Competing Recombinant Technologies for Environmental Innovation: Extending Arthur's Model of Lock-in

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Abstract

This article presents a model of sequential decisions about investments in environmentally dirty and clean technologies, which extends the path-dependence framework of Arthur (1989). This allows us to evaluate if and how an economy locked into a dirty technology can be unlocked and move towards the clean technology. The main extension involves the inclusion of the effect of recombinant innovation of the two technologies. A mechanism of endogenous competition is described involving a positive externality of increasing returns to investment which are counterbalanced by recombinant innovation. We determine conditions under which lock-in can be avoided or escaped. A second extension is "symmetry breaking" of the system due to the introduction of an environmental policy that charges a price for polluting. A final extension adds a cost of environmental policy in the form of lower returns on investment implemented through a growth-depressing factor. We compare cumulative pollution under different scenarios, so that we can evaluate the combination of environmental regulation and recombinant innovation.

JEL classification: O33, Q55.

Key words: externalities, hybrid technology, lock-in, *R&D*, sequential decisions.

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1 Introduction

Various studies have modeled competition between two or more distinct technologies to study adoption or investment in $R\&D$ (Dosi, 1982; Arthur, 1989; David and Foray, 1994). Here we extend this literature in two ways to address environmental problems. First, we add the pollution intensities of competing technologies and introduce an environmental policy that taxes pollution. Second, we allow for diversified technological choices that stimulate the emergence of hybrid technological solutions. Our motivation is that in many, if not most, 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 technological adoption.

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 one 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 model of competing technologies that produces different scenarios of techno-

logical evolution and related pollution levels. A "dirty" and a "clean" technology compete in the market. Recombination of these technologies is possible, giving rise to a technology with favourable environmental (clean) and economic (viable) characteristics. This model allows to address the issue of unlocking the economy from the undesirable 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. Relevant research questions are then if and how pollution dynamics is affected by the increasing returns of technological adoption and by the expectation of recombinant innovation, and how a government should intervene to guide the development of environmentally clean technologies. This is where our model finds its main motivation.

The optimal diversification of research portfolios has been studied by Dasgupta and Maskin (1987) and, more recently, van den Bergh (2008) and Zeppini-Rossi and van den Bergh (2008). The latter two analyse the optimal investment in two technologies when recombinant innovation is taken into account, assuming the probability of recombination to be larger the more diversified is the technological portfolio. One general finding is that in an uncertain environment parallelism of investments should not be considered as waste, unless increasing returns outweigh the benefits from diversification. An investment in recombinant innovation represents an activity of exploratory research, which typically involves uncertainty about whether a successful recombination will appear or not.

Our model sets the recombinant innovation problem in a sequential investment decision framework similar to Banerjee (1992) and Bikhchandani et al. (1992). This allows us to address path dependence and lock-in of technology investments. The basic idea 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 is counterbalanced by recombinant innovation, which can possibly trigger unlocking.

With our model we study the distribution of outcomes in terms of technology diffusion and pollution levels. We distinguish between scenarios 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. We further analyse the combined effect of an environmental policy and a hybrid technology solution, represented by recombinant innovation. We find that the latter limits the pollution abatement if the environmental policy is strong. But if policy stringency can not be high, recombinant innovation represents a good compromise. This basic picture does not change when we also consider policy costs.

Resuming, the environmental dimension of our work include four aspects: different pollu-

tion intensities of two competing technologies; increasing returns to scale possibly leading to lock-in of the dirty technology, which can be countered by recombinant innovation resulting in a hybrid technology; environmental policy that affects selection of technologies; the effects of a cost of such policy.

The paper is organized as follows. Section 2 presents and studies the model without environmental policy. Section 3 extends the analysis with environmental policy with and without costs. Throughout we employ numerical analysis. Section 4 concludes.

2 The model

2.1 Competing clean and dirty technologies

Arthur (1989) proposed a famous model of competing technologies to explain technological path-dependence and lock-in. Here we extend his model in two ways. First, we introduce pollution emission of competing technologies. Second, while there is no innovation in Arthur's model, we allow for recombinant innovation of the two competing technologies. The recombinant innovation never reaches the state where it enters the competition between technologies. What we study here is how the expectation of its occurrence affects agents' decisions and, in turn, technological dynamics.

