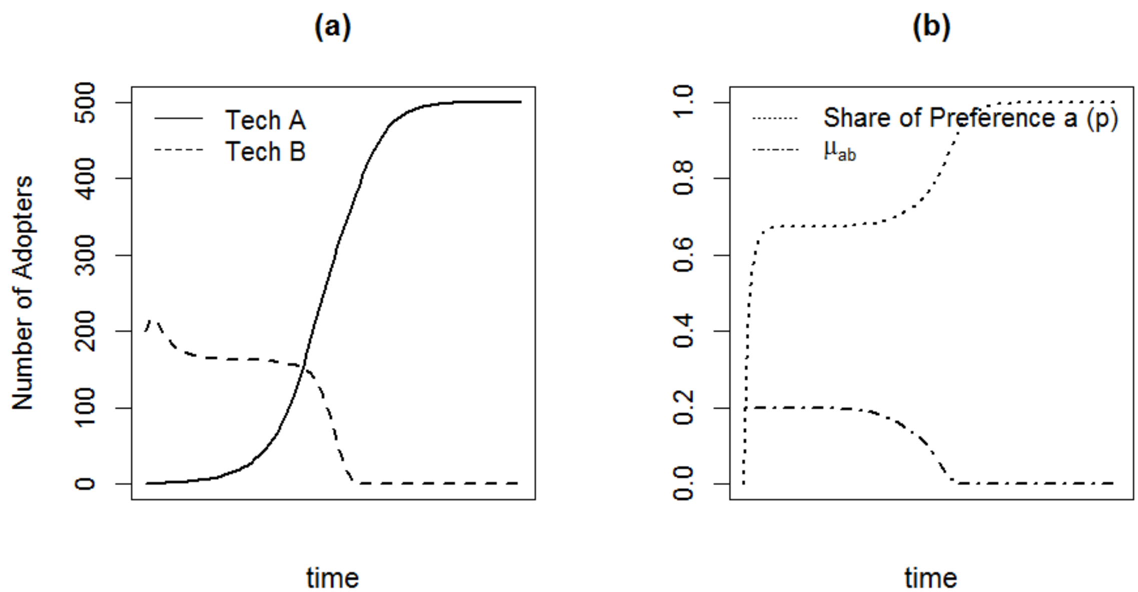


Figure 4. Strong social preference learning
($\lambda = 0.2$, $\alpha_1 = 0.5$, $\mathrm{K} = 500$, $\eta = 0.2$, $\delta = 0.2$, $\mathrm{N_A}(0) = 1$)

The second raise of p in Figure 4b is due to the decreasing hedonistic learning bias, $\mu_{ab}(\bullet)$. The strongly increasing number of A-adopters leads, for example, to the emergence of a supporting infrastructure that makes this technological choice more convenient. Therefore, in the course of A's diffusion, the hedonistic learning bias initially favoring technology B vanishes as well as cost differences due to scale effects (as measured by the competition coefficients β_{AB} and β_{BA}). Even such a very influential role model would, however, fail as an agent of innovative change if the conformity bias were large holding down p. This would be the case if the society in question is a very conservative one, not open to technological change (e.g., if $\eta = 0.4$). The vast majority of role models M2 and M3 would then show preference b representing the majority among most sets of role models, i.e., conformity would hinder the spreading of a and counteract the influence of M1.

Based on these findings, we suggest the following proposition:

Proposition 1: *Preference acquisition processes based upon social learning can override a technology's relative cost and/or hedonistic disadvantages and therefore lead to its diffusion in a population of interacting adopters.*

Hence, by spreading ecological preferences, reference groups or cultural role models can, to a certain extent, offset negative economic factors, such as a technology's relatively higher costs or hedonistic disadvantages, on its diffusion. The decision to use green products partly results from social or ecological – and not exclusively economic – motives. This also illustrates the potential role of prestigious role models as agents of collective change, such as the media, in the diffusion of environmentally-friendly technologies (see Welsch and Kühling, 2009). Changing consumers' preferences via social learning is, therefore, an important instrument of environmental policy (also Brennan, 2006).

