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A percolation model of eco-innovation diffusion: The relationship between diffusion, learning economies and subsidies

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ABSTRACT

An obstacle to the widespread adoption of environmentally friendly energy technologies such as stationary and mobile fuel cells is their high upfront costs. While much lower prices seem to be attainable in the future due to learning curve cost reductions that increase rapidly with the scale of diffusion of the technology, there is a chicken and egg problem, even when some consumers may be willing to pay more for green technologies. Drawing on recent percolation models of diffusion, we develop a network model of new technology diffusion that combines contagion among consumers with heterogeneity of agent characteristics. Agents adopt when the price falls below their random reservation price drawn from a lognormal distribution, but only when one of their neighbors has already adopted. Combining with a learning curve for the price as a function of the cumulative number of adopters, this may lead to delayed adoption for a certain range of initial conditions. Using agent-based simulations we explore when a limited subsidy policy can trigger diffusion that would otherwise not happen. The introduction of a subsidy policy seems to be highly effective for a given high initial price level only for learning economies in a certain range. Outside this range, the diffusion of a new technology either never takes off despite the subsidies, or the subsidies are unnecessary. Perhaps not coincidentally, this range seems to correspond to the values observed for many successful innovations.

1. Introduction

The diffusion of new technologies often depends upon the interrelations between social and technical aspects [1]. On the one hand, communication channels and social networks play a central role in the widespread adoption of innovations [2]. Information contagion and imitation effects are widely recognized as crucial factors in the process of diffusion of innovations. In the particular case of energy technologies, and especially in the case of hydrogen and fuel cells technologies, demonstration effects and increased confidence play a significant role. On the other hand, technical factors such as the degree of complexity, compatibility and special features [3] directly influence the initial cost levels of innovations. High upfront costs are among the main factors that prevent the widespread diffusion of new technologies, and this is especially true for environmental energy technologies. The degree of learning economies is of primary importance in this context. New technologies characterized by high learning cost curve reductions will have a greater chance to break into mainstream markets. If a new technology has the chance to develop first in niche markets one could then exploit cost reductions in these markets due to learning curve effects when it is introduced into the mainstream market.

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For instance, in the case of environmentally friendly energy technologies, a potential niche for market entry might be created by the willingness of some particularly environmentally conscious and high-income consumers to pay more for products that are perceived to be green (an example is the Toyota Prius hybrid car in the US, called “Hollywood's latest politically correct status symbol” by the Washington Post[2]).

However, even if much lower prices seem to be attainable in the future due to learning curve cost reductions that increase rapidly with the scale of diffusion of the technology, there is a chicken and egg problem, even when some consumers may be willing to pay more for green technologies. It is not clear when a technology will pass the threshold that permits widespread adoption and competitive market pricing, and when it will fail. The latter seems too often to be the case without long-term subsidies.

There exist a wide variety of policy options available to decision makers to influence this process. They may be roughly divided in two categories: demand-pull and technology-push policies. Even if a mix of the two is actually necessary, especially in the case of renewable energy sources [4], we will analyze the effect of one particular policy option that belongs to the first category: adoption subsidies for consumers. According to Turkenburg [5], the innovation diffusion process can be split into two parts: early deployment in which costs decline, and widespread dissemination in which institutional barriers are overcome and investments increase. A potential policy strategy related to the first phase of diffusion is represented by temporary subsidies followed by a phasing-out policy during the period of pervasive diffusion. In practice, however, especially with regard to environmentally friendly energy technologies, we often find permanent subsidy policies because the diffusion of such innovations is frequently not self-sustainable. Thus one can ask what policy actions may be implemented to support the diffusion of a new energy technology to market maturity that are socially profitable? In other words, which kinds of subsidy policies can trigger a self-sustained diffusion of these particular technologies that ultimately justify the upfront social expenditures?

Drawing on recent percolation models [6–9] of diffusion, which combine the contagion aspect (e.g., epidemic models) with the heterogeneity of agent characteristics (e.g., Probit or heterogeneous threshold models), we develop and analyze a model of new technology diffusion. While this model is clearly applicable to a more general category of (perhaps all?) innovations that start out with a disadvantage with respect to incumbent and competing technologies, it is especially applicable to the case of eco-innovations, where there may be strong ecological externalities justifying their diffusion but market forces may initially be unfavorable. While regulation or very high permanent subsidies may break this deadlock, we are particularly interested in the minimal policy interventions that could ‘kick-start’ a market-based diffusion process. Using agent-based simulations (ABS) we explore when a limited subsidy policy can trigger diffusion that would otherwise not happen. As a main result we find that subsidies are not helpful both when learning economies are too low (and thus reasonable temporary subsidies fail to trigger diffusion), and when learning economies are too high, (and diffusion would take off anyway). However, for a certain range of learning coefficients a temporary subsidy policy may indeed trigger self-sustained diffusion provided that the level of subsidies is high enough.

