Competing Recombinant Technologies for Environmental Innovation

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Abstract

This article presents a sequential decision approach to study investments in environmentally dirty and clean technologies. We develop two models and compare the results to check for robustness. After showing how the system can converge to lock-in into an undesirable dirty technology, we examine the effects of recombinant innovation of the existing technologies. A mechanism of endogenous competition is described involving a positive externality of increasing returns to investment. Increasing returns are counterbalanced by recombinant innovation, which is a force characterized by a negative or positive externality depending on the dynamics of the system. We find conditions in which lock-in can be avoided or escaped. Finally we study the symmetry breaking of an environmental policy that charges charges a price for polluting. We evaluate if and how an economy locked into a dirty technology can be unlocked and move towards the clean technology. In addition, we compare the cumulative pollution output of different scenarios, so that we can evaluate the most attractive policy from an environmental angle irrespective of whether escape from dirty technology occurs at all, or occurs early or late.

JEL classification: O33, Q55.

Key words: increasing returns, lock-in, *R&D*, sequential decision, spillovers.

1 Introduction

Various studies have modeled competition between two or more different technologies for adoption or investment in *R&D* (Dosi, 1982; Arthur, 1989; David and Foray, 1994). Here we want to extend this literature by relieving assumptions and complicating the conceptual framework. In many cases a new technology is the result of recombining two or more existing technologies in a modular way. The expectation of fruitful recombinant innovations may therefore drive decisions about *R&D* investment in the existing technologies (van den Bergh, 2008). We propose recombinant innovation as a force that counterbalances the positive externality of the competition mechanism.

Modularity of technologies and their complementarity are likely to be crucial ingredients of successful recombination. This may involve the application of a new technology to a core technology, or be the result of spillovers between different industries. Complementary technologies are usually recombining in a modular way, as is the case in microelectronics, where different units are combined to form a new electronic instrument. Many examples of recombinant innovation are found in the area of environmental technologies. The hybrid car combines a conventional internal combustion engine with an electric propulsion system. In a Combined Cycle Power Plant a gas turbine generates electricity while waste heat is used to make steam to generate additional electricity via a steam turbine. Even more striking is the integrated photovoltaic and gas-turbine system, where wasted heat is collected by photovoltaic devices (Jaber et al., 2003). A further example are power plants and vehicles based on fuel cells: different types exist, which are based on alternative electrolytes (alkaline solutions, polymer membranes, etc.); these allow for spillovers and recombination. Another case is photovoltaic films, which combine solar cells and thin layers technologies. In general recombinant innovation creates links between industries that were previously far from each other. One example are the construction and solar technology industries, with the so-called Building-Integrated Photovoltaics: photovoltaic materials are used to replace conventional building materials in parts of the building envelope such as the roof, skylights or facades.

We may conceptually widen the pool of competing recombinant options considering that two technologies must not necessarily be substitutes to compete. Even if two technologies show some degree of complementarity, capital and labour constraints mean a choice is needed between developing the one or the other. Consequently the two technologies becomes substitutes in the investment decision of this firm. This is the case of large corporations that are active in more than an industry. For example, Sanyo and Sharp, which are traditionally active in consumer electronics, are now also developing and selling renewable energy technologies, especially photovoltaic devices.

We propose a theoretical model of competing recombinant technologies that can explain the different historical paths of technological advance and possibly indicate if and how to intervene to guide the development of environmentally clean technologies. We consider competition between a "dirty" and "clean" technology. Recombination of these technologies is possible, which gives rise to a technology with favorable environmental (clean) and economic (viable) characteristics. This model allows to address the issue of unlocking the economy from the undesired dirty technology. More generally, the need for more efficient systems of energy production and consumption often calls for combining technologies that before were competing or unrelated. This is where our model finds its main motivation.

The optimal diversification of research portfolios has been studied by Dasgupta and Maskin (1987): in an uncertain environment parallelism of investments should not be considered as waste, unless increasing returns outweigh the benefits from diversification. Zeppini-Rossi and van den Bergh (2008) analyse the optimal investment in two technologies when recombinant innovation is taken into account, assuming the probability of recombinant innovation to be larger the more diversified is the system of parent technologies. Recombinant innovation is the emergence of a new technology or product resulting from the combination of two or more "parent" technologies that already exist. An investment in recombinant innovation represents an activity characterized by exploratory research, which typically involves uncertainty about whether a successful recombination will appear or not. Investment in an established technology, instead, represents a more certain strategy.

The model here sets the recombinant innovation problem in a sequential decision framework similar to the ones of Banerjee (1992), Bikhchandani et al. (1992) and Kirman (1993). The sequential decision framework of the investment decision allows to address path dependence and lock-in. The basic idea of our model is that at each time t one firm sets its share of capital invested in the two competing technologies. This firm thus decides whether to specialize or to diversify its technological portfolio, taking into account increasing returns on investment and the probability of recombinant innovation. Both depends on history, i.e. on previous decisions by other firms. The event of lock-in is caused by the self-reinforcing mechanism of increasing returns. This mechanism counterbalances recombinant innovation, which can possibly trigger unlocking.

Our model can be seen to uniquely combine elements of Arthur (1989) and Zeppini-Rossi and van den Bergh (2008). We develop a sequential decision model of recombinant innovation in which we introduce the self-reinforcing effect of increasing returns on investment. We offer a second model which extends the urn schemes of Arthur et al. (1987) and Dosi et al. (1994) with recombinant innovation. This allows us to compare the results and check the robustness of our findings. We distinguish between different situations in which lock-in can be avoided or not. By introducing a critical mass effect into the probability of recombinant innovation we also show situations in which a convergence path leading to the dominance of one technology may be reverted, so that lock-in may be escaped. Finally, we extend the model with an environmental policy that charges a price for pollution. Different emission intensities of the clean and dirty technologies break the symmetry of the system. Recombinant innovation limits the pollution abatement if the environmental policy is strong. But if policy stringency can not be high, recombinant innovation represents a good compromise.

The paper is organized as follows. In Section 2 we develop the model of sequential investment decisions with recombinant innovation and with the positive externality of increasing returns to investments. In Section 3 we take a classical urn model of increasing returns and extend it with a mechanism of recombinant innovation. Section 4 studies the symmetry breaking of environmental policy and the effects of recombinant innovation on the abatement of pollution. Section 5 concludes.

2 Investments with recombinant innovation

2.1 A sequential decision model

Arthur (1989) proposed a famous model of competing technologies to explain technological path-dependence and lock-in. Our model is different from his in two important respects. Firstly, our model entails an investment decision problem, and not the adoption of a technology. Secondly, there is no innovation in Arthur's model, while we allow for recombinant innovation of the two competing parent technologies. The recombinant innovation never reaches the state where it enters the competition between technologies, but the expectation of its occurrence affects agents' decisions.

The model is constructed as follows. There is a pool of infinitely many firms that are called, each one at a different time, to make a decision on the allocation of capital on two technological projects. All firms are equal, in that they do not have heterogeneous intrinsic preferences for one or the other technology. Time is discrete, and in every period t a firm makes an investment decision for the two available technologies. Such a decision is expressed by a share α_t which is the proportion devoted to technology a. The rest goes to technology b. Extreme cases are specialization (either $\alpha_t = 0$ or $\alpha_t = 1$) or symmetric diversification ($\alpha_t = 1/2$). Technology a is dirty, meaning that it is more polluting, while technology b is clean. These two technologies are competing with each other, but at the same time may also recombine to deliver an innovative technology. Recombinant innovation emerges with some positive probability p_t, which is larger the more diversified is the investment. The probability p_t depends on the proportion of the cumulative investment in parent technologies.

Firms are boundedly rational and set α_t taking into account the value of the probability of recombinant innovation in the previous period p_{t-1} and the actual proportions of parent technologies. Let $n_{a,t}$ and $n_{b,t}$ be the values at time t of cumulative capital invested in technology a and in technology b, respectively. Investment by each firm is normalized to 1, so that, if at time t a firm chooses to focus on technology a, for instance, $n_{a,t}$ increases by a unit, while $n_{b,t}$ stays unchanged. This is formalized in the following equations:

$$\begin{aligned} n_{a,t} &= n_{a,t-1} + \alpha_t \\ n_{b,t} &= n_{b,t-1} + 1 - \alpha_t \end{aligned} \tag{1}$$

If $w = n_{a,0} + n_{b,0}$ is the initial condition, the total number of investments is given by $n_{a,t} + n_{b,t} = w + t$. The dynamics of α_t is driven by the sequential decisions of firms. The decision problem is twofold: a firm must decide whether to specialize or to diversify; and, in case specialization is preferred, which technology to choose (a or b). When facing the investment decision the firm has to balance two forces, namely the probability p_t and the returns to adoption for each technology. The first means a force towards maximal diversity or $\alpha = 1/2$, while the second produce a force towards specialization.

