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A PERCOLATION MODEL OF MULTI-TECHNOLOGY DIFFUSION: INFORMATION FEEDBACKS, LEARNING ECONOMIES AND SUBSIDY POLICY

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A percolation model of multi-technology diffusion: information feedbacks, learning economies and subsidy policy

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Abstract

This paper deals with the diffusion of innovations in a multi-technology setting. High up-front costs of adoption, heterogeneity among potential adopters, network interactions, information feedbacks and subsidy policies are reproduced by an agent-based percolation model of multi-technology diffusion. In our model a new technology incorporated in a final product ready to be commercialized may spread in a market of heterogeneous consumers who decide whether to adopt it or not depending on both the net benefit from adoption and on locally available information. A new desirable technology, characterized by a high up-front cost of adoption, may not be able to overcome the obstacles to its diffusion despite potential future cost reductions. It may fail to spread in the market because of the pressure from its competitors (i.e. other technologies that serve a similar function) or because heterogeneity among potential adopters confine the spread of useful information to isolated sub-communities. We ask if a subsidy policy would trigger a self-sustained diffusion of a desirable technology. We run the model in two specific network topologies: bi-dimensional regular lattice and small world network. We show that a) information feedbacks and learning economies give raise to a positive feedback loop almost independently on the topology of the network: more information feedbacks $\rightarrow$ decrease in price $\rightarrow$ higher probability of conquering potential adopters $\rightarrow$ more information feedbacks etc; b) market dominance depends on the probability of the initial adopters to belong to an expanding cluster which is a function of both the network topology and heterogeneity of potential adopters; c) in a multi-technology setting a subsidy policy should be set not only according to future costs reduction and heterogeneity but also to competition and technologies interdependence: reaching the necessary critical mass of diffusion may depend on how successfully the overall spread of other undesirable technologies is prevented.

JEL classification: C61; H23; O32; O33

Keywords: Multi-technology diffusion; Learning economies; Percolation; Networks; Heterogeneous agents; Adoption subsidies; eco-innovations

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1. Introduction

This research explores the realm of economics of innovation by investigating specifically the phase of diffusion. High up-front costs of adoption, epidemic-like contagion mechanisms, locally available information and heterogeneity are among the barriers to frictionless diffusion (see Stoneman, 2002). Although the waves of innovation look diverse depending along the coast of which territory they rise and fall, nonetheless they all seem to be driven by learning curve costs reduction. By drawing on successful applications of percolation theory to the diffusion of innovations (Antonelli, 1996; Solomon et. al, 2000; Silverberg Verspagen, 2005; Frenken et al., 2006; Honhisch et al., 2008; Cantono and Silverberg, 2009), we develop an agent-based percolation model of multi-technologies diffusion, we explore the relation between learning economies and information feedbacks and we propose reflections about some necessary features of a subsidy policy devoted to support the spread of a desirable new technology.

In this paper we mainly focus our attention on the specific problem of the diffusion of new technologies that exhibit initial high upfront costs and are characterized by learning economies (i.e. costs reduction attainable in the future). We treat the emergence of innovations as exogenous and we investigate demand-side factors. We assume that a certain technology has been already incorporated into a new product and sold to final consumers. Although there might be adopters willing to pay more for an innovation (i.e. potential adopters are heterogeneous), a new desirable[2] technology may not be able to overcome the obstacles to its propagation. Public authorities may be called to sustain its diffusion at the early stages of its deployment. We model the case of short-term and long-term adoption subsidies and we investigate their impact on the diffusion of desirable technologies.

Since the pioneering work of Griliches (1957), many barriers to innovations diffusion have been unveiled (Mansfield, 1961, 1968; David, 1969; Davies, 1979). The models of technology diffusion roughly falls in one or the other of the following two categories: epidemic and rank models. The essence of epidemic models lies in the contagion mechanism. In a homogeneous population the emergence of a technology is exogenously given. As soon as potential consumers are "infected" by it, the technology spreads over the entire population. Slowly at the very firsts instants and faster as more and more consumers adopt it until it reaches the asymptotic level of cumulative buyers *N*. The merit of epidemic models is that of explicitly considering information contagion. Moreover those are disequilibrium models, e.g. models in which the equilibrium cumulative number of adopters is reached only at the end of the process. Nevertheless they suffer from the hypothesis of homogeneity of population, from the uniformity of benefits and from the intrinsic feature of reproducing an autonomous process of diffusion (once the innovation has been adopted by at least one consumer, sooner or later it will be adopted by all the others via contagion).

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[2] The simplest example of a socially desirable technology is that of eco-innovations. However, it is usually difficult to detect which new environmental technologies is the best among the many available. Here we make our life simple by assuming the most promising technology is detectable which is hardly the case in reality. Finding a the proper strategy in this respect could a relevant topic for future research.

The economic behaviour and the effects of heterogeneity that lies behind the decision to adopt a new technology are instead at the heart of probit or rank models where the profitability and arbitrage conditions dictate that a technology is adopted only if benefits exceed costs of adoption and only at the moment that assures the highest benefits. However the first and second order conditions just stated do not explain the sigmoid path of diffusion, in fact elucidated by exogenous costs changes over time. The disadvantage of these kind of models is that of considering the individual benefit independently distributed and unrelated to the number of previous adopters.

In this model epidemic-like contagion mechanisms, heterogeneity, learning economies and policy interventions are merged together as in Cantono and Silverberg (2009). Here we extend their model to a multi-technology setting and we explore the effects of information feedbacks. In our setting, new technologies will spread because of both the dissemination of information and as a consequence of the choice of heterogeneous rational consumers distributed as nodes on a network. The dissemination of information has been found to be significant in defining the pace of diffusion. Rather then treating information as global, we will consider it as local. But the meaning of an underlying network might also be understood in the following terms: even when potential adopters might be aware of the presence of a new technology, they may still be reluctant to adopt it if they think it is difficult to use and/or unreliable. Thus the presence of an underlying network structure does not only advance our understanding in terms of the effects of locality. It explicitly allows us to take into account the effects of the reduction of risk on commercial transactions when economic actors do not solely rely upon market mechanisms (Granovetter, 1985). Moreover we address the effects of information feedbacks which arise when potential adopters sample among buyers in order to collect information on the new technology: a new technology may be difficult to use and thus it may require the collection of additional information. The more buyers of a technology the highest the chance that technology would be selected. Information feedbacks have been introduced by Arthur and Lane (1994) and have been studied in isolation from learning economies or other self-reinforcing mechanisms. Finally we show the effects of a subsidy policy over the initial cost of adoption and we offer some interesting results which call for mixed strategies.

The rest of the paper is organized as follow. In Section 2 we illustrate the details of the model. In Section 3 we describe the results and we give an interpretation. Section 4 concludes.

2. The Model

Our model is based on the percolation model of innovation diffusion developed by Cantono and Silverberg (2009). Here we extend their model to a multi technology setting.

Let us locate M potential adopters at each node of a certain network topology. We model two types of networks: the two-dimensional regular lattice (where the neighbourhood is represented by the four nearest neighbours, i.e. Ising network) and the small world networks (Wattz and Strogatz,1998). As opposed to a regular lattice where every node has the same amount of neighbours, in a small world the number of neighbours is diverse depending on the node.