The article is organized as follows. Section 2 gives a brief overview of the existing literature on percolation diffusion models, learning curves and subsidies. The details of the model and the methodology are discussed in Section 3. In Section 4 we present the results. Interpretations and conclusions are discussed in Section 5.

2. Extending standard models of diffusion by introducing percolation, learning curves and subsidies

Innovation diffusion has been investigated using different approaches [10]. In particular, the S-shaped diffusion models and the epidemic models stem from two lines of research originating in Griliches' empirical investigation [11] and Mansfield's contributions [12,13]. In general, diffusion models can be classified as epidemic models, Probit models, legitimation and competition models, and information cascades models [14]. In what follows we focus on the first two categories: epidemic and Probit models. While the former emphasizes the effects of information contagion, it usually presupposes agent homogeneity. The latter is especially relevant in stressing the effects of agent heterogeneity but it neglects a description of the interrelations among individuals. The percolation model developed in the present paper incorporates both information contagion and agent heterogeneity. Agents interact on a specific network structure called the *Ising* network [2]. According to Stauffer and Aharony [15], percolation was originally applied by Flory and Stockmayer during the Second World War to describe critical phenomena for the process of gelation. Broadbent and Hammersley introduced the name percolation theory in 1957. Percolation explains, for example, how a fluid can traverse a porous material. But it has been applied to other cases, like the investigation of forest fires or stock market bubbles. As a simple example we explain the simple case of an atemporal site-percolation model. In a two-dimensional square lattice, assign randomly either 0 or 1 to each site. The values are stochastically independent and P is the probability for the realization of value 1, $1-P$ for value 0. Percolation is said to occur if there exist at least one unbounded cluster of sites with value 1. It can be shown that there is a critical value P_c, such that for $P<P_c$ percolation will not occur. On the contrary, if $P>P_c$ percolation will occur with probability 1 (for the two-dimensional site lattice we use in this paper, it can be shown numerically that $P_c \approx 0.592743$). Percolation theory has been applied to social science [7] as well as to the economics of technology diffusion [8,9].

The process of diffusion of new products and technologies often occurs on different time scales. It often starts with a few early adopters, followed by an increasing cumulative number as time passes. Moreover, it often follows an S-shaped path of diffusion. The market price may have to fall below some threshold level, however, before this process of diffusion can take off.

[2] *The Washington Post*, June 2, 2002, p. C01.

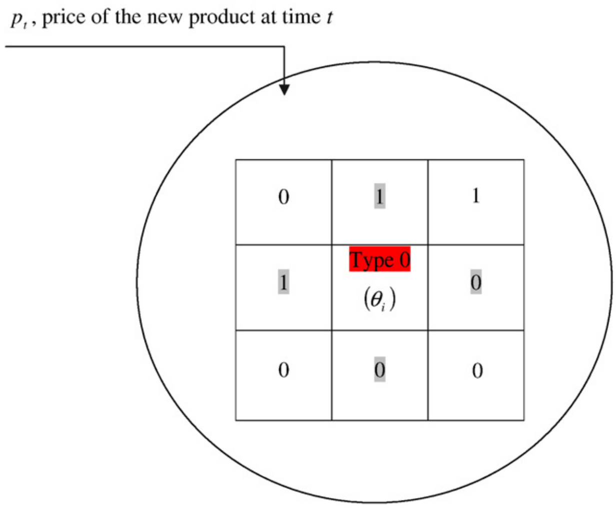

Fig. 1. A neighborhood of an agent on the lattice, where 0 represents non-adoption and 1 adoption of the technology by a neighbor. Θ_i is the reservation price of agent *i*.

Hohnisch et al. [9] have used percolation theory to explain what determines delayed take-offs in the diffusion of new products and what happens to the price's threshold level: macroscopic effects either on the demand side or on the supply side or both can trigger the process of diffusion even for price levels initially higher than the threshold. What they call macroscopic effects may be interpreted as interdependency among potential buyers' choices on the one hand and learning curve cost reductions on the other. The notion of learning curves is well known in the literature [16] and refers to the unit cost reductions due to increasing production. Thus costs and price decrease with the increasing number of new adopters. In [9] the model assumes that consumers' willingness to pay is drawn from a uniform distribution on the interval [0, 1]. In order to incorporate consumers' aptitude to "greenness", we assume that the reservation price is distributed according to the highly skewed lognormal distribution such is characteristic of many other economic variables such as personal income and wealth. We then develop a model that combines both the network effect and the heterogeneity of agents. While the present version adopts the *lattice*-type network structure (Fig. 1), in principle it can easily be generalized to other network topologies that better reflect the communication channels influencing consumer behavior at both the local and global levels.

The approach in [9] can be enriched by introducing policy actions intended to trigger widespread adoption of a new product such as subsidy policies. We modify their model in order to explore when subsidies may trigger the process of diffusion of eco-innovations. In particular, we investigate when diffusion can become self-sustaining after an initial policy of temporary subsidies. In the next section we specify the details of the model's structure and equations.