The *probability of recombinant innovation* p_t is formalized as the balance of the cumulative investment in the two technologies (Zeppini-Rossi and van den Bergh, 2008):

$$p_t = 4e\frac{n_{a,t}n_{b,t}}{(n_{a,t} + n_{b,t})^2} \qquad e \in [0, 1] \tag{2}$$

where $e \in [0, 1]$ is a measure of the effectiveness of the recombination process. It captures how easily the two technologies recombine.[1] Note that p can be expressed as the product of the proportions of technology investments: if we define the proportion of technology b as $x_t = n_{b,t}/(n_{a,t} + n_{b,t})$, we have $p_t = 4ex_t(1 - x_t)$.

In order to close the model we need an equation that sets the value of the firms' investment share α_t. Firms decide based on the following rule of thumb: if the probability of recombinant innovation is large, it is better to diversify the investment. If it is low, it is better to go for specialization. The part of the investment that is not equally allocated goes to technology a with probability q. All this is expressed by the following rule:

$$\alpha_t = \frac{1}{2}p_{t-1} + \beta_t(1 - p_{t-1}) \qquad \beta_t \sim binomial(0, 1; q) \tag{3}$$

There are five variables and two parameters in this model: one variable (y_t) is random, while the others ($n_{a,t}$, $n_{b,t}$, α_t and P^e_t) are deterministic and depend on each other in a "circular" way: $\underline{n}_t \to P^e_t \to \alpha_{t+1} \to \underline{n}_{t+1} \ldots$. If we "freeze" the random variable, we have a deterministic two-dymensional system: knowledge of the vector $(n_{a,t}, n_{b,t})$ is enough to compute all variables at time $t + 1$. We develop the model starting from a simple scenario in which the specialization decision between the two technologies is completely random and does not depend on actual proportions (we call this "binomial specialization"). Later on we introduce a positive externality from actual proportions due to increasing returns in the specialization decision.

2.2 Constant probability of choice

We start assuming that q is constant, which makes β a simple random variable with Bernoully distribution. In this setting the only feedback from previous decisions occurs

[1] The factor 4 normalizes the maximum value of this balance function to 1, which is attained when the two technologies are equally represented ($n_{a,t} = n_{b,t}$).

through the probability of recombinant innovation p_t. Two equally good technologies are described by $q = 1/2$. The firm's decision α_t is a stochastic process that depends on the random draws of β_t. So are also p_t and $(n_{a,t}, n_{b,t})$, through equations (2) and (1). In table 1 we list the values of α_t corresponding to some values of p, for the two possible realizations of β_t. Once the statistical distribution of β_t is specified by the definition of q in (3), it is

	$p = 0$	$p = 1/2$	$p = 1$
$\beta_t = 0$	0	1/4	1/2
$\beta_t = 1$	1	3/4	1/2

Table 1: Values of α_t under different conditions

possible to compute the conditional expected value of next period investment share. If q is constant we have:

$$E_t[\alpha_{t+1}] = \frac{1}{2}p_t + E_t[\beta_{t+1}] - p_t E_t[\beta_{t+1}] = \left(\frac{1}{2} - q\right)p_t + q \tag{4}$$

In the particular case $q = 1/2$ we have $E_t[\alpha_{t+1}] = 1/2$. Allowing q to be different from 1/2 we have a superior technology. In the context of an environmental innovation, the dirty technology a is assumed to perform economically better, in the sense of larger returns to investment stemming from lower costs and higher efficiency. This requires to set a value $q < 1/2$. The recombination effectiveness e sets the strength of recombinant innovation and supposedly determines whether the system locks-in into one technology or converges to a diversified scenario. Figure 1 presents a simulation[2] for the case $q = 0.2$. The dirty technol-

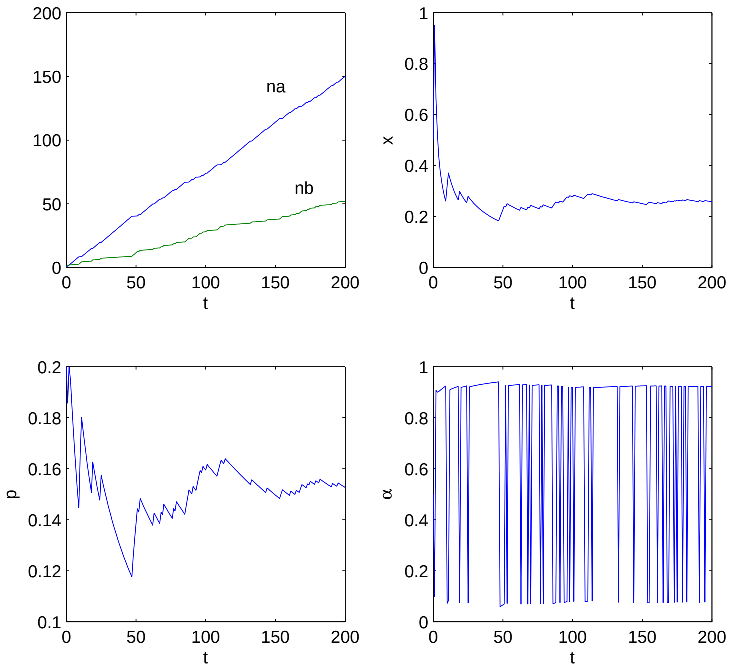

Figure 1: Constant probability of choice. One simulation run for $e = 0.2$ and $q = 0.2$.
Notes: up-left is the cumulative value of the investments. Up-right is the proportion of investment in technology b. Down-left is the probability of emergence p_t. Down-right is the investment share α.

ogy (a) grows much faster than the clean one. The probability of recombinant innovation p_t oscillates well below the effectiveness e, due to unbalanced cumulative investments $n_{a,t}$ and $n_{b,t}$. Many more firms decide to focus on the dirty technology.

2.3 Choice as a Polya process

Now we introduce a self-reinforcing mechanism of increasing returns to investment in parent technologies. Assume the probability q of the binomial variable β_t (equation 3) is a function of the proportion of technological investments. The resulting process for α_t is formally identical to the one expressed by equation (3). The substantial difference is that q now depends on past realization of x_t and then also on past realizations of α_t. Let us substitute equations (2) and (3) in (1):

$$n_{a,t+1} = n_{a,t} + 2e\frac{n_{a,t}n_{b,t}}{(n_{a,t}+n_{b,t})^2} + \beta_{t+1}\left[1 - 4e\frac{n_{a,t}n_{b,t}}{(n_{a,t}+n_{b,t})^2}\right] \qquad (5)$$

This equation can be written in terms of the proportion of investments $x_t = n_{b,t}/(n_{a,t}+n_{b,t})$:

$$\begin{aligned} x_{t+1} &= x_t\frac{w+t}{w+t+1} + \frac{1}{w+t+1}\left[2ex_t(1-x_t)(1-2\beta_{t+1}) + \beta_{t+1}\right] \qquad (6) \\ &\simeq x_t + \frac{1}{w+t}\left[2ex_t(1-x_t)(1-2\beta_{t+1}) + \beta_{t+1}\right] \end{aligned}$$

where the approximation holds for a time $t >> 1$. The process x_t resembles the generalized Polya processes of Arthur et al. (1987). We will refer to this model as AEK henceforth. Such processes fall into the class of non-homogeneous Markov chains.[3]

The binomial variable β_t now depends on previous values of x_t. The positive feedback of increasing returns to investments is expressed by setting the probability q equal to an increasing function f of x_t called *allocation function*. A straightforward specification is the identity function $f(x) = x$: in this case the probability of the event $\beta_t = 1$ (the firm at time t invests more in technology b) is

$$q_t \equiv x_t = \frac{n_{b,t}}{n_{a,t}+n_{b,t}} \qquad (7)$$

When $n_{b,t} > n_{a,t}$ we have $q_t > 1/2$, while $q_t < 1/2$ as soon as $n_{b,t} < n_{a,t}$. Increasing returns enter the investment share process α_t, together with the bet on recombinant innovation. These two forces are opposing each other: the first one pulls α_t either to 0 or 1; the second one is directed towards $\alpha = 1/2$. Here we report some simulations of this model. The graphs of figure 2 are to be compared with the ones of figure 1: with a very low effectiveness of recombinant innovation ($e = 0.2$), the positive feedback $q = x_t$ produces an effect similar to a constant $q = q^* \neq 1/2$ in the previous model. The proportion x_t drifts away from an equal share and the cumulative investments $n_{a,t}$ and $n_{b,t}$ grow very differently. The investment share α attains more often values close to 0 than to 1 and it is characterized by a large volatility. The main difference with respect to the previous model is that here no one knows which technology will ultimately dominate the other. Only initial realizations matter. Recombinant innovation has a weak impact. A quite different picture arises when the effectiveness is large (figure 3, $e = 0.8$): now the investment share oscillates very close to 0.5, so that the two technologies keep an almost equal proportion.