Every individual has the chance to choose one technology out of a set of *m* possible technologies that serve a similar function (i.e. they are perfect substitutes). Each individual will become an adopter only if both of the following conditions hold: at least one of her neighbours (defined according to the network topology) has already bought one of the available technologies; the market price of the technology is lower than her reservation price. Reservation prices are distributed according to a log-normal distribution, $\theta \approx LN(\mu, \sigma)$. A consumer is allowed to adopt a technology only once. The market price of technology *i* at each simulation time step *t*, $p_{i,t}$, decreases with the increase in the cumulative number of adopters according to:

$$p_{i,t} = p_{i,0}\left({N_{i,0}}\Big/{N_{i,t}} \right)^{\alpha_i} \qquad [1]$$

where $p_{i,0}$ is the initial price of technology i, $N_{i,0} = 1$ is the number of early birds[3] per each technology *i*, $N_{i,t}$ is the number of cumulative adopters at time *t* and α_i is the learning coefficient specific to each technology. Eq. [1] shows the price dynamics: as the number of adopters increases over time, the price of the technology adopted decreases. The learning coefficient represents the extent of price decrease due to the rise of units sold / produced.

Let us define as $P_0 = [\, p_{i,0}, \ldots, p_{m,0} \,] \forall i = 0,1,\ldots,m$ the vector of the initial market price of the technologies at the disposal of potential adopters. And $P_t = [\, p_{1,t}, p_{2,t}, \ldots, p_{m,t} \,]$ the vector of prices at each simulation time-step. Depending on the choices of her neighbours, a potential consumer will select one technology according to the *wheel mechanism*.

In particular, let us the final the level of attractiveness of technology *i* at time *t*, $A_{i,t}$,as:

$$A_{i,t} = w_{i,t} \qquad [2]$$

where $w_{i,t}$ represents the number of neighbours that have chosen technology *i* at time *t*.

The wheel probability for technology *i* to be chosen at time *t*, $\pi_{i,t}$, is:

$$\pi_{i,t} = \frac{A_{i,t}}{\sum_{j,t} A_{j,t}}, \ \pi_{i,t} \geq 0, \ \Pi = \sum_{i,t} \pi_{i,t} = 1. \qquad [3]$$

The wheel mechanism works in the following way. Suppose to have the values of the cumulative distribution for every $\pi_{i,t}$. Assume that the cumulative distribution can be depicted on a circle with perimeter equal to 1. Distribute the values $s_{1,t} = \pi_{1,t}$, $s_{2,t} = \pi_{1,t} + \pi_{2,t}$, $s_{3,t} = \pi_{1,t} + \pi_{2,t} + \pi_{1,t}$ along the circle. Draw a random number *R* from $X \approx I(0,1)$. If R falls in the interval $[\, 0, s_{1,t} \,]$ then

[3] We treat the emergence of a technology as exogenous, we assume that the technology has been already incorporated into a product to be sold to final consumers.

technology 1 is chosen and afterwards compared to the reservation price. Technology 2 is chosen if R falls in the interval ($s_{1,t}$, $s_{2,t}$]. For R in the interval ($s_{2,t}$, $s_{3,t}$] technology 3 will be chosen.

The results of the simulations are presented in the next section.

3. Results and interpretation

We run the model in networks with a total number of nodes (potential buyers) $M = 10000$. This model does not explain the emergence of an innovation, indeed the number of early birds is an exogenous parameter. Throughout the paper, the number of early birds is kept constant and equal to 1 for each technology ($N_0 = 1$). We are investigating the process of multi-technology diffusion in both a two-dimensional regular lattice and a small world network (with different values of rewiring probability). We first describe the results in an environment without learning economies, e.g. $\alpha_i = 0$ for each technology *i*. We thus show the effects of learning economies and information feedbacks by allowing the learning coefficient to vary ($0 \le \alpha \le 0.5$)[4]. The critical price depends on the parameters of the distribution of the reservation price. For a Lognormal distribution with parameters $\mu = 1$ and $\sigma = 2$, the critical percolation price is $p_c \cong 1.7$: without learning economies, a technology with an initial price $p_0 > 1.7$ never percolates over the entire network.

The results are described by the Herfindahl Index (H_Index), that is an index of market share. The number of technologies is a parameter $nP = 3$. Thus the H_Index ranges from about 0.33 to 1: the lower limit represents a situation of perfect equal share in the market, whereas the upper limit depict a situation of perfect dominance of one technology over the others. The results for each parameter configuration are averaged over twenty simulation runs to minimize the effects of statistical variation. Let us separately illustrate the outcomes of our analysis in a learning economies free environment first (3.1). Then we show the relationship between learning economies and information feedbacks (3.2). And finally we offer some policy implications (3.3).

3.1 Price Simulations

All the three technologies have the same initial price and the same number of early birds. In a learning economies free Ising network, they end up sharing the market equally: if the network structure is a two-dimensional regular lattice, information feedbacks do not emerge. Every technology spreads as if it were in a separate island. Figure 1[5] shows the value of the H_Index versus the value of the initial price p_0 for different values of the rewiring probability. In a small world network, where potential buyers have the chance of sampling information, and for values of p_0 around the percolation phase transition, e.g. $p_c - \delta < p_0 < p_c + \delta$ with $\delta > 0$, the H_Index shows signs of inhomogeneity (Figure 1).

In general it can be stated that:

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[4] The choice on the range of the learning coefficient is based on empirical evidence (see McDonald and .Schrattenholzer, 2000).

[5] All the figures and tables are in the Appendix.

- In a learning economies free Ising network information feedbacks have a negligible impact;
- in a small world network, long distance links slightly increases the chance for a technology to dominate; however their effects is confined to values of p_0 around the percolation phase transition and only at low levels of the rewiring probability (Figure 2). The increase in the rewiring probability, when learning economies are not at work, is that of increasing the number of islands of diffusion (Figure 3 and 4).

3.2 Learning Economies Simulations

Percolation might take place also when $p_0 > p_c$, provided that learning economies are high enough to drive p_0 down to p_c before the process gets stuck. In Figures 5, 6, 7 and 8 and in Table 1, we set $p_0 \cong 3p_c$ and we let the learning coefficient α to vary.

Figure 5 shows the H_Index versus the rewiring probability for different values of alpha. The combined effect of learning economies and information feedback may drive a technology to market dominance. For high values of the learning coefficient ($\alpha \geq 0.2$) the H_Index does not depend on the network structure: changes in the rewiring probability do not significantly influence the H_Index. The curve $\alpha = 0.1$ shows more variability with the increase in the rewiring probability. Figure 6 shows an increase in the H_Index around $\alpha \cong 0.2$. At that level of α, and for those values of the parameters, there is the percolation phase transition: as the series of figures show (Table 1), for a given high initial price, diffusion takes place at values of $\alpha \geq 0.2$. For values of alpha around the percolation phase transition information feedback effects appear. While failures dominate at low levels of the learning coefficient (documented by the small number of successful runs at $\alpha = 0.1$, Table 1)[6].

The results given so far might be influenced by a small sample bias. Although they seem to be stable enough, further runs should be implemented. Moreover the Herfindahl Index describes the relative dominance of a technology but it does not reflect how much the process of diffusion was successful.

Finally, we would like to discuss in more details how learning economies and information feedbacks mechanisms interact with each other with the support of graphical tools. Figures 7 and 8 shows some interesting features of the diffusion process:

- The effect of susceptibility at *p*: at an initial price p_0 far from the critical price p_c, the probability for a seed of falling in a non expanding cluster is very high, especially if the rewiring probability is low. This means that in addition to the self-reinforcing mechanisms of both learning economies and information feedbacks, market dominance is also a result of the susceptibility condition that depends on both the network structure and, indirectly through the critical density, on the distribution of reservation price.

[6] The high value of the H_Index at low levels of alpha ($\alpha < 0.2$) is also influenced by many cases of unsuccessful diffusion. Whereas, those around the phase transition ($\alpha = 0.25$) and over are supported by a higher number of realizations (Table 1).

- With the increase in the rewiring probability, the effect of learning economies is more evident: this is due to the fact that long range links can partly overcome the obstacles eventually encountered at the beginning of the propagation process.
- The increase in the rewiring probability boosts learning economies: sampling and learning effects origin a positive feedback loop: more information feedbacks $\rightarrow$ decrease in price $\rightarrow$ higher probability of conquering potential hubs $\rightarrow$ more information feedbacks etc.