3. The model

Consider a finite number of consumers distributed on a two-dimensional lattice with periodic boundary conditions (i.e., a torus). Each consumer is faced with the choice of whether or not to buy a new technology available in the market. Whether she will buy it depends on two factors: her neighbors' choices and her willingness to pay for that new product. She will first consider purchasing the product if it has already been bought by at least one of her neighbors. If this condition is fulfilled she will then compare the market price of the new technology to her reservation price: she will buy it if the latter is higher than the former.

The model explains diffusion as a process of spreading news or "keeping up with the Jones's". This reflects the fact that the adoption of new products may often be the result of imitation behaviors (in the particular case of hydrogen and fuel cells technology, a testimony of reliability and safety may be fundamental). In part this may simply result from status considerations, but it may also be an essential element in reducing informational uncertainty about product characteristics and suitability. In addition, the model analyzes diffusion as resulting from the interaction of heterogeneous behaviors. Consumers' initial willingness to pay for the new product is drawn from a lognormal distribution at the beginning of the simulation. One possible explanation is that agents with high incomes and educational status are characterized by a higher reservation price, both because they have a greater ability to pay and higher environmental consciousnesses, but for the purposes of the model any highly skewed sociological characteristics suffice to motivate this population heterogeneity.

A schematic representation of such a network neighborhood is presented in Fig. 1. Consumer *i* is of type 0: she has not yet acquired the technology. Type 1 consumers such as the ones on the left and above have already adopted the technology in previous periods. She knows about the availability of the new product[3] (e.g. at least one of her neighbors has already bought it). Her

[3] We assume in this model that consumers collect information at zero cost.

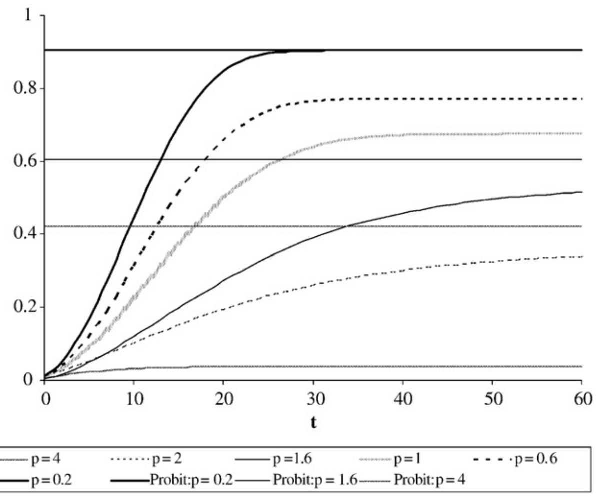

Fig. 2. Share of adopters over time for different values of the product price p, assumed time constant.

reservation price is θ_i, $\theta_i \in [0,\infty]$, where $\theta \approx \exp N(\mu, \sigma)$ with $\sigma \geq 0$ and $\mu > 0$ (μ and σ are parameters of the model corresponding to the mean and standard deviation of the underlying normal distribution). A standard learning curve will be applied to the price of the new technology at time t according to Eq. (1):

$$p_t = p_0 \left(\frac{N_0}{N_{t-1}} \right)^{\alpha} (1 - s), \tag{1}$$

where N_0 is the initial number of adopters (N_0 is a parameter of the model) and $N_{t-1} = \sum_{i=0}^{t-1} n_i$ is the cumulative number of adopters (n_i is the number of adopters in period i). The initial price $p_0 \in [0, +\infty]$ and $\alpha \geq 0$ are parameters, where α represents learning in the model. The subsidy rate on the price is s, $0 \leq s \leq 1$. In contrast to [9], the only macro effect modeled in our analysis is represented by the learning curve. We do not assume that the consumers' reservation prices will decrease with the number of adopters. In the basic percolation model, percolation occurs when the probability that θ_i is greater than the market price p_t is greater than the critical value P_c. With a lognormal distribution, the integral of the density function at p_t must be less than $1 - P_c$. In that case product diffusion will take off. After the occurrence of percolation we know that a certain number of agents, depending on the path of diffusion of percolation, have bought the product. According to the Probit model, if the reservation price is lognormally distributed then the probability to buy Prob $\{y > 0\}$ in the static case is:

$$\mathrm{Prob}\left\{\theta > \theta^*\right\} = \mathrm{Prob}\{y > 0\} = 1 - F(p), \tag{2}$$

where $F(p)$ is the cumulative probability function at p, the market price of the new product. In the case with learning this leads to dynamic equations of the form:

$$\mathrm{Prob}\left\{\theta > \theta^*\right\}_{t+1} = \mathrm{Prob}\{y > 0\} = 1 - F(p_t), \tag{3}$$

where $p_t = p_0 \left(\frac{N_0}{N_t}\right)^{\alpha}$ and $N_t = N \cdot$ "$\mathrm{Prob}\{\theta > \theta^*\}_t$. N is the total number of potential adopters, N_0 is the initial number of buyers, N_t is the cumulative number of adopters at time t, and p_t is the market price of the new technology that is dependent on the initial price