[2] This and the following models have been implemented with *Matlab*.

[3] The non-homogeneity is due to the presence of t in the equation of motion ($n_{a,t} + n_{b,t} = w + t$).

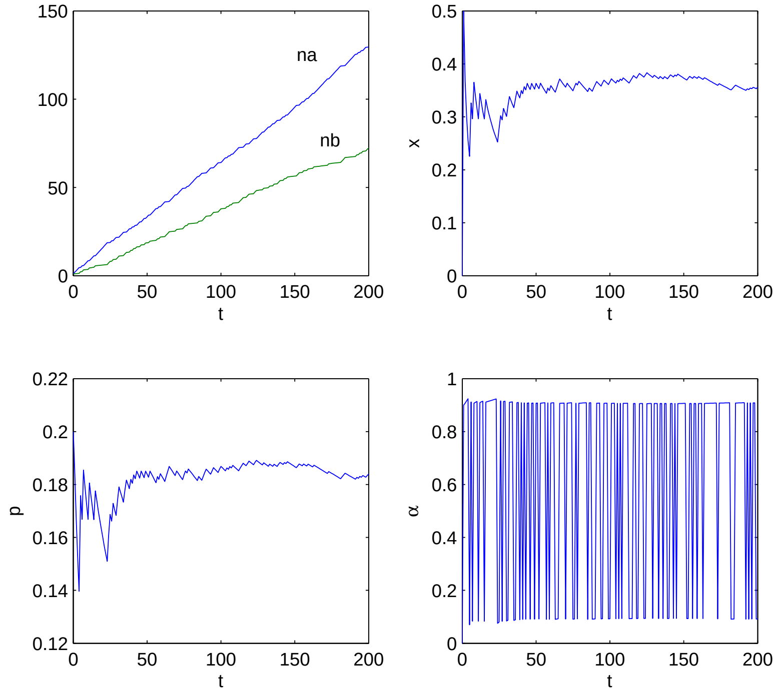

Figure 2: Choice as a Polya process. One simulation run for $e = 0.2$.

Notes: up-left is the cumulative value of the investments. Up-right is the proportion of investment in technology b. Down-left is the probability of emergence p_t. Down-right is the investment share α.

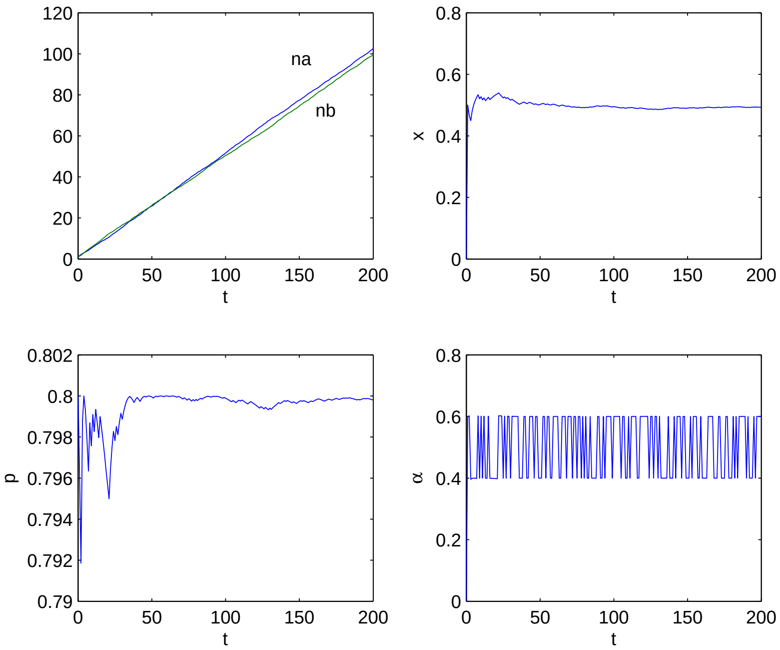

Figure 3: Choice as a Polya process. One simulation run for $e = 0.8$.

Notes: up-left is the cumulative value of the investments. Up-right is the proportion of investment in technology b. Down-left is the probability of emergence p_t. Down-right is the investment share α.

In order to get an intuition about the behaviour of the model in the long run we perform several simulations for a few different conditions. Figures 4 and 5 report seven simulation runs of the proportion x_t. Different realizations of x_t seem to converge always, although not to a predefined limit. As Arthur et al. (1987) show, this is a peculiar attribute of a standard Polya process, due to the infinite number of fixed points of the allocation function $f(x) = x$ (equation 7). Recombinant innovation does not alter this feature, although it reduces the ranges of possible values for the long run limit of the process: as e becomes larger, the proportion process x_t converges to values close to 1/2.

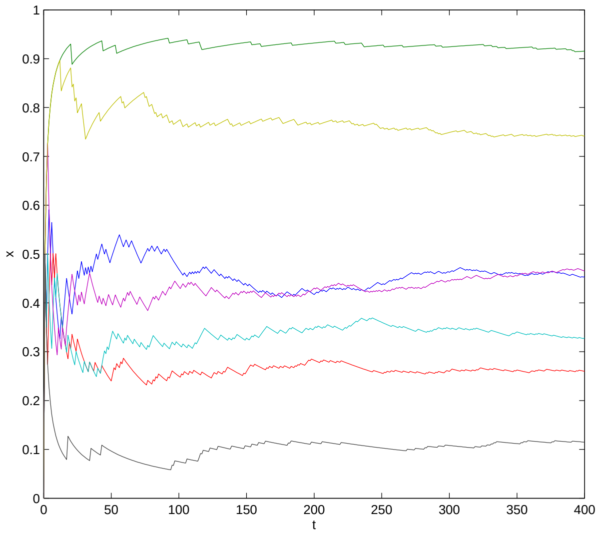

Figure 4: Choice as a Polya process. Seven simulation paths of x_t for $e = 0.1$.

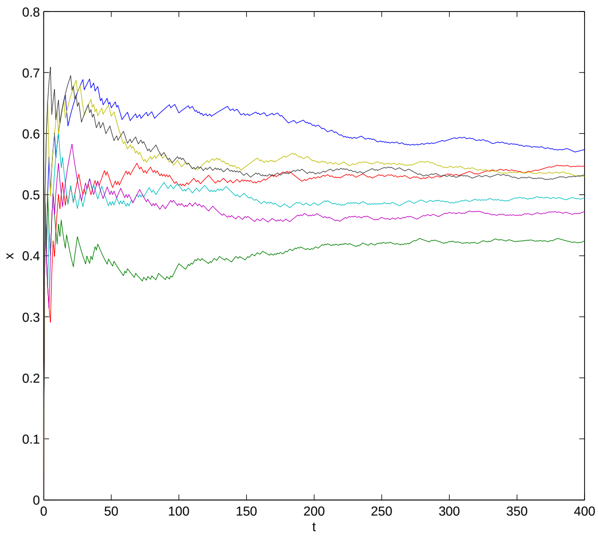

Figure 5: Choice as a Polya process. Seven simulation paths of x_t for $e = 0.7$.

2.4 Choice as a generalized Polya process

When the probability of choosing one technology is equal to the actual value of that technology's proportion, the process always converge to a limit value (which is not known initially, though). In order to better describe technological investment decisions, the allocation function $q_t = f(x_t)$ must have the following characteristics:

- It must be an endomorphism $f : [0, 1] \longrightarrow [0, 1]$.
- It must be increasing: $f'(x) > 0 \quad \forall x \in [0, 1]$
- It must have three fixed points x_1, x_2, x_3 with $x_1 < x_2 < x_3$ such that x_2 is unstable while x_1 and x_3 are stable.