3.3 Policy Simulations: an informative exercise

We investigate the effects of a subsidy policy that supports the spread of a technology characterized by an initial high up front cost, potential learning economies and environmental desirability. Would a limited subsidy policy trigger a self-sustaining process of diffusion of that technology?

We differentiate between short-term and long-term policy. A short-term policy is a policy that last for 4 simulation time-steps, whereas a long-term policy lasts for 8 simulation time-steps. There are three technologies competing for market share: technology 1, 2, 3. Technology 1 represents the "green" technology (for instance fuel cell stationary heating system), characterized by a high up-front cost ($p_0 = 6$) and a relatively high learning coefficient ($\alpha = 0.2$). Technology 2 (for instance photovoltaic technology) is characterized by a lower initial price ($p_0 = 2$) and weaker learning ($\alpha = 0.1$). Technology 3 (as an example technology 3 might represent a traditional fossil fuel-based energy technology) has a low initial price ($p_0 = 1$, infact lower than p_c) but cannot benefit from learning economies ($\alpha = 0$). Suppose it is possible to detect the most promising green technology and let it be technology 1. Assume the public authority wants to support it with a 50% constant subsidy over the initial cost of adoption, i.e. $s_1 = 0.5$ and:

$$p_{1,t} = p_{1,0}\left({N_{1,0}}/{N_{1,t}} \right)^{\alpha_i} (1 - s_1)^7 \qquad [4]$$

Would this limited static subsidy policy trigger technology 1 to market dominance, and if yes, under which conditions? Let us illustrate the cases of a short-term and long-term policy.

- *Short-term policy*: Figures 9, 10, 11, 12, 13, show the extent of diffusion for each simulation run performed (in total 10 runs). Figure 9 shows the extent of diffusion in a regular lattice (the rewiring probability is equal zero) and without subsidies. As expected, technology 3, the one with the lowest initial price, always win. In this case, technology 1 suffers because of the criticality or susceptibility discussed above. While technology 2, although potentially successful, does not have time enough to reach the critical mass (i.e. it does not benefit from its potential learning economies) and thus it does not spread. Figure 11 depicts diffusion when a subsidy policy to technology 1 is implemented. As the figure shows there is not much difference between this case and the previous one: the subsidy policy is not sufficient. The following figures (11, 12, 13) show the extent of diffusion for the three

[7] See Cantono and Silverberg (2009)

technologies at different levels of the rewiring probability (0.05, 0.1, 0.2). Despite an increase in the rewiring probability and thus and increase in the chances of information feedbacks effects, the short-term subsidy policy is still insufficient: technology 1 does not even conquer the 10% of the market.

- *Long-term policy*: let us see the results in the case of a long-term policy. The parameters are the same as before, as well as the organization of the figures (Figure 14 – rewiring probability RP = 0 and Technology 1 is subsidized, $s_1 = 0.5$; Figure 15 – RP = 0.05; Figure 16 – RP = 0.1; Figure 17 – RP = 0.2). The only change is related to the length of subsidies: we are implementing now a subsidy policy to technology 1 that last for 8 simulation time-steps. The situation for technology 1 looks slightly better, however the number of successful realizations is still very low: technology 1 seems destined to fail.

The policy exercise that we just presented leads to some reflections. Arbitrarily setting the level of subsidy does not guarantee the success of a technology, no matter how much desirable it is. The amount of subsidies, which is even budget-constrained (one important aspect which we do not deal with), should be set according to the combination of mechanisms at work: a mixed strategy, where taxes obstruct the diffusion of undesirable technologies (technology 3 in our simple example) is probably the winner one. Moreover a dynamic subsidy strategy should be considered: relatively high up-front costs should be faced by high subsidy provided at the outset of the innovation and it is likely the case that they will be less and less necessary over the late stages of the propagation process. Finally, our simple model gives decision makers (though it does it in an approximate way and depending on available empirical evidence) the opportunity to test whether a technology is potentially successful or not and it contributes to identify potential wastes of resources.

4. Conclusions

In this paper we analyzed the dynamics of diffusion paths in a multi-technology setting. We developed a percolation model of multi-technology diffusion by extending the stand-alone technology model developed by Cantono and Silverberg (2009). We accounted for learning economies, included heterogeneity and rationality, illustrated the effects of information spreading and possibly described an economic system not exclusively grounded on market mechanisms. We proposed some reflections about static adoption subsidy policies and, hopefully, paved the way for further research in this direction.

Let us briefly summarize the main results. In a two-dimensional regular lattice and a learning economies free environment, information feedbacks do not arise. In a small world network, long distance links slightly increase the chance for a technology to dominate; however their effects is confined to values of p_0 around the percolation phase transition and show up only at low levels of the rewiring probability. The increase in the rewiring probability, when learning economies are not at work, is that of increasing the number of islands of diffusion. At an initial price far from the critical price, the probability for a seed of falling in a non expanding cluster is very high, especially if the rewiring probability is low. This means that in addition to the self-reinforcing mechanisms of both learning economies and information feedbacks, market dominance is also a result of the susceptibility condition that depends on both the network structure and, indirectly through the critical density, on the distribution of reservation price. The combined effects of learning economies and information feedbacks give rise to a self-reinforcing mechanism only in the imminence of the percolation phase transition: more information feedbacks $\rightarrow$ decrease in price $\rightarrow$ higher probability of conquering potential hubs (or simply potential adopters in the Ising network) $\rightarrow$ more information feedbacks etc.

We finally investigates the implications of a subsidy policy. In particular whether a subsidy policy would trigger a self-sustained process of diffusion of a desirable technology with high initial up-front costs. Competition and technologies interdependence are essential elements: the same subsidy policy useful to trigger a self-sustained process of diffusion of a stand-alone technology might not be enough when many technologies are competing in the same market. It is not only a matter of reaching the critical mass, but also a matter of time: if we want a socially desirable technology to diffuse in the market, it is also necessary to prevent the spread of other undesirable ones. The question is not only on whether is better to tax the old technology or to subsidized the new one, but which combination of taxes and subsidies should be implemented. In this paper we investigated the effects of a static policy strategy.

A challenge left to future research is that of validating the results against real historical data on the one hand, and of collecting information on the empirical values of the parameters in order to produce policy forecasts on the other. The latter may be a difficult task. Learning economies have been widely analyzed and empirically measured (see for instance McDonald and Schrattenholzer, 2000). But the characterization of the network topology may be harder as well as the identification of potential adopters' heterogeneity. Although the policy implications of our model may be of help to decision makers, nonetheless the amount of available data needed to configure our system might not be sufficient.

Another limitation of our model consists in the assumption of a static distribution of adopters' willingness to pay, for in reality it is both likely to display a dynamic character and hardly independent on future expectations. This issue is, in our opinion, as relevant as the empirical validation.

Finally, although we contribute to the literature by showing the dynamics of multi-technology diffusion in different network topologies, our network structure is still static and thus does not allow either for endogenous or for sudden emergence of both new consumers and new technologies.