A second scenario emphasizes the importance of timing in policy intervention. The provision of information is a major tool of policy and might improve mechanisms by which preferences spread. Policy makers can function as a common source of information, potentially based on science as one important actor in the social learning process (see Luks and Siebenhüner, 2007), or they may identify and support key actors that are particularly persuasive (see Geroski, 2000), such as non-governmental organizations or other activist groups. When model M1 represents the media and their agenda-setting role in societal discourse, their influence probably varies with coverage of environmental issues: if sustainability problems are prominent in the media during a certain time span, people are more likely to change attitude toward green technologies in this period. If, however, media coverage of sustainability vanishes later on, the established technology's relative cost and hedonistic advantages might lead to a subsequent crowding out of previously acquired "green preferences".

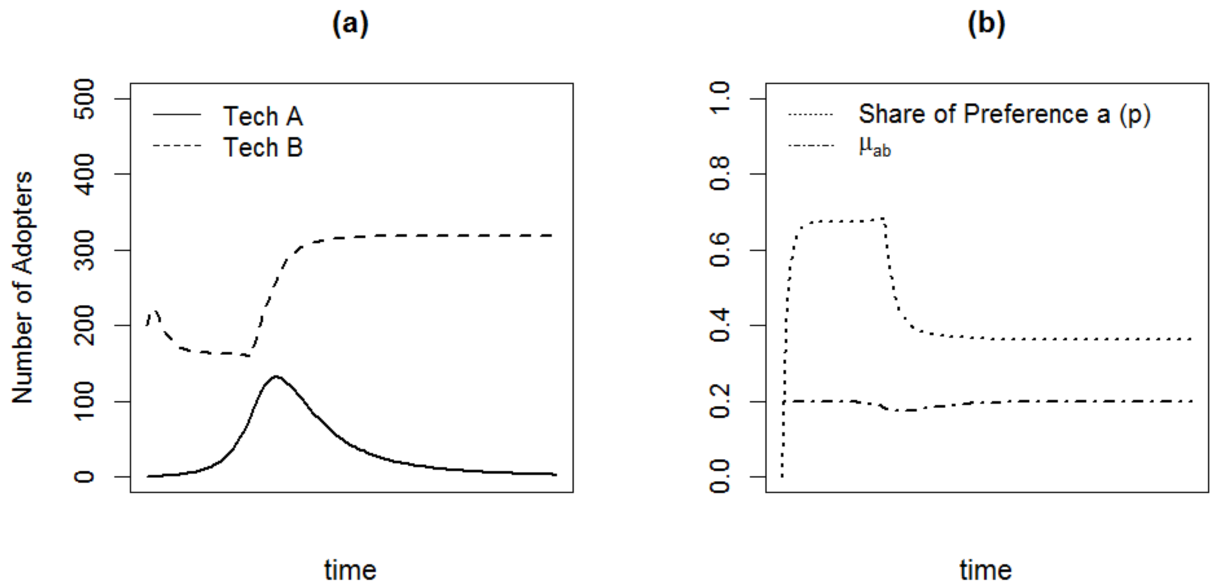


Figure 5. A temporarily high influence of role model M1
($\lambda = 0.2$, $\mathrm{K} = 500$, $\eta = 0.2$, $\delta = 0.3$, $\mathrm{N_B}(0) = 200$, $\mathrm{N_A}(0) = 1$)

Figures 5a and b illustrate the impact of a political, media, or science-based information campaign, which is limited in time, on technological diffusion. We suppose a highly influential role model M1 to take effect during the first 25 iteration steps (total of 100) capturing progressing time ($\alpha_1 = 0.5$). This entails a strong increase in the share of preference a holders (as measured by p, see Figure 5b) and the beginning of a diffusion process of technology A at the expense of the established conventional technological option (see Figure 5a). Such a time-limited campaign would, however, not have a lasting effect on the dissemination of A: as M1's influence decreases again after period 25 ($\alpha_1 = 0.2$), the share of the a preference also drops (Figure 5b) preventing further diffusion of the green technology and facilitating the resurrection of B (Figure 5a).