A function of this type has an S shape. For two equally good technologies without external intervention (environmental policy) the unstable fixed point is $x_2 = 1/2$ and the following symmetry holds true: $f(1 - x) = 1 - f(x)$. There are a few specifications that satisfy these properties. The specific choice is not critical for the simulation results. We choose a sinusoidal function:

$$q_t = f(x_t) \equiv \frac{1}{2}\left\{1 + sin\left[\pi\left(x - \frac{1}{2}\right)\right]\right\} \tag{8}$$

Figures 6 to 8 report seven simulation runs for x_t with different values of the effectiveness of recombinant innovation (namely $e = 0.$, $e = 0.4$ and $e = 0.5$). When the effectiveness

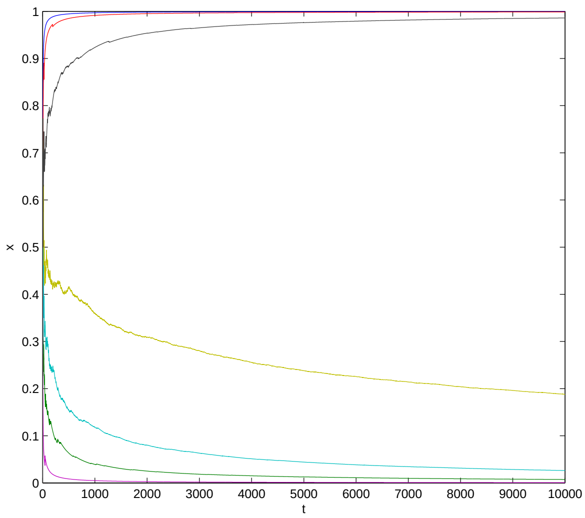

Figure 6: Choice as a generalized Polya process. Seven simulation paths of x_t for $e = 0.1$.

is very low, the process x_t happens to converge either to $x = 0$ (lock-in into technology a) or to $x = 1$ (lock-in into technology b). Convergence may be fast or slow, depending on the initial events.[4] This is a typical character of path-dependent processes. By increasing the effectiveness e, limit values other than $x = 0$ and $x = 1$ appear, as is the case for $e = 0.4$ (figure 7). If we increase e even further (figure 8), the proportion of investments converges to $x = 1/2$. Lock-in to a single technology is avoided and the two technologies

[4]The functional specification does not alter the qualitative behaviour of the model, but only the speed of convergence to a fixed point. If one chooses an allocation function which is much steeper in $x = 1/2$, convergence to $x = 0$ or to $x = 1$ is much faster.

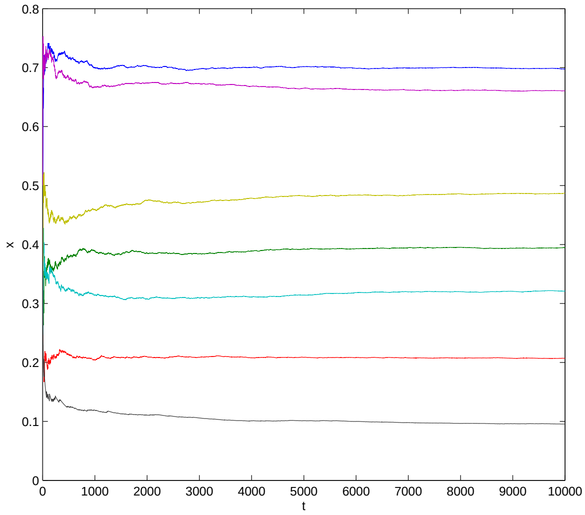

Figure 7: Choice as a generalized Polya process. Seven simulation paths of x_t for $e = 0.4$.

coexist in the long run. We can summarize these results as follows: when the effect of recombinant innovation is weak, the usual character of self-reinforcing investment decisions is preserved, with lock-in into one or the other technology depending on initial realizations. If the probability of recombination of the two technologies is sufficiently large, instead, the two technologies converge to equal proportions. In between there are values of the effectiveness e for which none of these outcomes is realized: different runs of the model lead to convergence to limit values that are not known *a priori*, as was the case with the standard Polya allocation process. Of course the values of e for which lock-in is avoided depend on the choice of the allocation function.

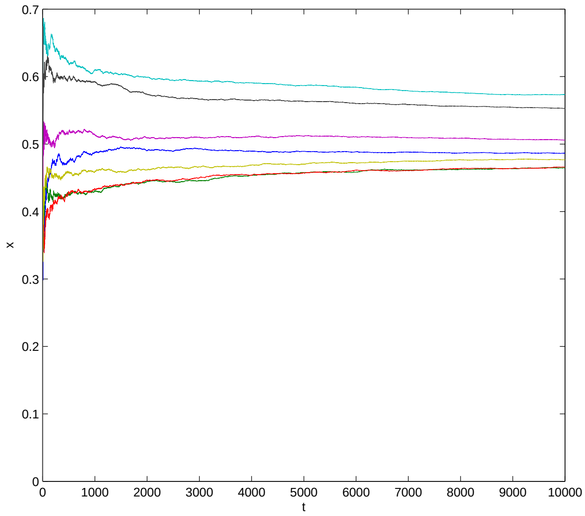

Figure 8: Choice as a generalized Polya process. Seven simulation paths of x_t for $e = 0.5$.

3 An urn scheme with recombinant innovation

3.1 The AEK model

An alternative way of combining increasing returns with recombinant innovation is by building directly on the *AEK* model of Arthur et al. (1987), rather than first writing a recombinant technologies model and than introducing the self-reinforcing effect. In the *AEK* model the equation of motion for the proportion of one technology is the following:

$$x_{t+1} = x_t + \frac{1}{w+t}\Big[\beta(x_t) - x_t\Big] \tag{9}$$

where w is the initial total number of choices and β is a random variable defined as:

$$\beta(x) = \begin{cases} 1 & \text{with probability } q(x) \\ 0 & \text{with probability } 1 - q(x) \end{cases} \tag{10}$$

This binomial random variable accounts for the increments of technologies' choices based on a probability given by the allocation function $q(x)$. The latter controls the type of feedback produced by the proportion x. As before, we are interested in positive feedback, which means an increasing function q. We adopt a binomial logit specification, which is a customary assumption of discrete choice models (Hommes, 2006):

$$q(x) \equiv \frac{exp(\lambda x)}{exp(\lambda x) + exp(\lambda(1-x))} = \frac{1}{1 + exp[\lambda(1-2x)]}$$

The intensity of choice $\lambda > 0$ measures the rationality of firms in making a decision. Extreme cases are $\lambda = 0$ (each technology is selected with equal probability, for any value of x) and $\lambda = \infty$ (one technology is selected with probability one, as soon as $x > 1/2$). The larger is λ, the more the allocation function resembles a step function, with stable fixed points approximated by 0 and 1.[5] Figure 9 reports seven simulations of the process x_t for $\lambda = 8$. Lock-in always occurs, with equal probability for each technology.

3.2 Adding recombinant innovation

Now we introduce the recombinant innovation force, which responds to the expectation that available technologies recombine with a positive probability. Equation (9) becomes

$$x_{t+1} = x_n + \frac{1}{w+t}\Big[\alpha(x_t) - x_t\Big] \tag{11}$$

where the decision variable α is defined as

$$\alpha(x;t) = \begin{cases} 1 & \text{with probability } [1 - p(x;t)]q(x) \\ 1/2 & \text{with probability } p(x;t) \\ 0 & \text{with probability } [1 - p(x;t)][1 - q(x)] \end{cases} \tag{12}$$

[5] We also used the sinusoidal allocation function $q(x) = 1/2\big\{1 + sin\big[\pi(x - 1/2)\big]\big\}$, but prefer the logistic one as it is more flexible in describing different conditions in terms of convergence of the decision process and possible asymmetries of available options.

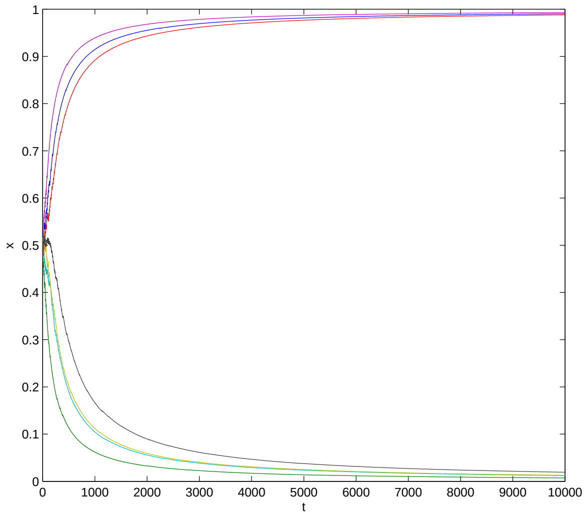

Figure 9: Urn model. Seven simulations of x_t with $\lambda = 8$.