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Appendix

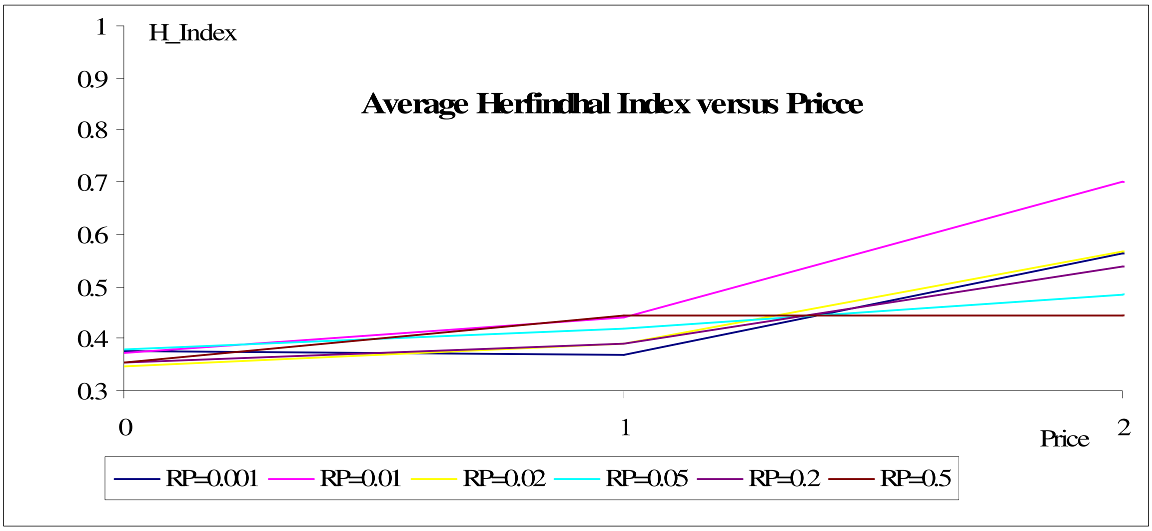

Figure 1: Average H_Index versus the initial price for different values of the rewiring probability (RP). The critical percolation price pc is around 1.7

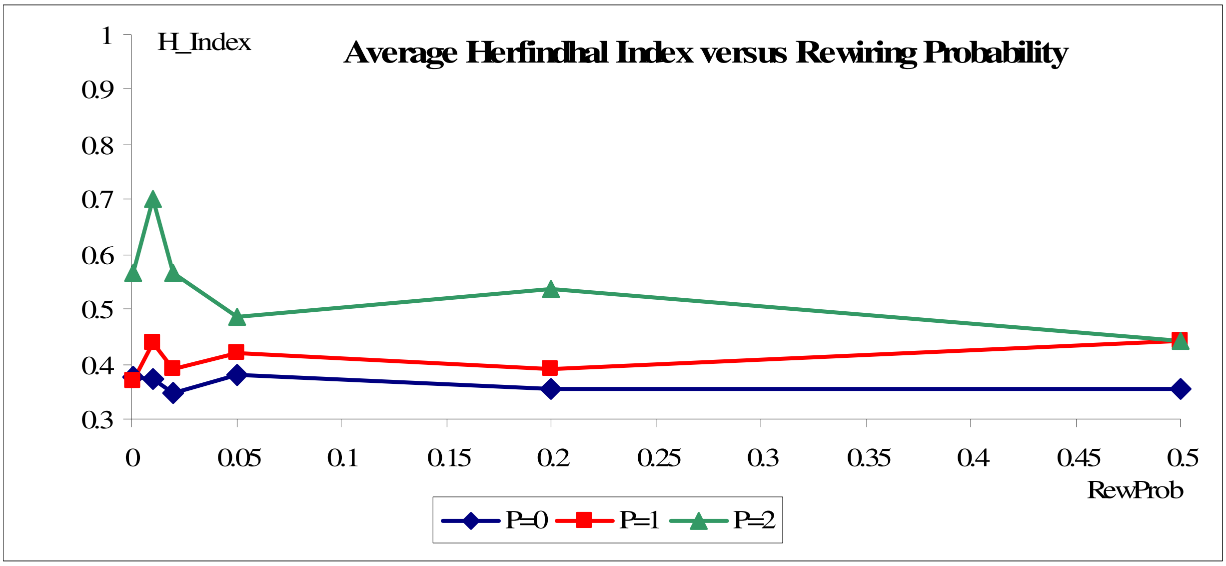

Figure 2: Average H_Index versus the rewiring probability for an initial price=0, 1, 2.

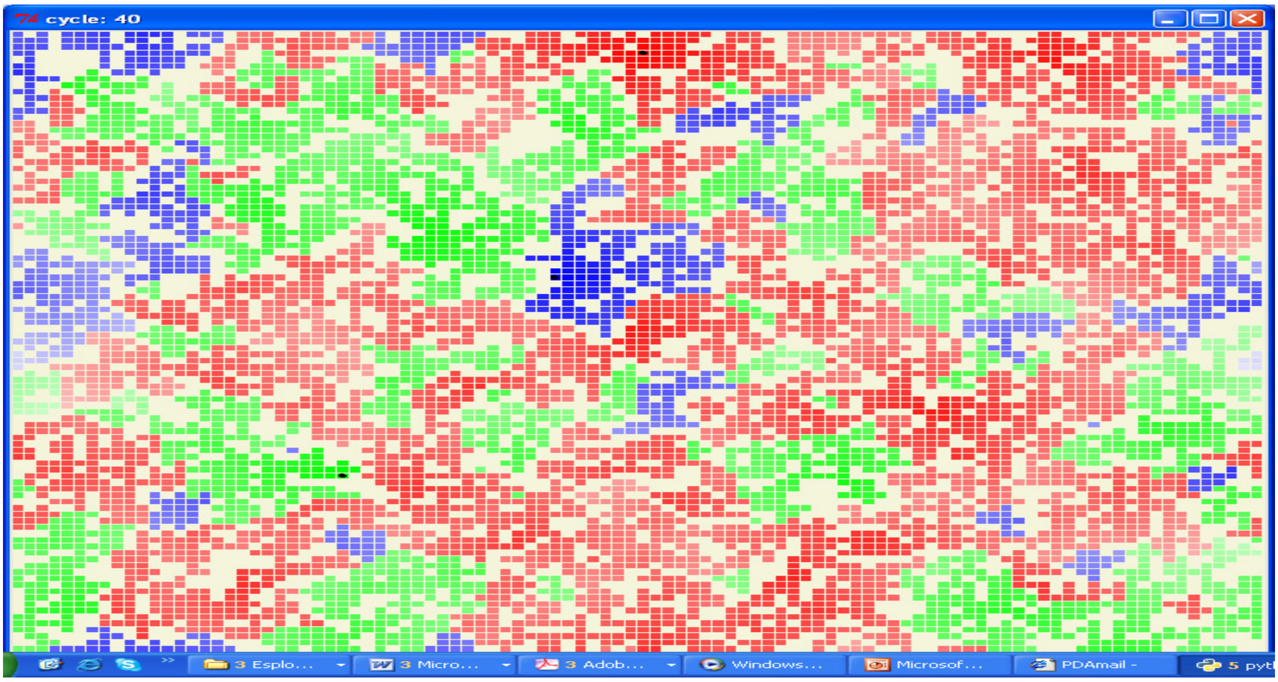

Figure 3: diffusion of the three technologies (red, green, blue) over the network with a rewiring probability = 0.05. All the technologies have an initial price pt < pc