Assume a large pool of firms that are called, each one at a different time, to make a decision about the allocation of capital to two available technologies. These happen to have very different pollution emissions: technology c is relatively clean, while technology d is relatively dirty. All firms are equal, and do not have heterogeneous intrinsic preferences for one or the other technology. Time is discrete: in every period t one firm makes an investment decision for the two available technologies. This is expressed by a share α_t, representing the proportion of investment devoted to technology d. The rest goes to technology c. Investment by each firm is normalized to 1. Specialization means either $\alpha_t = 0$ or $\alpha_t = 1$, while perfect diversification is denoted by $\alpha_t = 1/2$.

Let $n_{d,t}$ and $n_{c,t}$ be the values at time t of cumulative capital invested in technology d and in technology c, respectively. For instance, if at time t a firm chooses to focus on investing in technology d, $n_{d,t}$ increases by a unit, while $n_{c,t}$ stays unchanged. The general formulation of cumulative investments is as follows:

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

The initial condition is $w = n_{d,0} + n_{c,0}$. Then cumulative investments are $n_{d,t} + n_{c,t} = w + t$. This number grows linearly, while pollutive emissions at time t depend on the diffusion of the two technologies. If e_c and e_d denote the pollution intensities of c and d, respectively, with

$e_d > e_c$, then the total pollution generated at time t is $z_t = e_d n_{d,t} + e_c n_{c,t}$. We look at two indicators of pollution. The first is the cumulative emissions in $[0, t]$:

$$I_t \equiv \sum_{j=1}^{t} z_j \tag{2}$$

The second is the average pollution intensity:

$$\hat{z}_t \equiv \frac{z_t}{n_{d,t} + n_{c,t}} = (1 - x_t)e_d + x_t e_c. \tag{3}$$

Here $x_t = n_{c,t}/(n_{d,t} + n_{c,t})$ is the proportion of technology c. The proportion of the dirty technology is $1 - x_t$ then. This is a state variable of our system: from x_t we can compute $\hat{z}_t$, z_t and I_t. Because of path dependency, two paths of technological investments presenting different values of $\hat{z}_t$ also have different values of I_t (i.e. paths never cross).

2.2   Recombinant innovation

The dynamics of α_t is driven by the sequential decisions of firms. Firms are boundedly rational and set α_t taking into account the value of technological shares in the previous period. We consider two forces that determine the decision of firm: the first is the positive network externality of other firms' decision, as in Arthur's model. The second is the expectation that the two technology may recombine in an innovative hybrid technology. Recombinant innovation occurs with probability p_t, which is larger the more diversified is the cumulative investment. We formalize this probability as the balance of the cumulative investment in the two technologies (Zeppini-Rossi and van den Bergh, 2008):

$$p_t = 4\eta(t)\frac{n_{d,t}n_{b,t}}{(n_{c,t} + n_{b,t})^2} = 4\eta(t)x_t(1 - x_t) \tag{4}$$

Here $\eta(t) \in [0, 1]$ is a measure of the effectiveness of the recombination process, which captures how easily the two technologies recombine.[1] It is affected by general technological technological progress, resulting in a learning curve of recombinant technology. We assume this is increasing with a critical mass effect, which relates to the S-shaped path of technological growth (Mansfield, 1961). To reflect this phenomena, we define the effectiveness η as follows:

$$\eta(t) = \frac{e}{1 + exp(-v(t - t_0))} \tag{5}$$

The critical mass is represented by the flex point t_0. The parameter v controls the speed of technological advance. 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

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

investment or recognition before taking off. After this critical mass is reached, further improvements only add diminishing benefits to the innovation. The independent variable t has a double interpretation: it represents time as well as investment, since in each period one unit of capital is invested. Finally, the parameter $e \in [0, 1]$ is a static value of recombination effectiveness, which may be seen as an indicator of how distant the two recombinant technologies are in the technological space.

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 $\alpha = 1/2$, and the second towards specialization. In other words, 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:

$$\alpha_t = \frac{1}{2} p_{t-1} + \gamma_t(1 - p_{t-1}) \qquad \gamma_t \sim binomial(0, 1; q) \tag{6}$$

The random variable β_t makes x_t a stochastic process. If we "freeze" β, we have a deterministic one-dimensional system: knowing x_t is enough to compute p_t, α_{t+1} and x_{t+1}. Without recombination ($e = 0$), α_t is either 0 or 1, and we have Arthur's model.