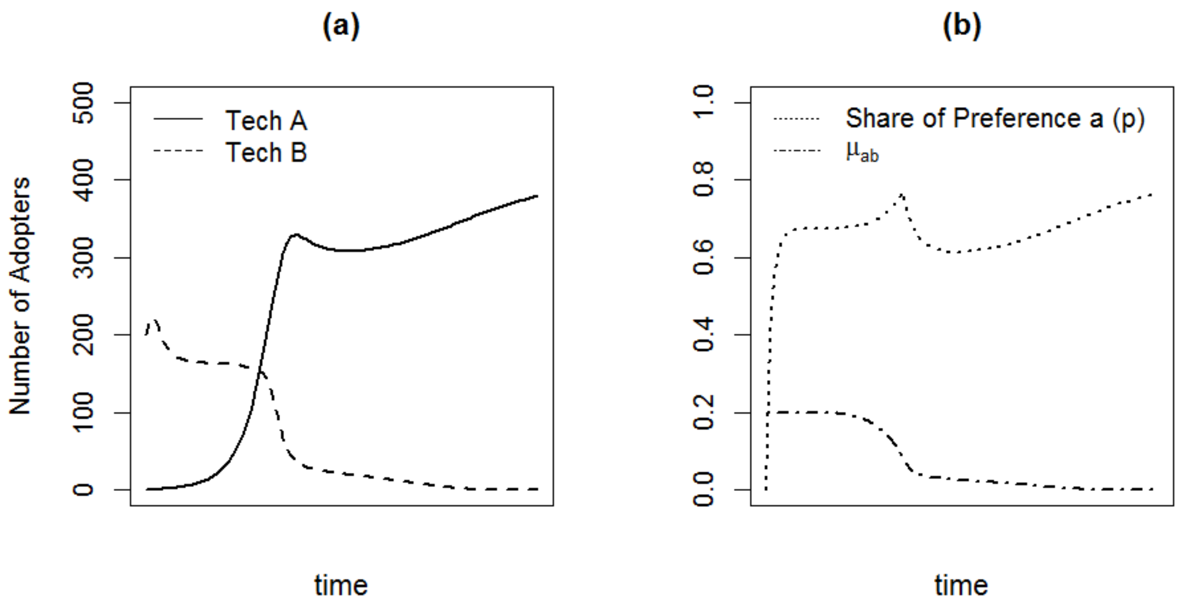


Figure 6. A prolonged high influence of role model M1
($\lambda = 0.2$, $K = 500$, $\eta = 0.2$, $\delta = 0.3$, $N_B(0) = 200$, $N_A(0) = 1$)

If, however, the campaign continues only ten additional time steps until iteration 35, it facilitates diffusion of technology A (see Figure 6a). Although there still is a significant temporary drop in the share of preference a holders (see Figure 6b), the concomitant reduction of the direct learning bias, $\mu_{ab}(\bullet)$, favoring technology B, enables a further increase of p also in a situation in which a less influential role model takes effect ($\alpha_1 = 0.2$ after period 35). The rapidly growing number of A-adopters closes the “hedonistic gap” between the two competing technologies.[8] Hence, the dynamics of preference acquisition on the part of consumers are an important determinant of the time path of technological diffusion.

Proposition 2: *If a dedicated cultural role model takes effect in consumers’ preference learning during certain critical time spans or “windows of opportunity”, it can persistently promote the diffusion of a green technology.*

[8] While this scenario bears some resemblance to the one depicted in Figure 4a, diffusion is slower due to lower values of p later in the diffusion process.

This setting hints at the importance of timing of political measures, such as information provision campaigns, politically motivated media coverage, or the appearance of key actors in societal discourse. Moreover, it indicates at the existence of critical “windows of opportunity” for policy to have an effect on technological diffusion (e.g., Sartorius, 2006). Another challenge for politics comes to the fore here: while the effects of information campaigns in terms of increasing numbers of adopters are modest in the beginning, they may, due to nonlinearities in the diffusion process, become highly effective within a short period of time when adopter numbers start to increase exponentially.