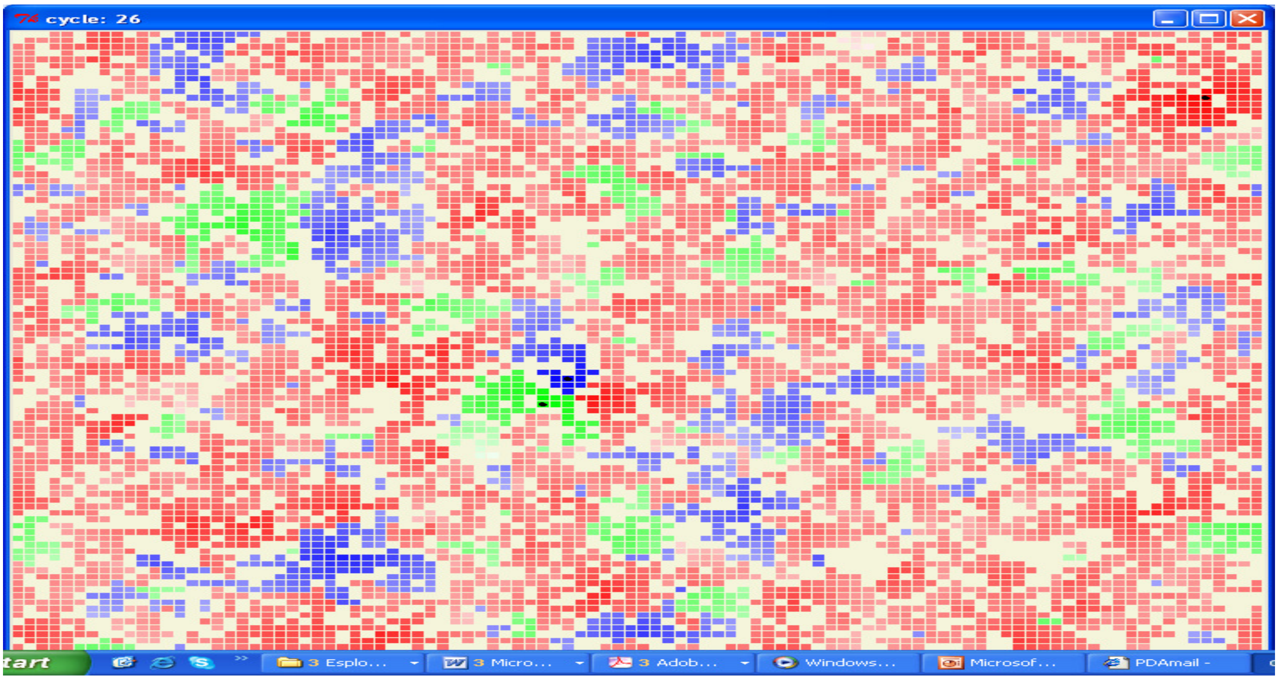

Figure 4: diffusion of the three technologies (red, green, blue) over the network with a rewiring probability = 0.2. All the technologies have an initial price pt < pc.

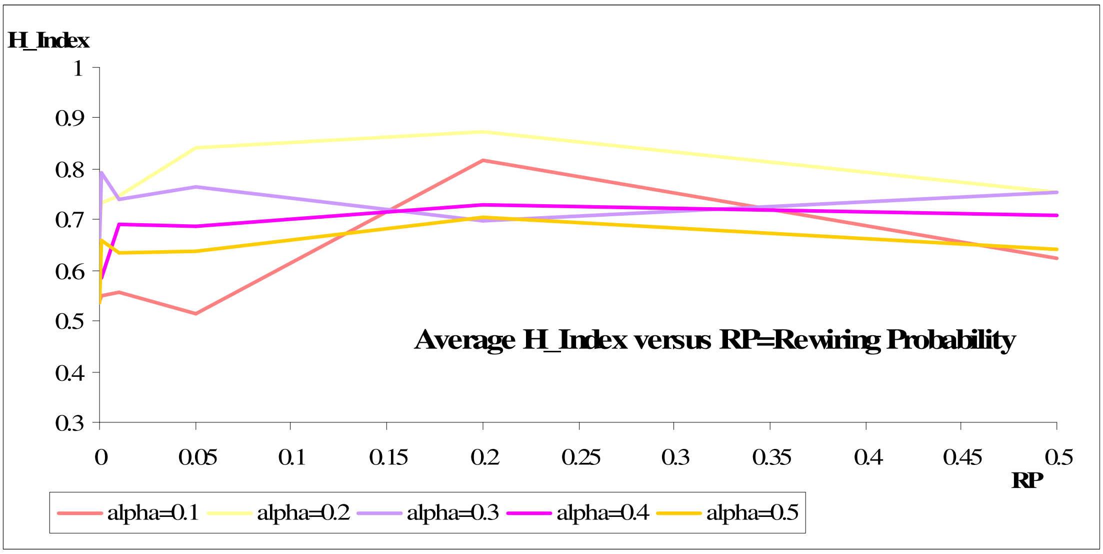

Figure 5: Average H_Index versus the rewiring probability for different values of alpha

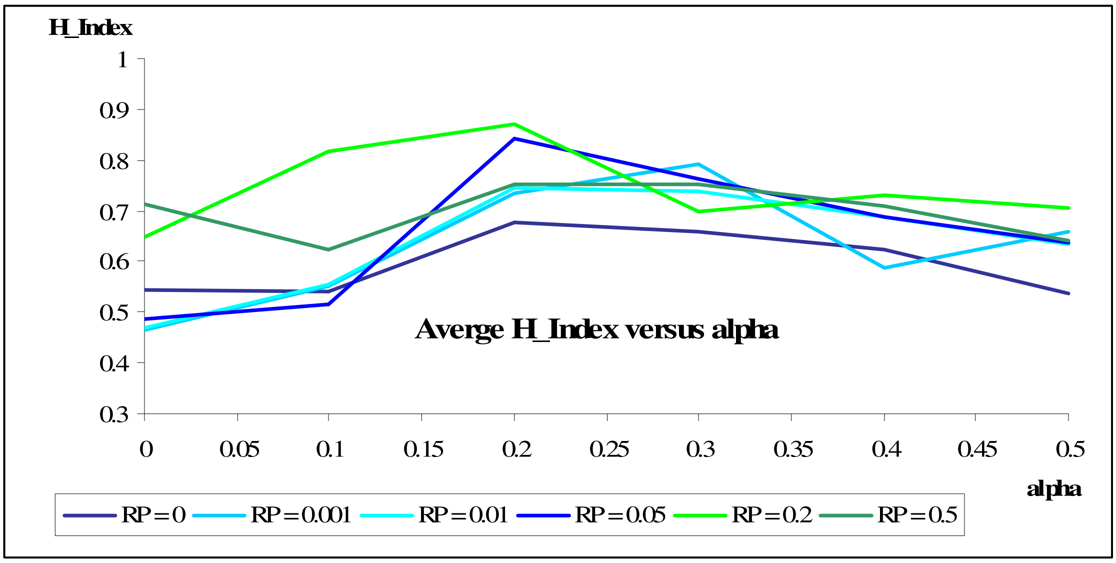

Figure 6: Average H_Index versus alpha for different values of the rewiring probability