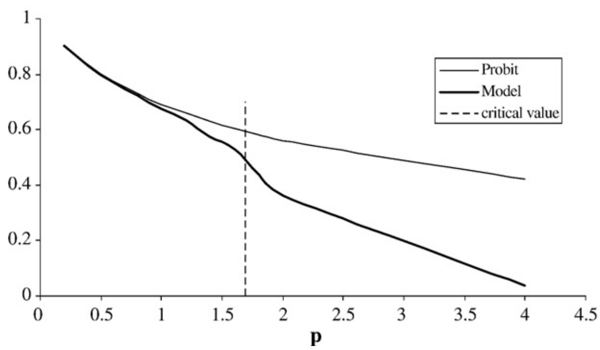

Fig. 3. A comparison between the final share of adopters for Probit and percolation models for different values of the time-independent product price p.

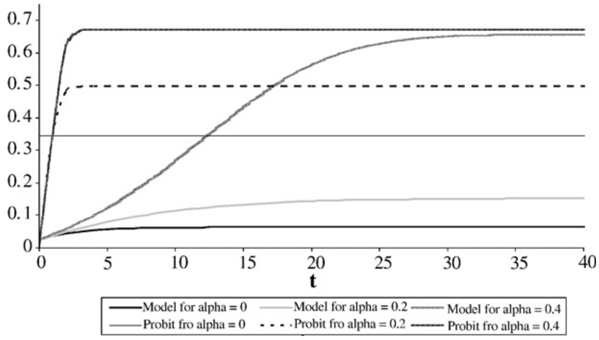

Fig. 4. Share of adopters over time. A comparison between Probit and percolation models with learning for different values of the learning parameter α.

p_0 and on the number of initial adopters at time t as specified in Eq. (1). In the following we will compare the cumulative percentage of adopters at the percolation threshold with the level predicted by the Probit model both without and with learning (respectively called lower and upper bounds of diffusion). The percentage of buyers from a percolation model will never exceed the value attained by the corresponding Probit model, since some adopters with a reservation price above the market price may never be reached by the contagion process, but it can when subsidies are introduced. The cumulative percentage of adopters computed by a Probit model with constant price provides a lower bound for it tells us the maximum number of consumers willing to buy the product in the absence of learning economies.

4. Results and interpretation

The following figures show the results obtained by simulating the model on a 100×100 square lattice. The results for each parameter configuration are averaged over ten simulation runs to minimize the effects of statistical variation. Consumers' reservation prices θ_i are drawn from a lognormal distribution $\Theta\approx\exp N(\Phi)$, where $\Phi\approx N(\mu,\sigma)$ is normally distributed with parameters $\mu=1$ and $\sigma=2$. The number of initial adopters is $N_0=100$ (that is, 1% of the total number of potential consumers). In an environment with learning economies, the initial level of price is $p_0=6$. According to the theory, for these numerical values percolation occurs with probability 1 for values of $p_t\leq1.698$ (see Eq. (2) with F the cumulative distribution for the lognormal). Hence, for an initial price $p_0=6$, we should not see any rapid diffusion of the new technology. Introducing price dynamics due to the learning curve may change this, however, due to the possibility of delayed take off [9].

In an environment without learning economies ($\alpha=0$), the ultimate percentage of adopters decreases with the exogenous level of prices (Fig. 2). In addition, it can be seen how much the difference in the computed percentage of adopters between the Probit model and the percolation model increases with the price level: for $p=0.2$ the results of the two models are almost the same. As p increases, the difference becomes increasingly large. Finally, the percolation model describes a delayed diffusion of the new technology even without learning economies: the percentage of adopters increases slowly over time and the path is S-shaped.

Fig. 3 illustrates the relationship between the percentage of adopters in both Probit and percolation models versus price levels. In the percolation model there exists a more non-linear relationship between price level and diffusion. There is a threshold level of p (1.69 for the assumed parameters of the lognormal distribution) at which percolation takes place. We see that for values of price lower than the threshold the percentage of adopters in the percolation model rapidly approaches the results given by the Probit, which forms an upper bound.

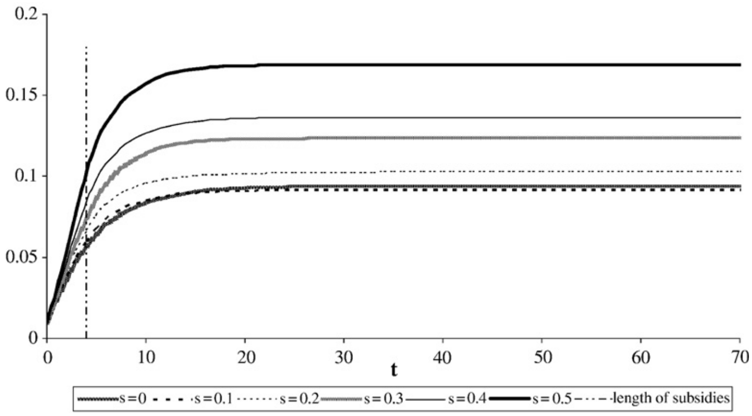

Fig. 5. Cumulative share of adopters over time for $\alpha=0.1$ and tMax$=4$ for different value of the subsidy rate.