The probability of recombinant innovation is defined as:

$$p(x; t) = 4\eta(t)x(1 - x) \tag{13}$$

This definition corresponds to the former equation (2). The effectiveness of recombinant innovation is now dependent on time and represented by an increasing factor $\eta(t) = e[1 - exp(-vt)]$ which describes the advancement in the recombination technology. In other words, we assume that given the parent technologies, the probability of recombinant innovation grows exogenously as a result of technological advancement. Now recombinant innovation is controlled by two parameters, namely e and v that together with c and d (increasing returns), set the conditions for the historical technological paths. In particular we want to find conditions where convergence to $x = 0$ or $x = 1$ (lock-in) is avoided. Figure 10 reports some simulation paths with $e = 0.5$ and $v = 1$. As we see, recombinant innova-

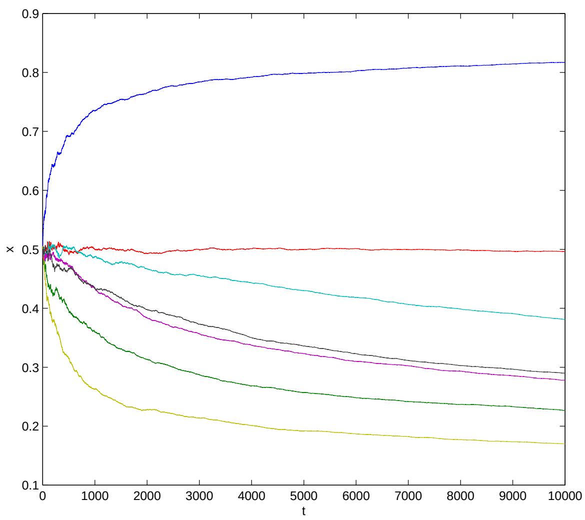

Figure 10: Urn model plus recombinant innovation. Seven simulations of x_t with $\lambda = 8$, $e = 0.5$ and $v = 1$.

tion slows down convergence to one technology and in some case even avoids lock-in. The difference with respect to the paths of figure 9 is remarkable. This effect is more evident the larger the static effectiveness e.

3.3 A critical mass effect

The results of previous sections indicate that recombinant innovation may prevent lock-in into one technology, as long as the effectiveness e is large enough and initial events do not let one technology overcome the other too quickly. But by no means can recombinant innovation as represented by the probability (13) unlock the system once the convergence path has been initiated. What is missing is a regime shift, the occurrence of conditions that could reverse the initial path. In this section we upgrade the model in this sense, by introducing a critical mass effect in the probability of emergence. In order to do that we re-define the dynamic effectiveness η as follows:

$$\eta(t) = \frac{e}{1 + exp(-v(t - t_0))} \tag{14}$$

The critical mass is represented by the flex point t_0. The parameter v controls the speed of technological advance, and together with t_0 sets the initial value of the function. The critical mass t_0 separates two different regimes: below t_0 marginal effects are increasing, while above t_0 they are diminishing. This is a typical feature of technological innovation, where a new idea or technique needs to acquire a minimal amount of investment or recognition before taking off. After this critical mass is reached, further improvements only add diminishing benefits to the innovation.

By running several simulations we have seen how the critical mass effect becomes evident if we set t_0 sufficiently ahead in time, when the variance of the process is low enough and one technology has clearly outperformed the other. In figures 11 and 12 we show some simulated paths for $t_0 = 2000$. The proportion of technology b changes its convergence

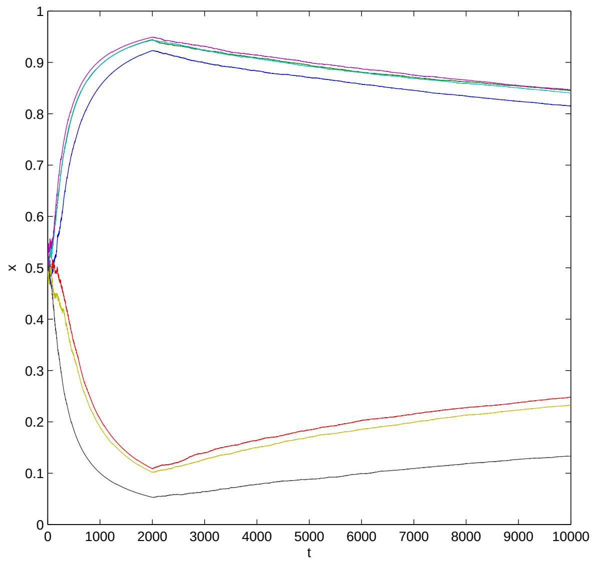

Figure 11: Urn model plus recombinant innovation with a critical mass effect. Seven simulation of x_t with $e = 0.9$, $v = 10$ and $t_0 = 2000$.

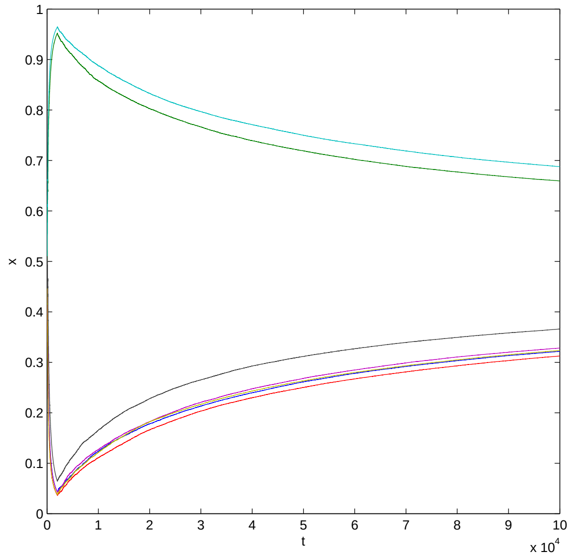

Figure 12: Urn model plus recombinant innovation with a critical mass effect. Seven simulation of x_t with $e = 0.9$, $v = 10$ and $t_0 = 5000$.

path in correspondence with the critical mass t_0. After the reversal x_t converges to 0.5. Several conditions have been tried and the steepness v does not seem to play a role in this model. Much more important is the static level of the effectiveness: e must be sufficiently large in order to cause reversal. Based on simulation runs that we do not report here the transition value for $v = 10$ and $t_0 = 2000$ lies between 0.5 and 0.6. A relatively smaller value of e can still lead to reversal when we use the sinusoidal allocation function. We want to report some results for this function because it presents an interesting behaviour for middle values of the effectiveness. Figure 13 shows how different runs may or may not escape lock-in. The realizations of x_t in the initial phase (before t_0) play an important

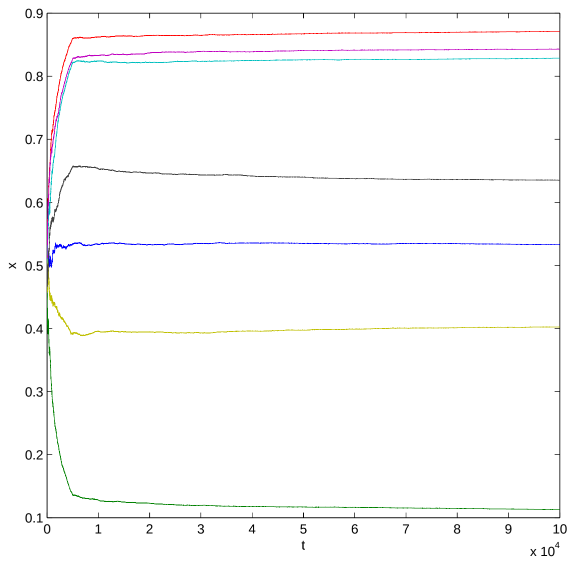

Figure 13: Urn model with sinusoidal allocation function plus recombinant innovation with a critical mass effect. Seven simulations of x_t with $e = 0.4$, $v = 10$ and $t_0 = 5000$.

role not just in selecting the leading technology, but also in the occurrence of a reversal: if x_t moves too far from 0.5 during this phase, the path of x_t will converge to either 0 or 1, depending on which direction was taken initially. At t_0 only a kink appears, with considerable reduction of the speed of convergence, but no reversal is seen and lock–in is not avoided. On the contrary, if the initial path of investments is such that x_t remains close enough to 0.5 before t_0, a regime shift occurs. Lock-in is then escaped, and the two technologies converge to an equal proportion.