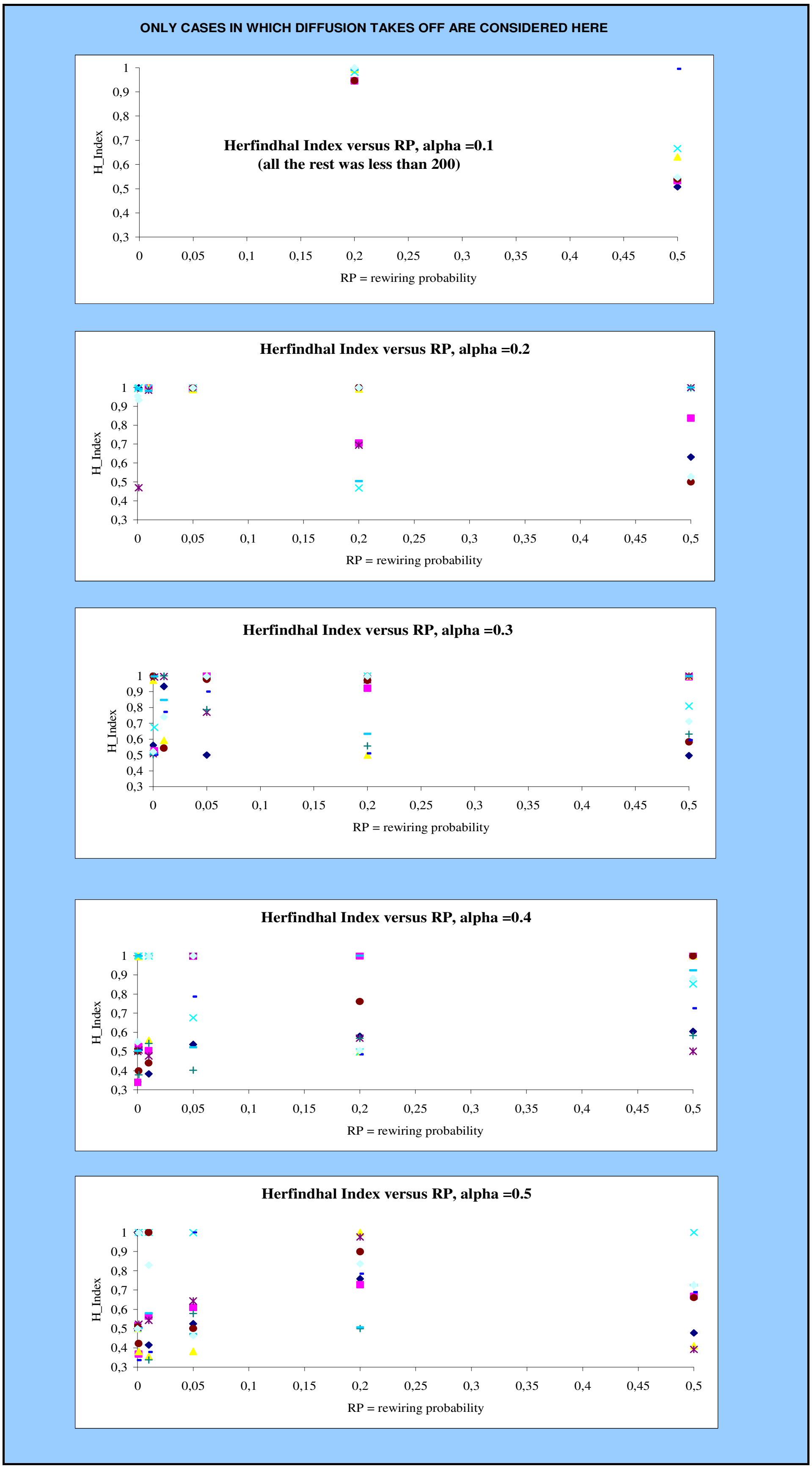

Table 1: in the series of figures we show the value of the H_Index (vertical axis) versus the rewiring probability (horizontal axis) for each run. Each figure describe the situation at a certain level of the learning coefficient, starting from alpha = 0.1 to alpha = 0.5.

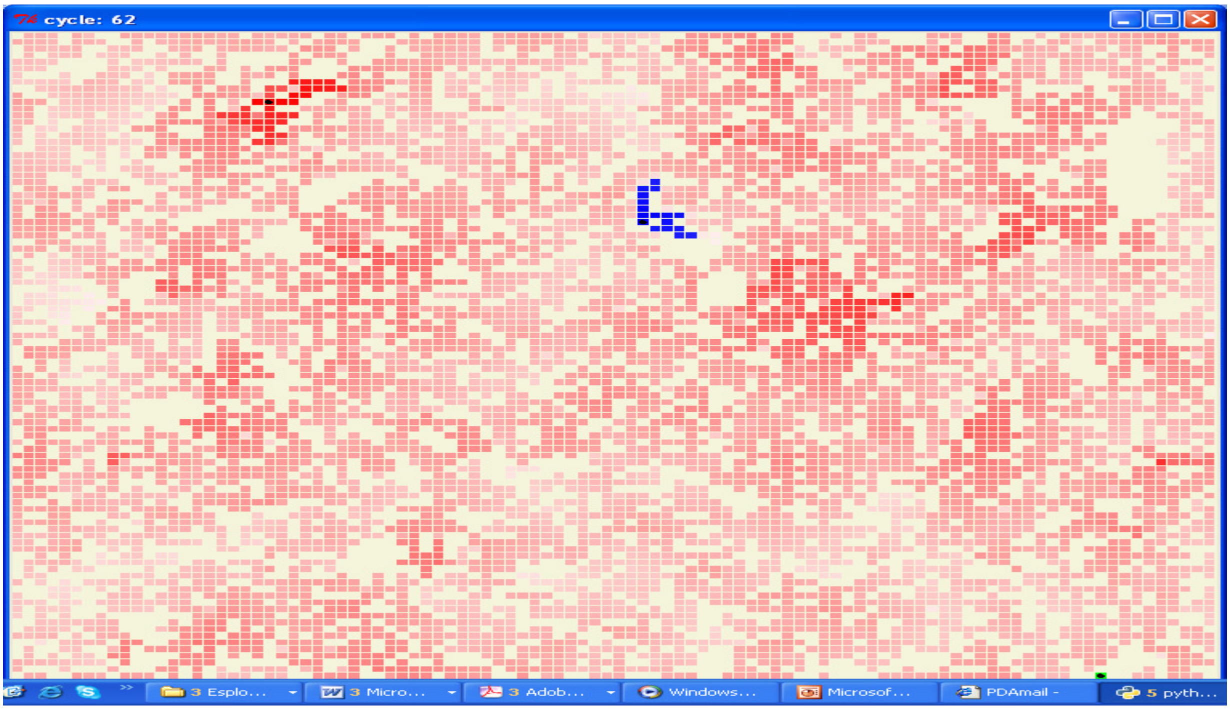

Figure 7: At a low value of the rewiring probability and with an initial price higher than the percolation price, the chance for a seed to fall in an expanding cluster is very low, even with high learning economies. The technology in red conquered all the market. The technology in blue just conquered a bunch of buyers, whereas the process of diffusion could not even start for the technology in green.

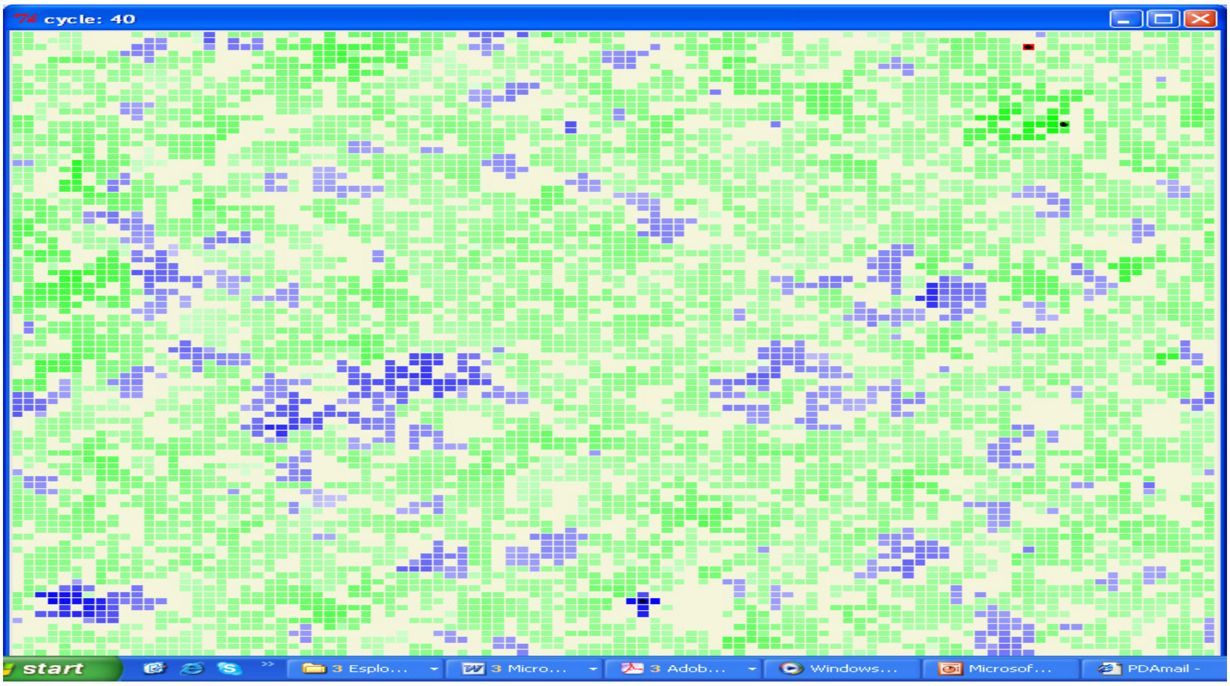

Figure 8: The increase in the rewiring probability slightly increases the chance for a technology to reach a considerable diffusion, although this is not true for each of the technologies. Indeed the process of diffusion for the technology in red could not even start.