Another avenue in public policy toward the promotion of the diffusion of green technologies is the deliberate creation of a “market niche” (e.g., van den Bergh, 2013). In our scenario setting, technology A’s prospects improve if the competitive effect of technology B on its growth rate is removed, i.e., if $\beta_{AB} = 0$ (or is close to zero). K_A then measures the market capacity of the niche for technology A unaffected by the number of adopters of B that results in relative cost differences (as measured by c_d). Policy makers can either subsidize technology A to remove these scale-induced cost differences or create a submarket – the “niche” – in which only products and services of technology A are allowed. One way to do the latter would be the banning of the environmentally more harmful “conventional mobility” from certain regions, such as inner cities, where then only electric mobility services would be permitted. In this case, politics would protect the technology “electric mobility” in order to establish it in the market for mobility services. In the “niche market” setting, A also does not impact on B’s market, i.e., $\beta_{BA} = 0$.

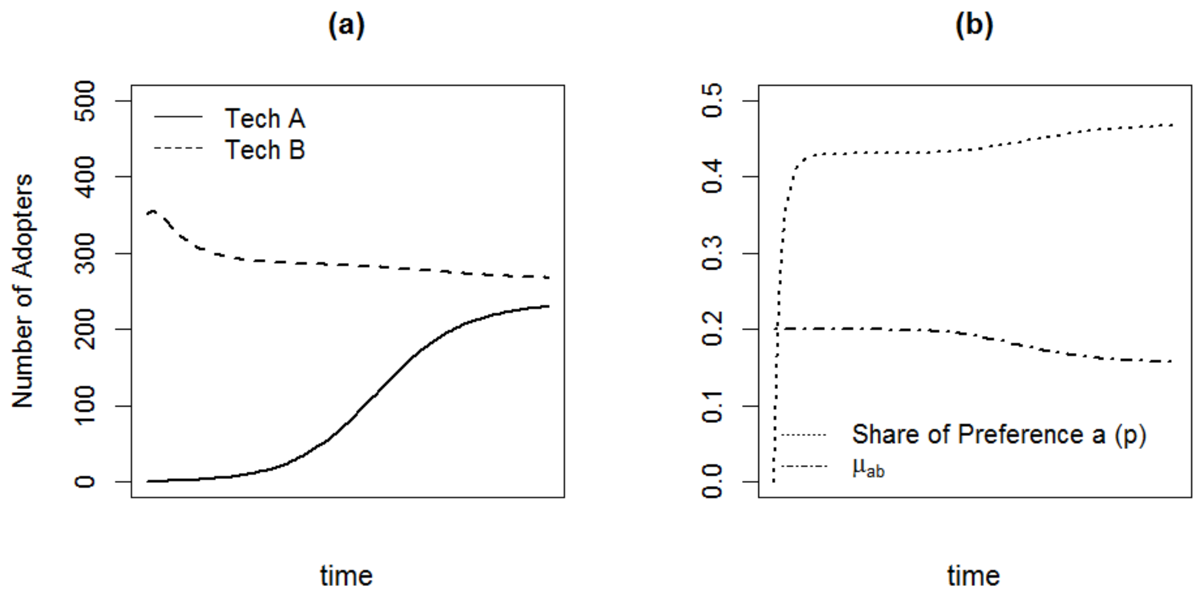


Figure 7. The "niche market" setting
($\lambda = 0.2$, $\alpha_1 = 0.25$, $\delta = 0.1$, $\mathrm{N_A}(0) = 1$)

Figures 7a and b show how such "niche creation policy" can affect the diffusion of A in a situation where the initial number of users of an established technology B is high relative to total market size ($\mathrm{N_B}(0) = 350$ and $\mathrm{K} = 500$): the alternative technological choice would first spread amongst adopters within its protected niche market (see Figure 7a). A prerequisite for this to happen is prior social preference learning that makes sure that a sufficient number of potential adopters acquires a preference for A that is then "revealed" in the context of the created market niche, $\mathrm{K_A}$ (see Figure 7b). In the course of this diffusion process, the increasing number of A-adopters, N_A, reduces c_d improving A's inter-technological competitiveness (Equations (8) and (9)). At the same time, the emergence of a supporting infrastructure – more or less enforced by the politically set "niche conditions" – lowers A's hedonistic inferiority, as measured by $\mu_{ab}(\bullet)$ (Figure 7b). If these effects are persistent and strong enough, we can expect technology A to also appeal to other adopters and diffuse in a common market competing with "conventional mobility" without further governmental protection or subsidies.