2.3 Network externalities

A self-reinforcing mechanism of increasing returns to investment describes the effect of network externalities in technological decisions. Assume the probability q of the binomial variable γ_t (equation 6) is a function of the proportion of technological investments x_t, and, in turn, of past realizations of α_t itself. Increasing returns to investments means that q is increasing in x_t. Formally we set $q_t = f(x_t)$ with $f(x)$ increasing. f is called the *allocation function*. A straightforward specification is $f(x) = x$: whenever the dirty technology is more diffused, $x_t < 1/2$, we have $q_t < 1/2$, which makes investment in the clean technology less likely than in the dirty technology. A discrete choice process where the probability of one option is equal to the actual proportion of that option is called a *Polya process*. Arthur's (1989) model relies on a generalization of such processes, called *generalized Polya processes*, which were studied in more detail in Arthur et al. (1987). We will refer to this model as *AEK* henceforth.

When we set $f(x) = x$, the process always converges to a limit value, which is not known *a priori*. Such a model is not suitable for technology dynamics, as it does not capture the stylized fact of lock-in of a technology: the share x_t needs to converge to an equilibrium where one technology is dominant. This is achieved using an S-shaped increasing allocation function, with three fixed points $x_1 < x_2 < x_3$ such that x_2 is unstable while x_1 and x_3 are stable. For

two equally good technologies without external intervention (environmental policy), $x_2 = 1/2$, while x_1 and x_2 satisfy the symmetry condition $f(x_1) = 1 - f(x_2)$.

2.4 Arthur's model extended

The AEK model of Arthur et al. (1987) and Arthur (1989) can be extended with recombinant innovation. We show that the resulting model coincides with our model in the sense of having the same distribution of realizations of the state variable. In the AEK model the equation of motion for the proportion x is the following:

$$x_{t+1} = x_t + \frac{1}{w+t}\Big[\alpha(x_t) - x_t\Big] \tag{7}$$

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

$$\alpha(x) = \begin{cases} 1 & \text{with probability } q(x) \\ 0 & \text{with probability } 1 - q(x) \end{cases} \tag{8}$$

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)[2]:

$$q(x) \equiv \frac{exp(\beta x)}{exp(\beta x) + exp(\beta(1-x))} = \frac{1}{1 + exp[\beta(1-2x)]} \tag{9}$$

This specification contains the implicit utility function $u(x_t) = x_t$. The intensity of choice $\beta > 0$ reflects the rationality of firms in making a decision[3]. Extreme cases are $\beta = 0$ (each technology is selected with equal probability, for any value of x) and $\beta = \infty$ (one technology is selected with probability one, as soon as $x > 1/2$). The left part of figure 1 reports some examples of $q(x)$: the larger is β, the more the allocation function resembles a step function, with stable fixed points approximated by 0 and 1. The right part of figure 1 shows seven simulations of x_t for $\beta = 8$. Lock-in always occurs, with equal probability for each technology.

The AEK model can be extended to include recombinant innovation, introducing the expectation that available technologies recombine with a positive probability. To do this we

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[2]We also studied results for the sinusoidal allocation function $q(x) = 1/2\{1 + sin[\pi(x - 1/2)]\}$, 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.