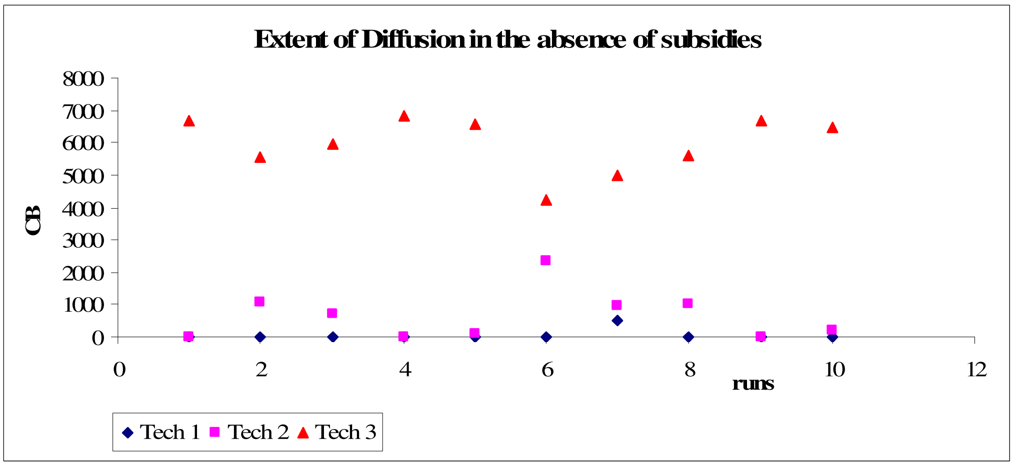

Figure 9: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the absence of subsidies in a regular lattice; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

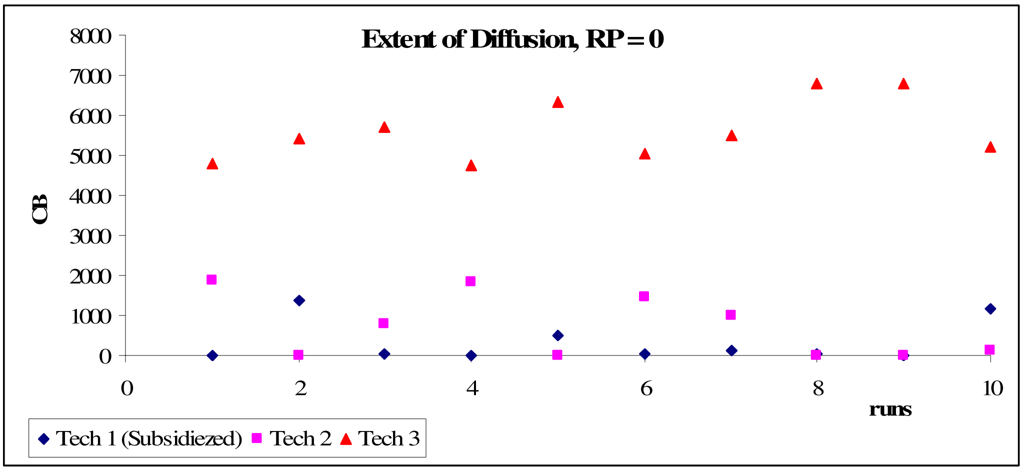

Figure 10: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a regular lattice; a short-term policy (4 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

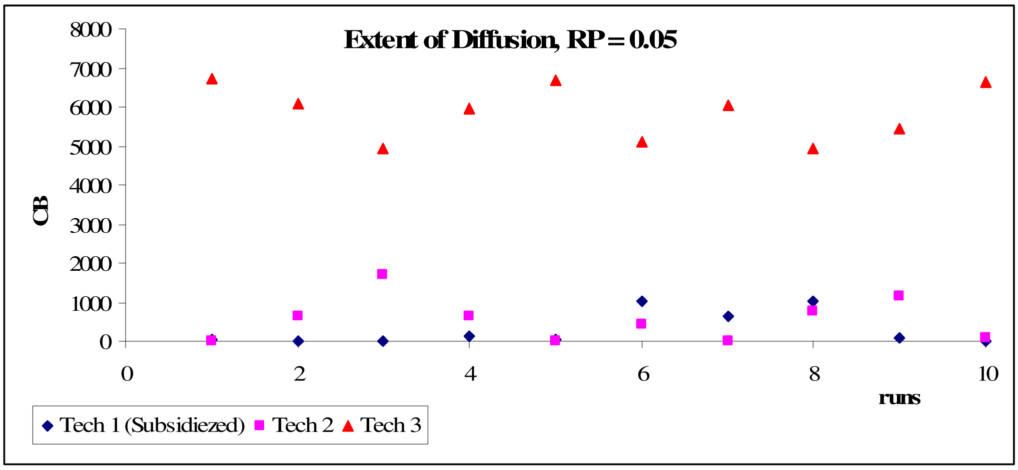

Figure 11: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.05; a short-term policy (4 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

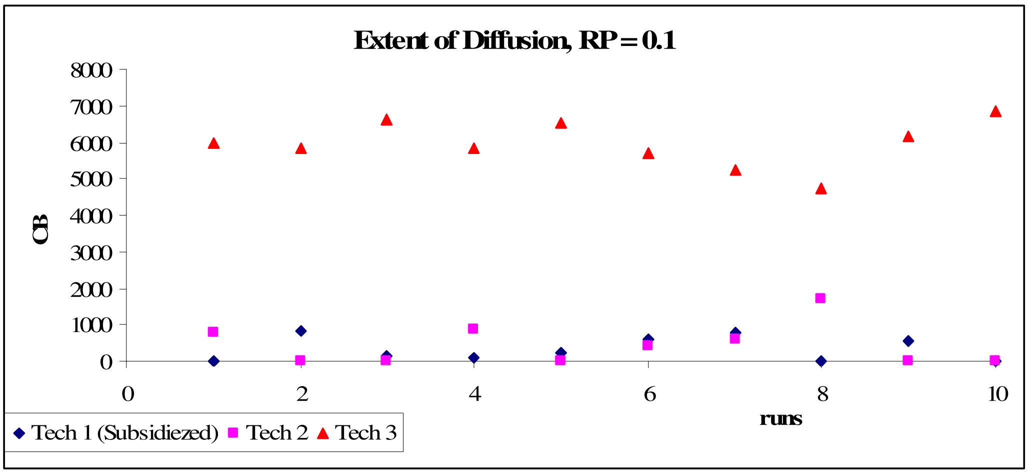

Figure 12: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.1; a short-term policy (4 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