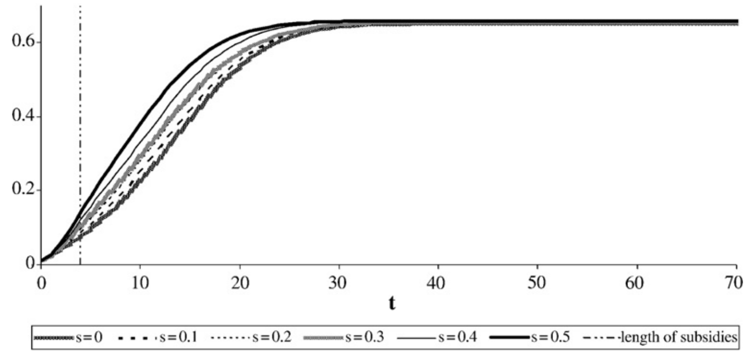

Fig. 6. Cumulative share of adopters over time for $\alpha = 0.4$ and tMax = 4 for different values of the subsidy rate.

Fig. 4 presents the results from the simulations in an environment with learning economies but no subsidies, with an initial price level $p_0 = 6$ and learning coefficients $\alpha = 0$, 0.2 and 0.4. With the increase of the learning coefficient the percentage of adopters rises. The percolation model has both a more delayed path of diffusion and a higher sensitivity to learning economies than the Probit model. The difference is lower for higher levels of α: for $\alpha = 0.4$ the results are almost the same.

The results for simulations in a world with learning economies and the introduction of subsidies are illustrated in Figs. 5–11, where we jointly vary the level of subsidies $s = [0;\ 0.1;\ 0.2;\ 0.3;\ 0.4;\ 0.5]$ and the length of subsidies in simulation time steps tMax = [4; 12; 20].

Often policy actions in favor of environmentally friendly technologies are a portfolio of different approaches implemented to encourage the emergence and the diffusion of the technology on both the supply and the demand sides. In the present paper we will only model direct subsidies to consumers. A good illustration of the kind of subsidy policy we have in mind is the Japanese policy for promoting photovoltaics [17], were the subsidy rate was gradually reduced as the technology became increasingly competitive with market prices. This policy seems to have succeeded in both fostering widespread and sustainable diffusion of photovoltaics and establishing the global dominance of Japanese producers.

When will a subsidy policy trigger a self-sustained process of diffusion? This depends upon the dynamics of adoption after the phasing out of subsidies. In order to analyze the latter issue we differentiate between three different policy options. Let us define as short-term, medium-term and long-term a policy that respectively lasts for 4, 12, 20 simulation timesteps. Figs. 5–8 illustrate the cumulative share of adopters over time for different values of the parameters s, α and tMax. Short-term subsidies ($0.2 \leq s \leq 0.5$ and tMax = 4) trigger a self-sustained process of diffusion when the learning coefficient is in the interval $0 \leq \alpha < 0.3$. The cumulative share of adopters is higher than in the case without subsidies ($s = 0$) and the process of diffusion also continues to increase after the phasing-out of subsidies. Fig. 5 illustrates the case in which $\alpha = 0.1$. The long-term effect of subsidies disappears as the level of α increases beyond 0.3 (see Figs. 9 and 6 for the case $\alpha = 0.4$, where it is also apparent that the rate of diffusion increases somewhat with s, even if the ultimate level does not). As the length of the subsidy period increases, the effect of subsidies is more striking, even for higher levels of the learning coefficient (see Figs. 7 and 8 for $\alpha = 0.4$ and tMax = [12; 20] respectively, as well as Figs. 10 and 11 for a complete overview). However only medium-term subsidies trigger a self-sustained process of diffusion: the cumulative share of adopters increases after the phasing-out of subsidies, even if to a lower extent than in the former short-term case. Long-term subsidies do not trigger a self-sustained diffusion: the process of adoption stabilizes before the phasing-out of subsidies at every level of both the learning coefficient and the level of subsidies. Adoption takes place entirely at a subsidized price level, but the level of diffusion is considerably higher than in the short-term subsidy case.