[3]Alternatively, if one thinks that firms decide based on some information about their environment, β is the inverse of the variance of the noise that affects such information.
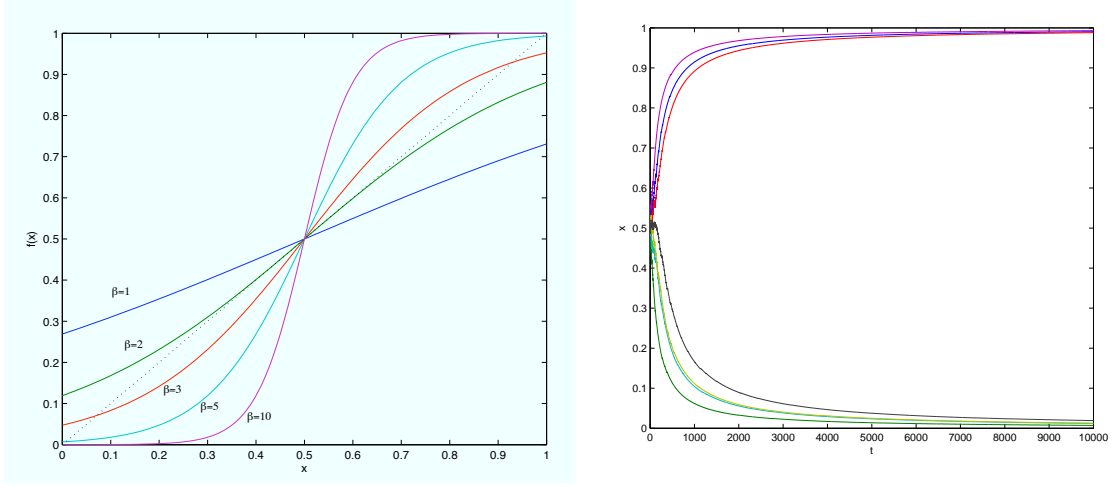
Figure 1: Left: examples of allocation function. Right: Seven simulations of the AEK model with $\beta = 8$.

redefine the decision variable (8) with

$$\alpha(x;t) = \begin{cases} 1 & \text{with probability } [1 - p(x;t)]q(x) \\ 1/2 & \text{with probability } p(x;t) \\ 0 & \text{with probability } [1 - p(x;t)][1 - q(x)] \end{cases} \tag{10}$$

With probability $1 - p(x;t)$ we still apply the Polya process mechanism equipped with an allocation function $q(x)$, and with probability $p(x;t)$ we diversify and update technological proportions with the balanced investment allocation expressed by $\alpha = 1/2$.

Now we show that our model and the extended AEK model converge to the same distribution. Substitute equation (4) in (6) and the result in (1):

$$n_{a,t+1} = n_{a,t} + 2e\frac{n_{a,t}n_{b,t}}{(n_{a,t} + n_{b,t})^2} + \beta_{t+1}\left[1 - 4e\frac{n_{a,t}n_{b,t}}{(n_{a,t} + n_{b,t})^2}\right] \tag{11}$$

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

$$\begin{aligned} x_{t+1} &= x_t\frac{w+t}{w+t+1} + \frac{1}{w+t+1}\left[2ex_t(1-x_t)(1-2\beta_{t+1}) + \beta_{t+1}\right] \\ &= x_t\frac{w+t}{w+t+1} + \frac{1}{w+t+1}[\alpha_{t+1}] = x_t + \frac{1}{w+t+1}(\alpha_{t+1} - x_t) \end{aligned} \tag{12}$$

This resembles Arthur's process (7). The main difference lies in the decision variable α_t, which is (6) in our model, and (10) in the extended AEK. We show how the distributions of the two models coincide in the long run. The expected value of (12) is:

$$E_t[x_{t+1}] = x_t + \frac{1}{w+t+1}\left[\frac{1}{2}p_t + q(x_t)(1 - p_t) - x_t\right]$$

The expected value of (7), with α given by (10), is:

$$E_t[x_{t+1}] = x_t + \frac{1}{w+t}\left[\frac{1}{2}p_t + q(x_t)(1 - p_t) - x_t\right]$$

8

The two expected values coincide as soon as time $t >> 1$. Then we can say the two model converge to the same distribution. For this reason, we will use the extended *AEK* model henceforth, and refer to it as to the model of competing recombinant technologies.

2.5 Simulation of the model

In order to apply our model to the environmental problem we set an unbalanced initial condition, with the dirty technology d being more diffused than the clean technology c. By simulating the model, we study the different scenarios produced by different values of the parameters. In this section we focus on the role of recombinant innovation, asking whether this effect can reduce emissions without any environmental policy.