Proposition 3 sums up these findings:

Proposition 3: *State regulation that temporarily creates a niche for a green technology by preventing competitive impacts of other technologies can help it decreasing cost or hedonistic disadvantages by gaining adopters in the niche market. Subsequently, a technology can be able to diffuse further even after the removal of this kind of governmental protection.*

Such a diffusion pattern demonstrates the potentially stimulating effect of decreasing costs or hedonistic disadvantages of green technologies on their adoption rates – if they are granted the opportunity to improve in these respects. An alternative to creating a niche market to promote green technology is taxing of the non-green technology to remove cost disadvantages (e.g., Janssen and Jager, 2002). This strategy would, however, not remove A's hedonistic disadvantages due to a lacking supporting infrastructure (as reflected by a high $\mu_{ab}(\bullet)$) that would probably be created in a niche setting. On the other hand, stimulating pathway technologies financially, such as energy storage technologies, may represent a way to reduce inter-technological hedonistic disadvantages and may be especially effective when combined with the implementation of a niche market. Speed limits to reduce hedonistic superiority or regulating advertisement (e.g., of fast cars with oversized engines) may be additional strategies for politicians to reduce hedonistic advantages of conventional mobility services.

Our theorems do imply some further intriguing qualitative results. In a last scenario, we first assume politics to actively intervene with relative costs, for example, by introducing a subsidy favoring the technological choice "electric mobility" or by carrying out public procurement programs that promote the number of A-users thereby decreasing its relative, scale-related cost disadvantage. This policy modifies the competition coefficients β_{AB} and β_{BA} via c_d and removes differences in competitive impacts (in our setting: $\beta_{AB} = \beta_{BA} = 0.6$). However, as can be seen in Figure 8a, this subsidy alone would be insufficient to promote the lasting dissemination of a newly introduced product or service of technology A, although it temporarily gains a significant, but finally decreasing, number of adopters. As will turn out below, this is the case if preference a has not been disseminated within the population via social learning beforehand ($p \approx 0.4$, see Figure 8b). Therefore, the competing new product or service of the established technology B diffuses and finally dominates the market for mobility services, also due to a high hedonistic learning bias, $\mu_{ab}(\bullet)$.