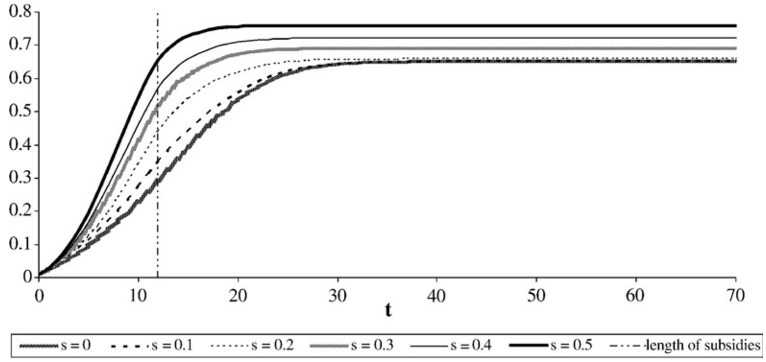

Fig. 7. Cumulative share of adopters over time for $\alpha = 0.4$ and tMax = 12 for different values of the subsidy rate.

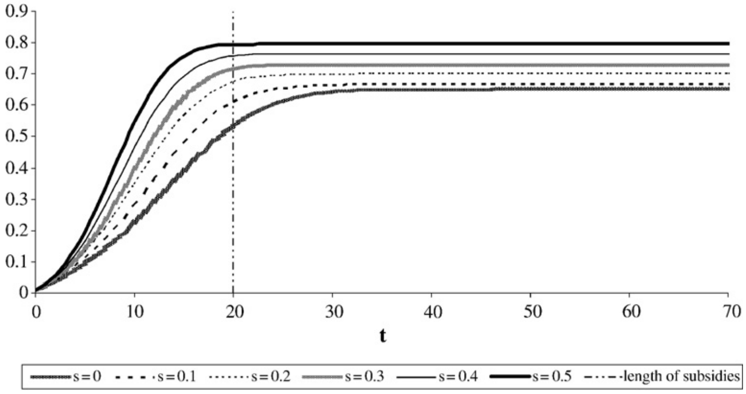

Fig. 8. Cumulative share of adopters over time for $\alpha=0.4$ and tMax = 20 for different values of the subsidy rate.

Whether a policy is a valuable option depends upon the desired level of diffusion. Let us take the Probit level of adoption as a benchmark. The new technology is adopted and diffuses widely even for initial price levels higher than the threshold ($p=1.698$). However, there exists a threshold level for the learning coefficient such that for α lower than this threshold diffusion does not take off (e.g., it does not exceed the lower bound represented by the level of diffusion given by the Probit model without learning).

In Fig. 9, where the length of subsidies tMax is four simulation time steps (the short-term subsidy case), the critical value of α decreases from 0.27 (with no subsidies, $s=0$) to 0.24 (for the highest value of subsidies, $s=0.5$). If the level of diffusion from the Probit model without learning is considered as the policy target, then a short-term policy may trigger a self-sustained diffusion to that target for values of the learning coefficient lower than the critical one but only to a certain extent (or, in other words, only in the interval $0.24\leq\alpha\leq0.27$). As the length of subsidies increases, the policy influences diffusion for ever larger intervals of α: a medium-term policy (tMax = 12) triggers diffusion for $0.13\leq\alpha\leq0.27$ (Fig. 10), whereas a long-term policy influences the cumulative percentage of adopters for $0.09\leq\alpha\leq0.27$ (Fig. 11).

The introduction of subsidies affects the threshold level of the learning coefficient: as we include a subsidy policy the critical value of α is likely to decrease. A subsidy policy may spur a self-sustained diffusion but the success of such policy actions strongly depends on the value of the learning coefficient as well as on the level and length of subsidies. If for example government would want to support the diffusion of new technology characterized by relatively low learning economies (say $\alpha=0.15$) a medium to long-term subsidy policy should be introduced: a short-term policy would not trigger diffusion to the target (Probit lower bound) for $\alpha=0.15$ (see Fig. 9), while both a medium-term (Fig. 10, $s=0.5$) and a long-term subsidy would (Fig. 11, $s=[0.4; 0.5]$).

In summary, short-term subsidies (Fig. 9) do not significantly enhance diffusion except for rather restricted values of the learning coefficient, when α belongs to the interval [0.24–0.27]. When α is too low ($0\leq\alpha\leq0.24$) the process does not take off even