Beside the analysis of simulations in the time domain, a more general understanding of the model is obtained through a statistical analysis of many simulation runs. This allows in particular to study the distributions of the outcomes of the model. First we want to look at the time evolution of such distribution. Figure 14 presents three histograms of the proportion x_t at different time horizons, namely $t = 100$, $t = 2000$ and $t = 10000$. After a short time horizon ($t = 100$) the proportion of investments in the two technologies

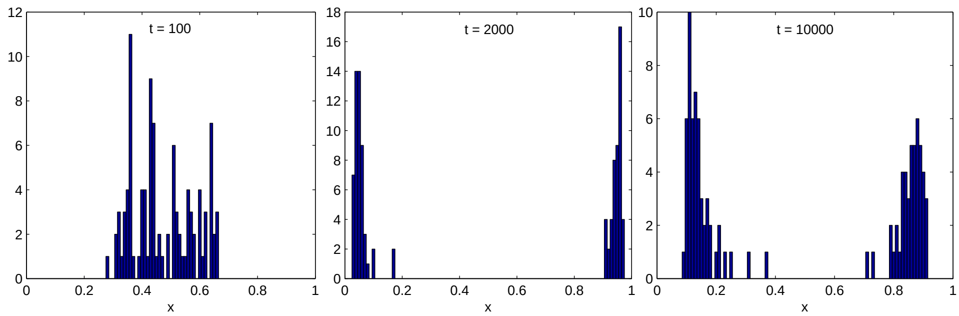

Figure 14: Urn model plus recombinant innovation with a critical mass effect. Distribution of x_t for $t = 100$ (left), $t = 2000$ (centre) and $t = 10000$ (right). 100 runs with $e = 0.9$, $\lambda = 8$, $v = 10$, $t_0 = 2000$ and $x_0 = 0.5$.

is equal on average. At $t = 2000$ the distribution is clearly bimodal: two clusters of counts of x_t below 0.1 and above $x = 0.9$ clearly indicate a lock-in scenario to one or the other technology. With an even longer time horizon ($t = 10000$) the distribution is still bimodal, but the two clusters of final values are closer to each other. This is an effect of recombinant innovation, which takes off after a critical mass is reached. By fixing the time horizon at $t = 10000$ we can study the distribution of x_t in different conditions of recombinant innovation. Figure 15 reports the results for three different values of the effectiveness: $e = 0.1$, $e = 0.4$, $e = 0.9$. With weak recombinant innovation there is almost

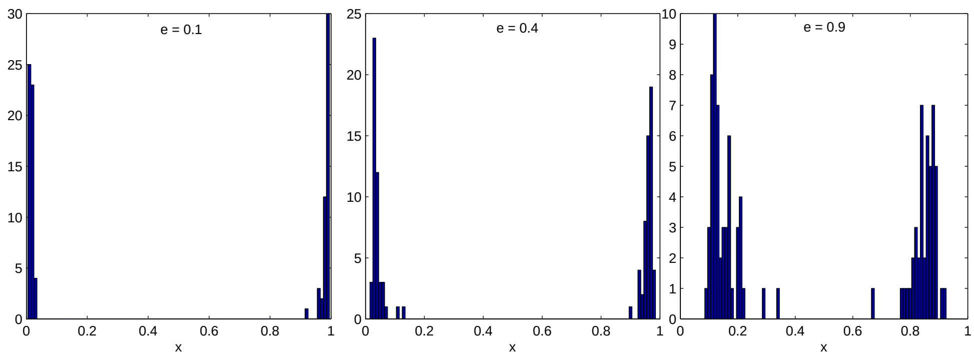

Figure 15: Urn model plus recombinant innovation with a critical mass effect. Distribution of x_t for $e = 0.1$ (left), $e = 0.4$ (centre) and $e = 0.9$ (right). 100 simulation runs with $t = 10000$, $\lambda = 8$, $v = 10$, $t_0 = 2000$ and $x_0 = 0.5$.

complete lock-in into one or the other technology. As recombinant innovation becomes more effective, the final outcome presents a more diversified scenario, with x_t clustering far away from 0 and 1. A further dimension of this analysis is obtained running 100 simulations for three different values of the intensity of choice λ and looking at the distribution of x_t. Figure 16 consider the cases $\lambda = 4$, $\lambda = 8$ and $\lambda = 12$. For A given condition of

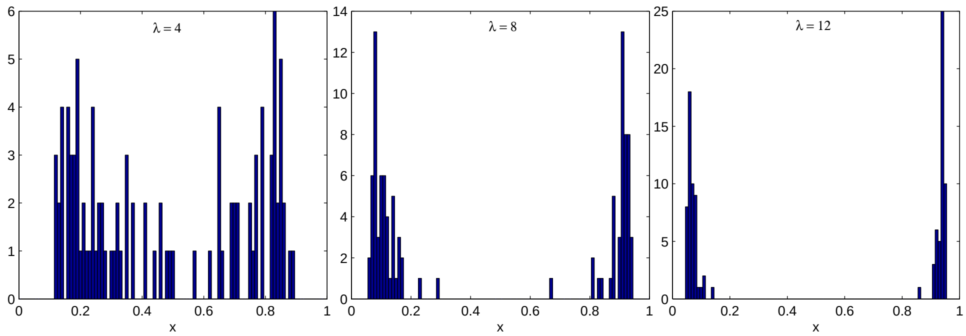

Figure 16: Urn model plus recombinant innovation with a critical mass effect. Distribution of x_t for $\lambda = 4$ (left), $\lambda = 8$ (centre) and $\lambda = 12$ (right). 100 simulation runs with $t = 10000$, $e = 0.4$, $v = 10$, $t_0 = 2000$ and $x_0 = 0.5$.

recombinant innovation we see how a higher intensity of choice leads to a more structured outcome. When λ is relatively low (myopic agents) many different values of final technology proportions are attained. Moving towards more rational agents, a clearer outcome realizes, with lock-in into one technology that outperforms the other.

4 Symmetry breaking from environmental policy

Up to here we have dealt with symmetric systems in that no technology has any intrinsic superiority or advantage (apart from the initial case with constant probability of choice). We have seen how a better environmental scenario can be achieved through recombinant innovation, because this mechanism allows escaping lock-in into an undesirable technology. Here we introduce the effect of an environmental policy that explicitly favours the clean technology. One way of modelling such policy is by introducing a new feedback in the allocation function $q(x)$ of the increments (10). In the previous model agents were deciding only under the influence of the positive externality of other agents' decisions, represented by the proportion x_t. Now we make this utility more general by redefining it with $u(x_{i,t}) = x_{i,t} - se_i x_{i,t}$, where s is the pollution charge that represents the instrument of environmental policy, and e_i is the intensity of pollution emissions by technology i, with $e_a > e_b$. According to this new definition the probability of choosing technology b becomes:

$$q(x) \equiv \frac{exp[\lambda(x - se_b x)]}{exp[\lambda(x - se_b x)] + exp[\lambda(1 - x - se_a(1 - x))]} = \frac{1}{1 + exp(a - bx)]}$$

with $a = \lambda(1 - se_a)$ and $b = \lambda[2 - s(e_a + e_b)]$. If $s = 0$ (no policy) we are back in the previous situation. It is interesting to consider the effects of recombinant innovation and policy on the distribution of the increments β with respect to the proportion x. Figure 17 reports the plots of the expected value $E[\beta(x)] = [1 - p(x)]q(x) + 0.5p(x)$ for a few different cases in the long run, where $\eta(t) \simeq e$. The environmental policy breaks the symmetry of the system and can make the distribution bimodal when recombinant innovation is at work.