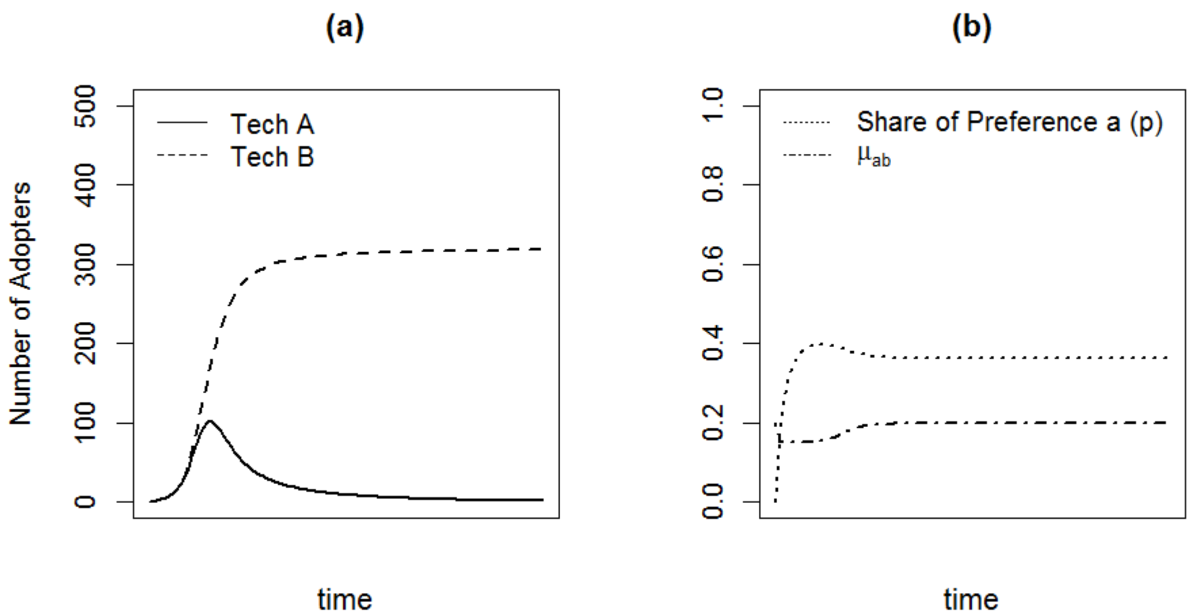


Figure 8. Introducing a subsidy
($\lambda = 0.2$, $\alpha_1 = 0.2$, $K = 500$, $\eta = 0.2$, $\delta = 0.5$)

If, alongside this subsidy, a marketing campaign, collective action, or science-based information increases the weight of an actor or organization represented by model M1 in social learning (e.g., $\alpha_1 = 0.4$), then, as depicted in Figure 9a, technology A has the chance to diffuse and replace "conventional mobility". As shown in Figure 9b, the prominent role model raises the level of the a preference in the population of adopters, p, preparing the ground for the spreading of the subsidized technology A. Moreover, with an increasing diffusion of A, $\mu_{ab}(\bullet)$ decreases enabling a further growth of p. This diffusion pattern demonstrates the importance of coordination of information provision campaigns and more traditional economic incentives in promoting novel technologies in a population of potential users. Agents must acquire a positive attitude toward a technology via social learning to facilitate its success (also Brennan, 2006).

Proposition 4: *Environmental policy instruments that comprise the promotion of "green preferences" via social learning in combination with measures to lower relative cost disadvantages can be expected to be more efficient and effective as to the fostering of a green technology's diffusion in a population of interacting adopters.*

Further simulation runs also show that if the conventional technology does not enjoy a too great advantage as to its hedonistic experiences ($\mu_{ab}(\bullet) \approx 0.2$), then a weak conformity bias (e.g., $\eta = 0.1$) contributes to the spreading of preference a and offsets a low influence of the cultural model M1 ($\alpha_1 = 0.2$). In this case, the subsidy, together with a low η, facilitates the diffusion of technology A in a society open to technological change.