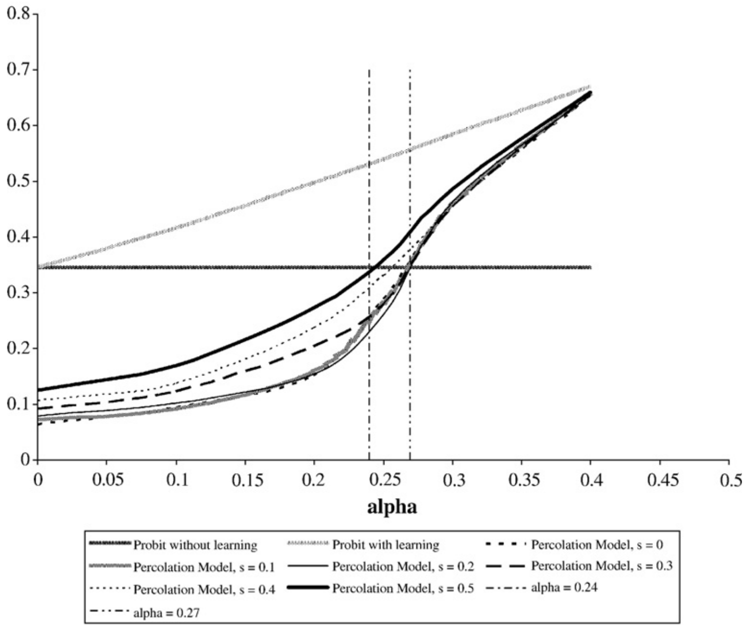

Fig. 9. Short-term subsidy policy and ultimate level of diffusion for tMax = 4 as a function of the learning exponent α for different subsidy rates.

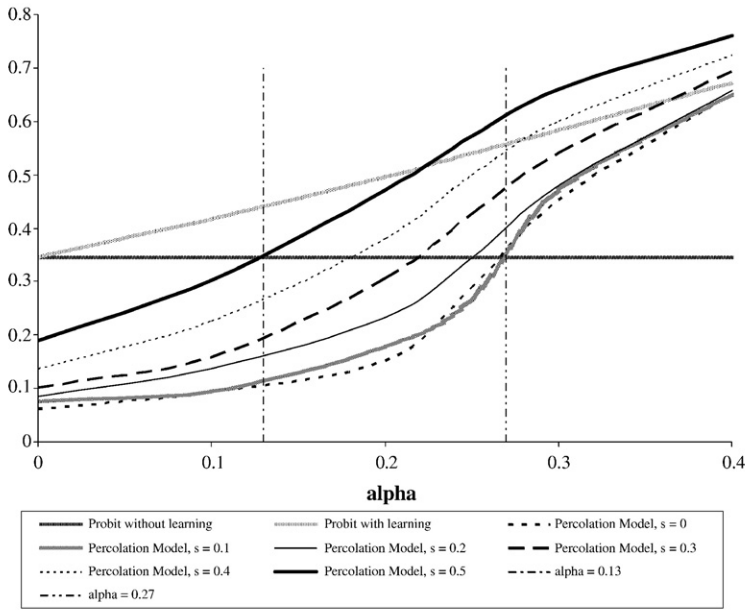

Fig. 10. Medium-term subsidy policy and ultimate level of diffusion for tMax = 12 as a function of the learning exponent α for different subsidy rates.

with a high subsidy ($s = 0.5$), and when α is high ($\alpha \geq 0.27$) diffusion takes off anyway. Especially for very high levels of the learning coefficient ($\alpha = 0.4$), the difference between the path of diffusion with and without subsidies disappears. This is less true the more the length of subsidies increases: medium-term subsidies (Fig. 10) affect the percentage of adopters, as do long-term subsidies (Fig. 11), but only when the level of subsidies is high enough (that is $0.3 \leq s \leq 0.5$ in the medium-term and $0.2 \leq s \leq 0.5$ in the long-term). Low subsidies do not guarantee a significant change in the degree of diffusion, even if we see a stronger effect when we switch from a medium-term to a long-term policy. However, the introduction of a subsidy policy is only sensible in conjunction with learning economies if the initial price is well above the percolation threshold.

We have seen that subsidies are only effective for learning parameters in a certain range (0.2–0.4). Subsidies on the demand side are in some sense dual to R&D expenditures on the supply side, which also serve to support developments efforts in a technology in the pre-commercial stage until the point where the technology "can stand on its own two feet". Empirical studies have shown that learning parameters of successful technologies are indeed, ex post, in this range [18]. This remarkable coincidence

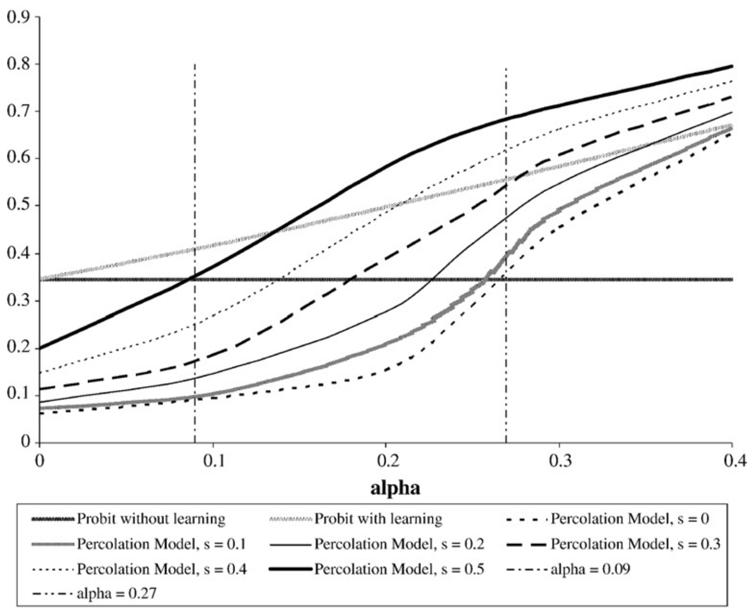

Fig. 11. Long-term subsidy policy and ultimate level of diffusion for tMax = 20 as a function of the learning exponent α for different subsidy rates.

is perhaps not so surprising, since only those technologies for which demand side or R&D subsidies had been successful investments will show up in the statistics on learning curves — there is an obvious selection bias.