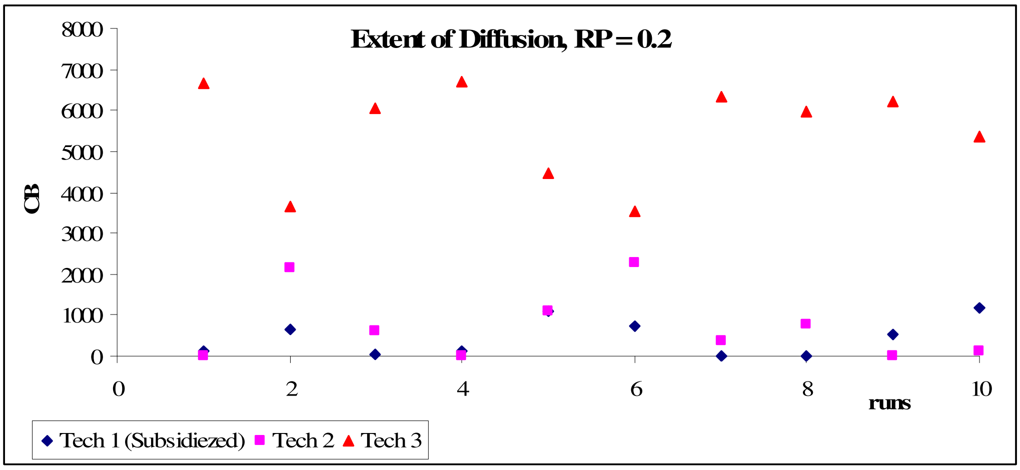

Figure 13: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.2; a short-term policy (4 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

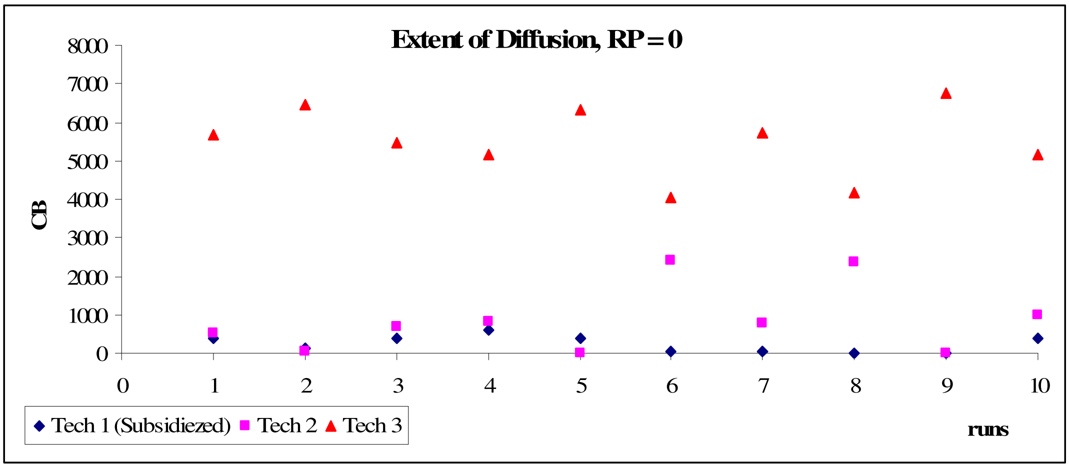

Figure 14: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a regular lattice; a long-term policy 8 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

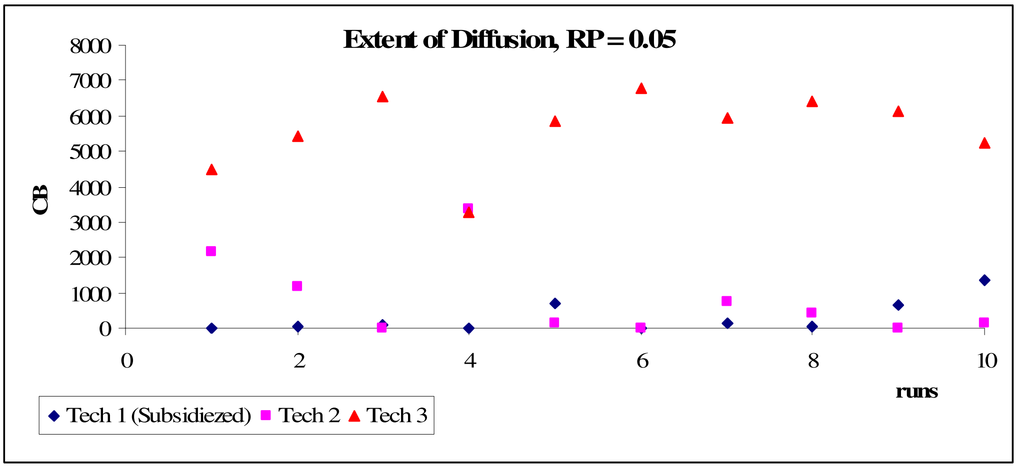

Figure 15: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.05; a long-term policy (8 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

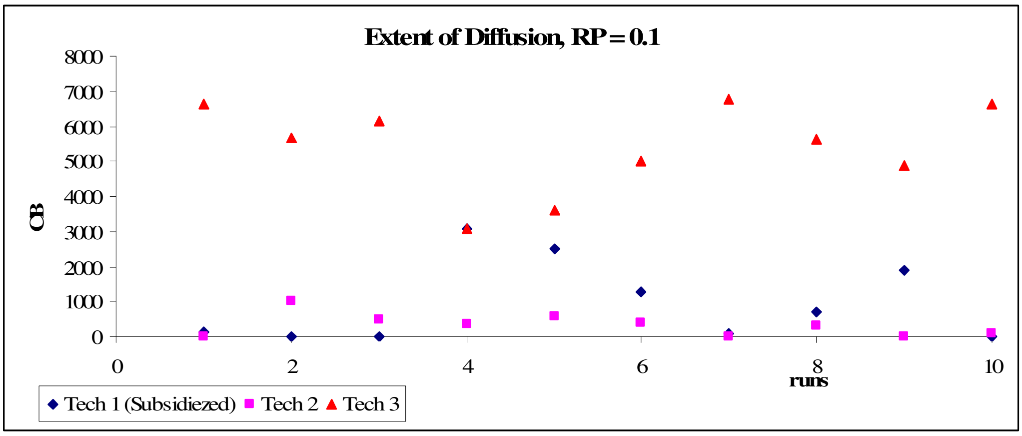

Figure 16: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.1; a long-term policy (8 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.

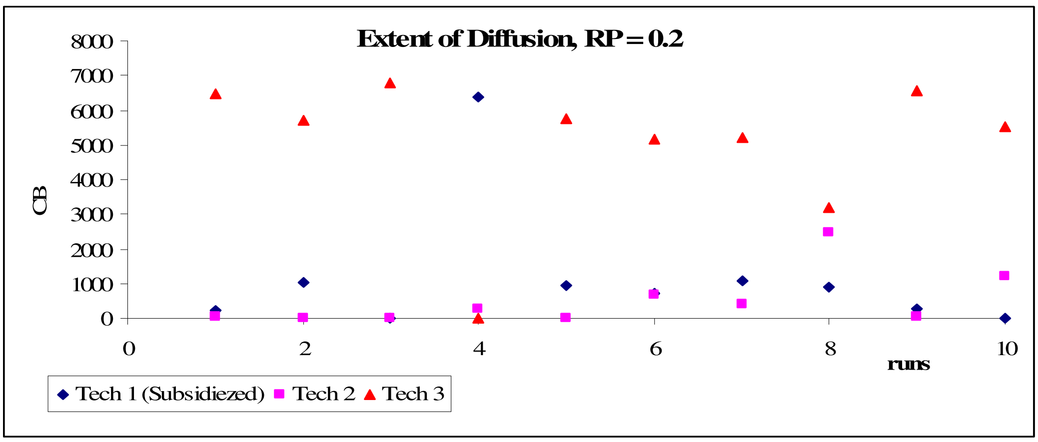

Figure 17: Extent of diffusion (cumulative buyers, CB, vertical axis) at each run (horizontal axis) in the presence of subsidies in a small world network with rewiring probability = 0.2; a long-term policy (8 simulation time-steps) is applied to only technology 1; s=0.5; alpha=[0.2, 0.1, 0] and p0=[6, 2, 1] for technology 1, 2 and 3 respectively.