Together with the proportion of technological investments we are interested in the pollution level $z_t = e_a n_{a,t} + e_b n_{b,t}$. Because this variable grows in every period due to

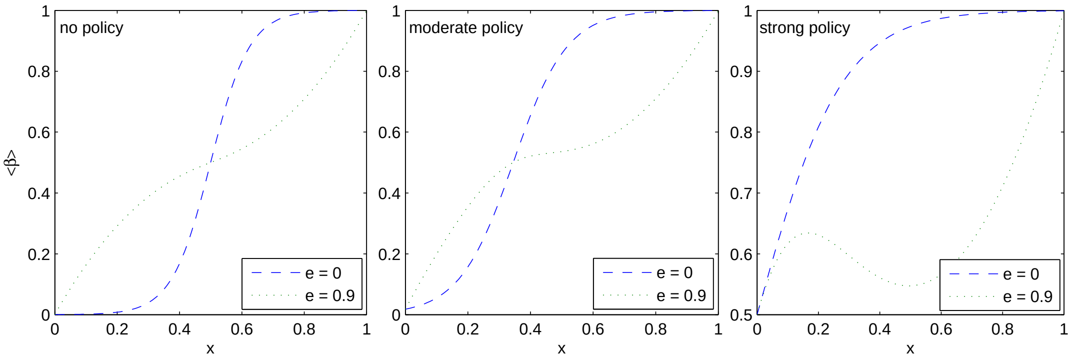

Figure 17: Plots of $E[\beta(x)]$ for three different degrees of policy, with and without recombinant innovation.
Notes: left is without policy (s=0). Centre is with s=0.05. Right is with $s = 0.1$.

repeated investments in one or the other technology, it is more interesting to study the average pollution intensity $\hat{z}_t$, defined as:

$$\hat{z}_t \equiv \frac{z_t}{n_{a,t} + n_{b,t}} = (1 - x_t)e_a + x_t e_b.$$

This variable expresses the effect of the relative dynamics of the two technologies on pollution. We can compute the cumulative emissions as the integral value until time t:

$$Z_t \equiv \sum_{j=w}^{w+t} \hat{z}_j \cdot j. \tag{15}$$

In the following we run some simulations for different cases of policy and recombination effectiveness. In all of these we assume that technology a (dirty) pollutes ten times more than technology b (clean), that is we set the intensities $e_a = 10$ and $e_b = 1$. Moreover we assume that the economy at time $t = 0$ is characterized by a large prevalence of the dirty technology, setting the initial value $x_0 = 0.1$. Let us first consider the case without recombinant innovation ($e = 0$). With a very low environmental policy stringency s the

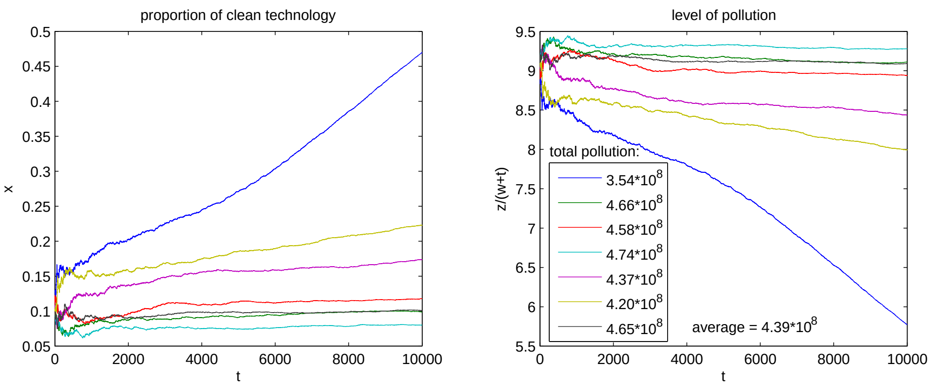

Figure 18: Urn model with environmental policy and without recombinant innovation.
Notes: left is the proportion x_t of the clean technology. Right is the pollution level $\hat{z}_t$.
Here $s = 0.06$, $e = 0$, $x_0 = 0.1$, $e_a = 10$, $e_b = 1$, $\lambda = 8$, $w = 100$.

economy remains locked into the dirty technology, due to the initial advantage of being already more diffused than the clean technology. It is necessary to raise s above some threshold value to realize in all simulation runs an escape from lock-in and a convergence to the clean technology. The level of policy stringency $s = 0.05$ represents an intermediate situation where in some case escape from lock-in occurs, as we see in figure 18. In one run the investments in the clean technology take off and escape lock-in, with substantial abatement of pollution. But in most of the other six runs this does not happen.

If we introduce recombinant innovation with moderate effectiveness, the environmental outcome improves, as we see in figure 19. In all simulation runs escape from lock-in of

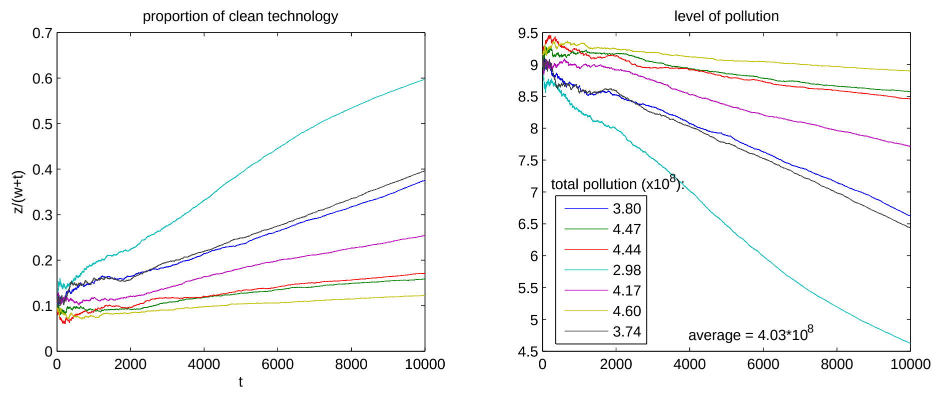

Figure 19: Urn model with environmental policy and recombinant innovation.
Notes: left is the proportion x_t of the clean technology. Right is the pollution level $\hat{z}_t$.
Here $s = 0.06$, $e = 0.2$, $x_0 = 0.1$, $e_a = 10$, $e_b = 1$, $\lambda = 8$, $w = 100$.

the dirty technology occurs, although the impact on pollution can be very different: in the best case the pollution level was abated by more than 50%, but in the worse case by less than 1%! If the effectiveness of recombinant innovation of the two technologies is large, the variability of the outcome is much reduced. Figure 20 reports seven simulations for $e = 0.9$. The shortcoming of a strong recombinant innovation is that the abatement of pollution is

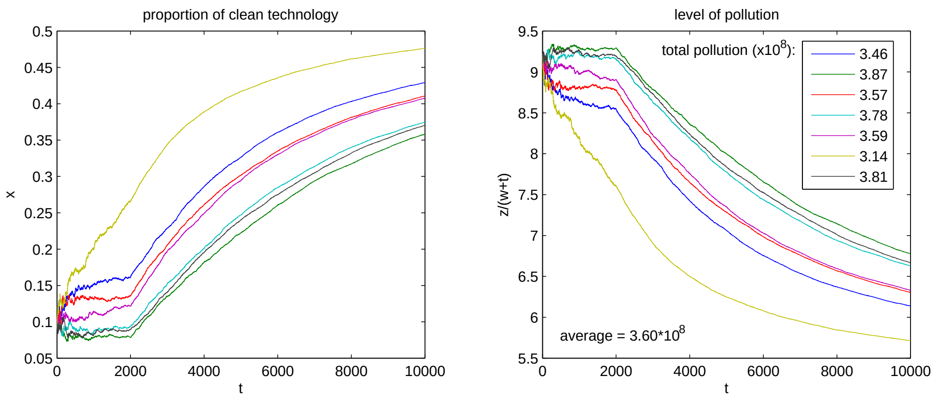

Figure 20: Urn model with environmental policy and recombinant innovation.
Notes: left is the proportion x_t of the clean technology. Right is the pollution level $\hat{z}_t$.
Here $s = 0.06$, $e = 0.9$, $x_0 = 0.1$, $e_a = 10$, $e_b = 1$, $\lambda = 8$, $w = 100$.

limited since the two technologies converge to equal shares. It is interesting to see what we obtain with a weaker environmental policy keeping recombinant innovation strong, as in figure 21: The variability of the outcome is relatively low, with all runs showing a moderate but clear escape from lock-in. Now a regime shift of technology investments occurs, with pollution levels increasing until a critical mass effect occurs, and subsequently going down.

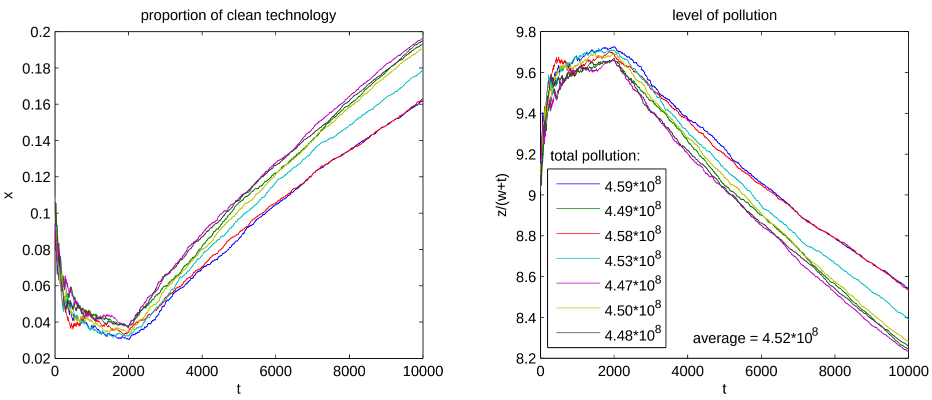

Figure 21: Urn model with environmental policy and recombinant innovation.
Notes: left is the proportion x_t of the clean technology. Right is the pollution level $\hat{z}_t$.
Here $s = 0.05$, $e = 0.9$, $x_0 = 0.1$, $e_a = 10$, $e_b = 1$, $\lambda = 8$, $w = 100$.