5. Conclusions and directions for further research

In this article we analyze the relationship between the diffusion of a new technology, learning economies, and subsidies. The aim of the research is to investigate the path of diffusion of a new energy technology when some consumers are willing to pay more for goods that are perceived as "green" and learning economies may reduce the price as a function of the extent of previous adoption. An obstacle to the widespread adoption of environmentally friendly energy technologies such as stationary fuel cells and the use of hydrogen is their high upfront costs. While much lower prices seem to be attainable in the future due to learning curve cost reductions that increase rapidly with the scale of diffusion of the technology, there is a chicken and egg problem, even when some consumers may be willing to pay more for green technologies. Policy actions devoted to spurring the diffusion of these kinds of technologies may help overcome initial barriers, but in order to be worthwhile, governmental interventions should trigger a self-sustained process. It is not clear when a technology will pass a threshold to widespread adoption and competitive market pricing, and when it will fail. The latter seems too often to be the case without long-term subsidies.

Among others approaches, epidemic and Probit models have been separately used to analyze the process of technology diffusion. We have developed a percolation model in which both information contagion and agent heterogeneity are taken into account and interact in nontrivial ways. The percolation model is then extended to allow for the introduction of learning economies, which then explain the delayed take off of new technologies. This results in a more non-linear relationship between price levels and the extent of diffusion than in a standard heterogeneous threshold (Probit) model. The percolation model has both a more delayed path of diffusion and a higher sensitivity to learning economies than the Probit model. The new technology is adopted and diffuses even for price levels higher than the threshold. But there exists a threshold level for the learning coefficient α below which diffusion does not take off.

Whether a policy triggers a self-sustained process of diffusion depends upon the dynamics of adoption after the phasing-out of subsidies. Short-term subsidies ($0.2 \leq s \leq 0.5$ and $t\text{Max} = 4$) trigger a self-sustained process of diffusion when the learning coefficient falls in the interval $0 \leq \alpha \leq 0.3$. Diffusion continues strongly even after the phasing-out of subsidies. But the effect of subsidies diminishes as the level of α increases. As the length of the subsidy period increases, the model shows that policy remains effective even for higher level of the learning coefficient.

However, whether a policy is a valuable option depends upon the desired level of diffusion. Let us take the Probit lower bound as the policy target. The introduction of subsidies affects the threshold level of the learning coefficient: as we include a subsidy policy the critical value of α is likely to decrease. A subsidy policy may spur diffusion but the success of such policy actions strongly depends on the value of the learning coefficient as well as on the level and length of subsidies. Given the target, short-term subsidies are of limited utility in two cases: when the learning coefficient is too low ($0 \leq \alpha \leq 0.24$) the process only takes off for very high levels of subsidies ($s = 1$), and when α is high ($\alpha \geq 0.27$) diffusion takes off anyway. Especially for very high levels of the learning coefficient ($\alpha = 0.4$), the difference between the path of diffusion with and without subsidies disappears. This is less true the more the length of subsidies increases: medium-term subsidies significantly affect the ultimate level of adopters, as do long-term subsidies. But this is true only when the level of subsidies is high (e.g. $s = 0.5$): a low level of subsidies ($s = [0.1; 0.2]$) does not guarantee a relevant change in the degree of diffusion, even if we see a stronger effect when we switch from a medium-term to a long-term policy.

To more fully evaluate the appropriateness of subsidy policies it is necessary to formulate some kind of cost-benefit analysis to measure the returns to subsidized adoption in terms of additional environmental goods (foregone pollution, for example, due to a wider and earlier diffusion of an environmentally friendly technology) versus the subsidy costs to the taxpayer. Our intuition says that there must be a "sweet spot" in parameter space and subsidy design space at which subsidies are maximally effective in triggering adoption and widespread diffusion without wasting money on adopters who would have adopted anyway. Because the system is so non-linear, the existence of such a "sweet spot" seems likely, although whether policymakers could always find it in practice, given the uncertainties surrounding the learning parameter and consumers' propensities to adopt, remains to be seen. We are currently working on simulation experiments in this direction.

Additional realism would be added by allowing for a portfolio of new technologies to be present instead of the standard assumption of just one innovation competing against an incumbent. A simple modification of the present model could address this question by using a multinomial decision mechanism to model each adopter's choice.

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