In what follows we set the following conditions: emission intensities $e_d = 10$, $e_c = 1$. Initial shares $x_0 = 0.1$, initial number of cumulative investment $w = 100$. The allocation function (9) has $\beta = 8$. The effectiveness of recombinant innovation (5) has speed $v = 10$ and critical mass $t_0 = 2000$. We run the model for $T = 10000$ periods. Figure 2 shows seven simulation runs
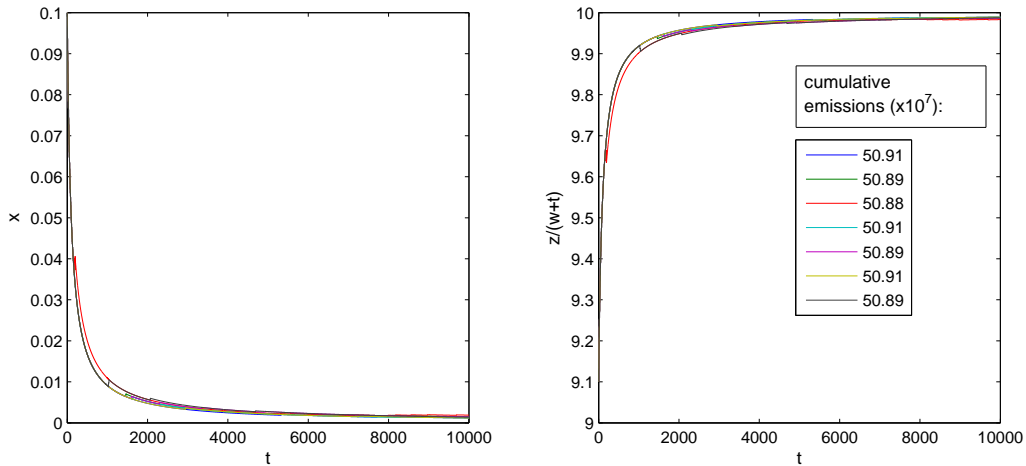
Figure 2: Seven simulation of the model without recombinant innovation. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

without recombinant innovation. The initial advantage of the dirty technology is too big: the system converges to a complete dominance of this technology, due to network externalities. Pollution increases and sets to a level dictated by the dirty regime. A different picture arises if recombinant innovation is strong (figure 3). With $e = 0.9$ the clean technology initially loses ground, then it recovers when the recombinant technology takes off. Accordingly, the pollution levels initially grow fast, and then go down when the critical mass of cumulative investments has been reached. A stronger recombinant innovation increases the variability of the model. In figure 3 different simulations may differ strongly both in technology share and in pollution levels. In one case, the clean technology only attains $x = 0.1$ after 10000 time periods, while in another case it gets to a share larger than $x = 0.3$.
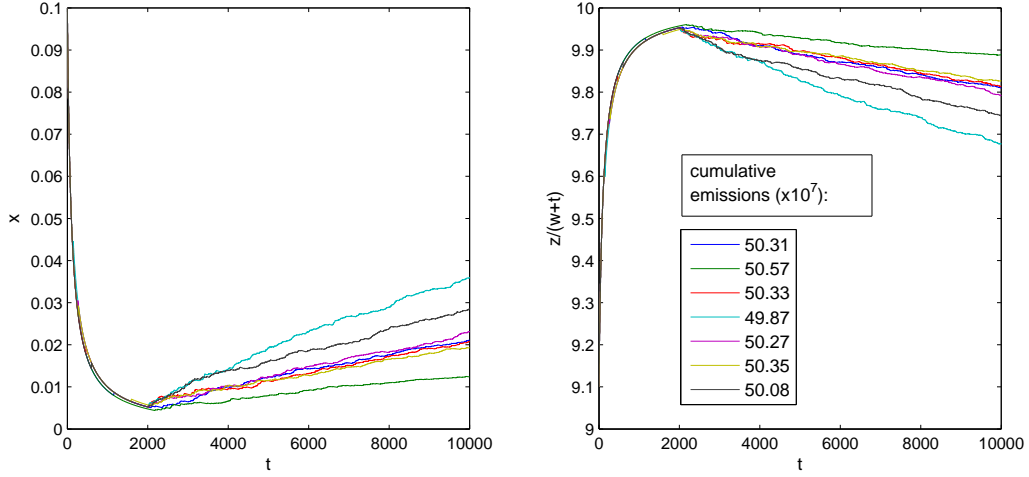
Figure 3: Seven simulation of the model with recombinant innovation $e = 0.9$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