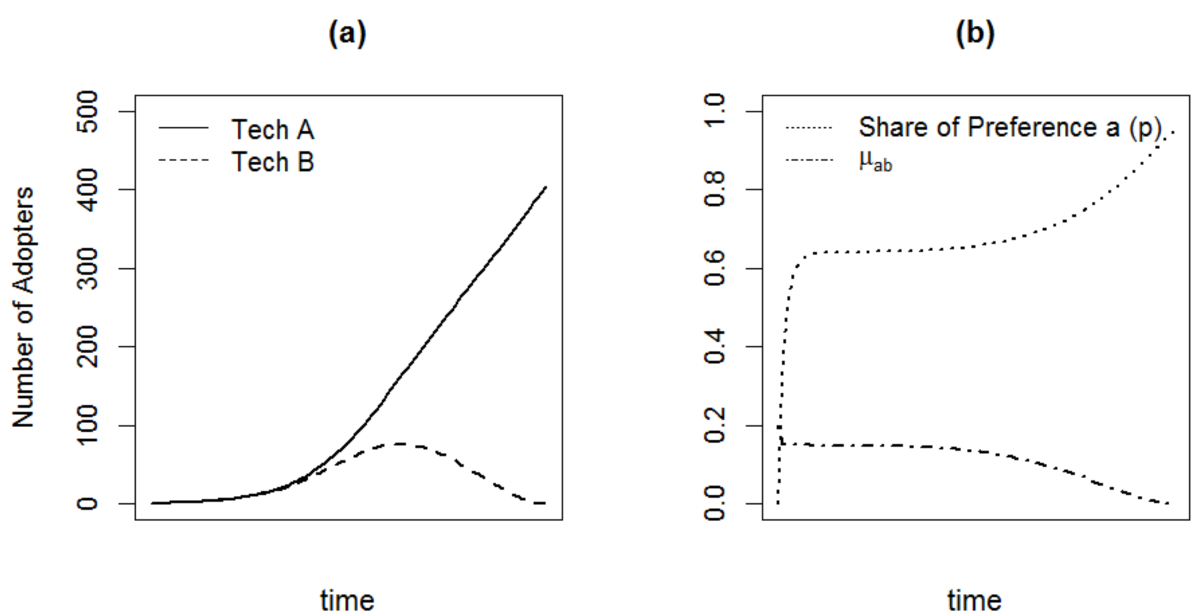


Figure 9. Subsidy supported by social preference learning

$(\lambda = 0.2, \alpha_1 = 0.4, \mathrm{K} = 500, \eta = 0.2, \delta = 0.1)$

In terms of policy conclusions we see that both economic considerations and the behavior of cultural models are important determinants of the diffusion of environmentally-friendly technology choice. Given our model's results, the explicit consideration of social determinants of individual behavior in order to assess the impact of environmental policies is inevitable and purely economic approaches can lead to misleading results. The belief that changes in behavior depend entirely on income, prices, and exogenous and invariant preferences potentially leads to the false conviction that policy makers can modify adopters' choice in any desired direction by influencing economic incentives alone. Extended behavioral assumptions within the scope of a socio-ecological research agenda entail that less importance is given to these instruments; price instruments without accompanying individual and social learning processes may be less effective and less efficient than traditional theory makes us believe (see van den Bergh et al., 2000; Pahl-Wostl et al., 2008; Garmendia and Stagl, 2010). Moreover, the coordination of policies, for example, media campaigns and accompanying incentive based measures, gains in importance. An effective policy package to promote diffusion of green technologies is likely to contain several different, complementary instruments (e.g., van den Bergh, 2013).

4. Conclusions

We brought models from population ecology and cultural evolution theory to bear on questions concerning adopters' preference acquisition and the competitive process between, and relative diffusion of, two technologies. This methodologically combined approach to diffusion theory showed how individual and social preference learning combined with more traditional economic considerations involving cost-based competition and hedonistic differences between technologies spurs or limits the adoption of sustainable technology in a population of interacting agents. Underlying our model of technology diffusion is a broadened behavioral conception of humans for the science of sustainability that emphasizes learning and social context.

More specifically, the formal approach developed in this paper demonstrated that preference acquisition processes based upon social learning in a population of potential users can override a technology's relative cost or hedonistic disadvantages and therefore lead to its diffusion. The often conflicting interplay of cost motives with (socially acquired) ecological motives took center stage in this context. Furthermore, the model showed that state regulation that temporarily creates a niche for a green technology by preventing competitive impacts of other technologies can help it decreasing cost or hedonistic disadvantages by gaining additional adopters. Subsequently, a technology can be able to diffuse further even after the removal of this kind of governmental protection. The model also demonstrated the importance of timing of policy interventions, such as information provision by activist groups or science and the accompanying introduction of a subsidy. There are critical time periods or "windows of opportunity" within which social preference learning can have a persistent influence on a (green) technology's diffusion path.

Finally, our analytical concept indicated that environmental policy instruments that comprise the promotion of "green preferences" via social learning in combination with economic incentives that lower cost differences or political measures that reduce hedonistic disadvantages can be expected to be more efficient and effective as to the fostering of a green technology's diffusion. Policy conclusions, therefore, suggest that only a mix of different political measures will probably promote the dissemination of environmentally-friendly technologies. They also stress the importance of individual and social preference learning for sustainable development alongside more traditional cost arguments.

Acknowledgements

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