As we have done before for the model without environmental policy, we study the distribution of many different runs of the model. In this case we consider the specific pollution level $\hat{z}_t$. First we look how the distribution evolves in a case without recombinant innovation. Figure 22 reports the histograms for three different time horizons, namely $t = 1000$, $t = 5000$ and $t = 10000$. As time goes by the mean pollution level goes down

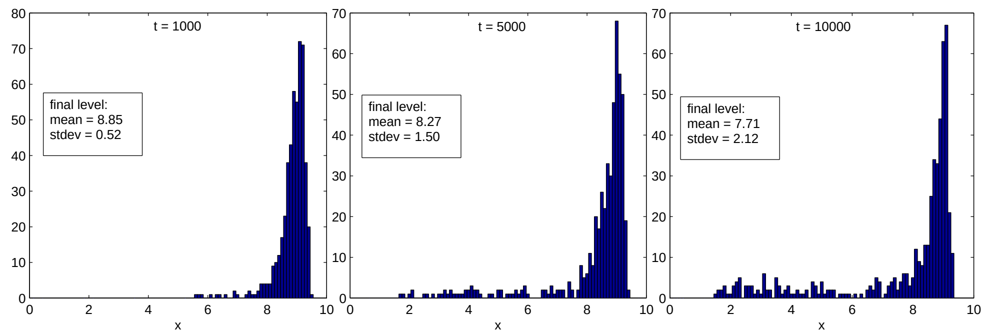

Figure 22: Urn model with environmental policy and recombinant innovation. Distribution of $\hat{z}_t$ for $t = 1000$ (left), $t = 5000$ (centre) and $t = 10000$ (right). 500 simulation runs with $e = 0$, $s = 0.06$, $x_0 = 0.1$, $\lambda = 8$, $t_0 = 2000$.

slightly, while the dispersion of final values increases considerably. Figure 23 considers the effect of a different stringency of environmental policy. The mean pollution level goes down

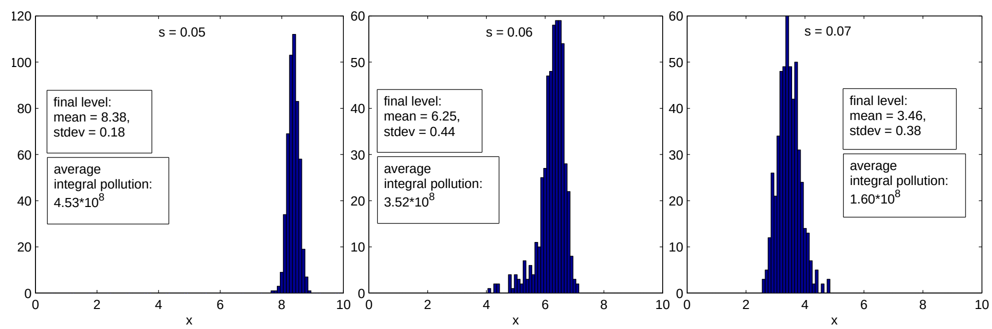

Figure 23: Urn model with environmental policy and recombinant innovation. Distribution of $\hat{z}_t$ for $s = 0.05$ (left), $s = 0.06$ (centre) and $s = 0.07$ (right). 500 simulation runs with $e = 0.9$, $t = 10000$, $x_0 = 0.1$, $\lambda = 8$, $t_0 = 2000$.

when the policy becomes more stringent, as expected. Regarding the standard deviation of final outcomes, the effect of stringency is not univocal. Nevertheless, also the cumulative pollution emission over the period considered ($t = 10000$) is much reduced with a more stringent policy. Finally we consider the role of recombinant innovation: figure 24 reports the simulation results for $e = 0$, $e = 0.2$ and $e = 0.9$. With stringency $s = 0.06$ we obtain

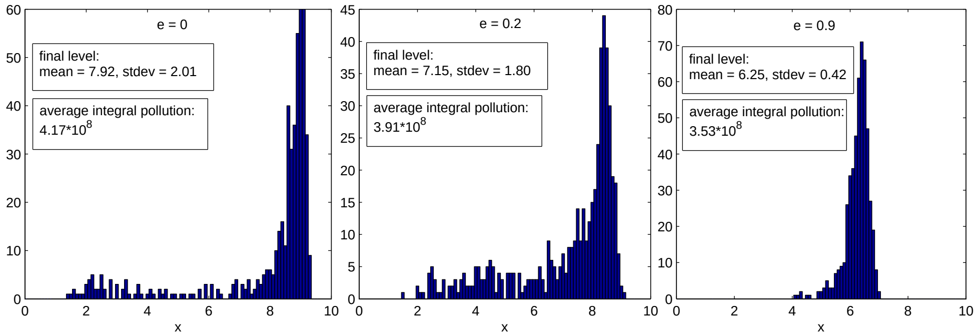

Figure 24: Urn model with environmental policy and recombinant innovation. Distribution of $\hat{z}_t$ for $e = 0$ (left), $e = 0.2$ (centre) and $e = 0.9$ (right). 500 simulation runs with $s = 0.06$, $t = 10000$, $x_0 = 0.1$, $\lambda = 8$, $t_0 = 2000$.

that more recombinant innovation leads to lower pollution final levels, as well as to lower cumulative pollution through to period considered ($t = 10000$). Moreover, recombinant innovation clearly reduces the variability of final outcomes.

Summarizing the results of this section, recombinant innovation helps to escape from the lock-in of the dirty technology, notably if policy stringency is not too high. If recombinant innovation is too strong, the outcome is a 50/50 scenario, with limited abatement of pollution. Nevertheless recombinant innovation reduces the variability of the outcome. To conclude, if the environmental policy is stringent, recombinant innovation is harmful. But if the government can not realize a stringent policy, then recombinant innovation helps to reduce pollution and also makes the possible final outcome less uncertain.

5 Conclusions

We have studied the decision problem of technological investments in a dynamic situation where two available technologies, a dirty and a clean one, present increasing returns to investments and can recombine to give birth to an innovative technology. Agents can choose one or the other out of two available technologies, and also set a diversified portfolio. We have followed two alternative ways to study the effect of recombinant innovation versus increasing returns in technological investments. First we constructed a model centred on the process of recombinant innovation and then introduced a self-reinforcing effect to account for increasing returns of technological choices. If the effectiveness of recombinant innovation is large enough, lock-in into one technology is prevented. If the effectiveness is too low, one technology will end up dominating the system. There are middle values of the effectiveness for which the proportion of the two technologies converges to values other than 0 or 1, which means that the two technologies coexist indefinitely.

A second model is based on an urn scheme and extends Arthur et al. (1987) and Dosi et al. (1994) with recombinant innovation. Also here recombinant innovation may prevent lock-in into one technology, but only if initial events are such that the proportions of technologies remain close enough to 0.5. Otherwise convergence to 0 or 1 always occurs. There is no convergence to other limit values. With a critical mass effect in the recombinant innovation process the initial path towards lock-in can be reversed, as long as the static effectiveness is large enough. The two technologies then converge to equal proportions after the reversal. With this last feature the model shows how recombinant innovation can provoke a regime shift in the technological path and unlock the economy from an undesirable dominant dirty technology, to the advantage of a clean technology.

We finally introduced an environmental policy in the model operating through negative feedback from pollution to investment choices. The system under study becomes asymmetric given that different technologies have different emission intensities. We studied the interaction of the three different forces active in the model, namely increasing returns, recombinant innovation and environmental policy. In general we find that recombinant innovation helps to escape from lock-in of the dirty technology, notably if the stringency of the environmental policy is low. If environmental policy is stringent, recombinant innovation limits the abatement of pollution, but it reduces the variability of the outcome.

To conclude, intense investment in recombinant innovation of dirty and clean technologies can be seen as a second best. But it represents a smoother way to make a transition from a fossil fuel based economy to one relying on renewable resources. In addition, as it allows for a less stringent policy, recombinant innovation comes out as a smart approach to address the environmental problem in periods of economic downturn, notably if the recovery of the economy is slow and limited as it is likely to be in the present time.

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