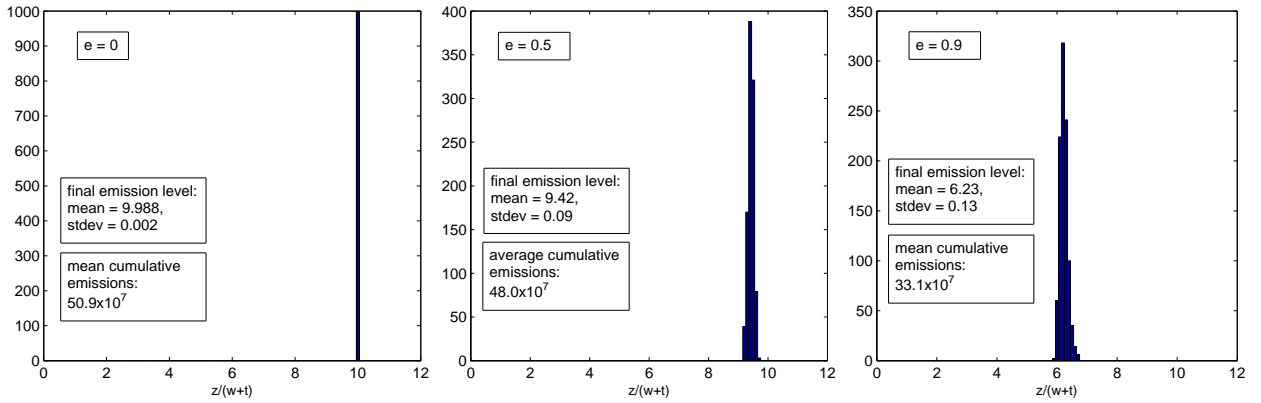We study the distribution of a large number of simulations (1000). Figure 4 presents

Figure 4: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ for $M = 1000$ simulation runs. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

the histograms of final pollution levels $\hat{z}_T$ for three sets of simulations with a different value of the recombination effectiveness: the stronger recombinant innovation is, the lower the location of the distribution of pollution levels and the larger its dispersion. Simulations with longer time horizons ($T \simeq 100000$) show that technology shares converge to equal proportions when e is large enough. This suggests the existence of a threshold level of recombination effectiveness, which is necessary to escape lock-in of the dirty technology. This threshold depends on the initial condition x_0 and on the shape of the learning curve of $\eta(t)$ (equation 5), but it is independent on the pollution level, because any feedback from this is missing without environmental policy. If recombinant innovation can unlock the system from the lock-in of the dirty technology, by no means it can revert the proportions and make the clean technology dominant: $x = 0$ or $x = 0.5$ are the only limit values of the model.

3 Environmental policy

3.1 Formulation of policy

The model presented so far is symmetric in the two technologies, meaning that no technology has an intrinsic advantage. Here we introduce an environmental policy that explicitly favours the clean technology, breaking the symmetry of the model. One way of modelling such policy is by introducing a new feedback in the allocation function $q(x)$ of the increments (8). 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. We make the implicit utility $u(x_{i,t}) = x_{i,t}$ more general now by redefining it as $u(x_{i,t}) = x_{i,t} - se_i x_{i,t}$, where e_i is the earlier defined intensity of pollution emissions of technology i, and s is the pollution charge that represents the instrument of environmental policy. According to this new definition the probability (9) of choosing the clean technology c becomes:

$$q(x) \equiv \frac{exp[\beta(x - se_b x)]}{exp[\beta(x - se_b x)] + exp[\beta(1 - x - se_a(1 - x))]} = \frac{1}{1 + exp(a - bx)} \tag{13}$$

with $a = \beta(1 - se_a)$ and $b = \beta[2 - s(e_a + e_b)]$. If $s = 0$ (no policy) we are back in the previous situation (equation 9). If stringency is too large and $se_i > 1$, the pollution externality overcomes increasing returns for technology i. We first look at the combined effect of recombinant innovation and policy on the distribution of the increments α with respect to the proportion x. Figure 5 shows the plots of the expected value $E[\alpha(x)] = [1 - p(x)]q(x) + 0.5p(x)$ for six choices of (e, s) in the long run, where $\eta(t) \simeq e$. Symmetry is lost whenever $s > 0$.
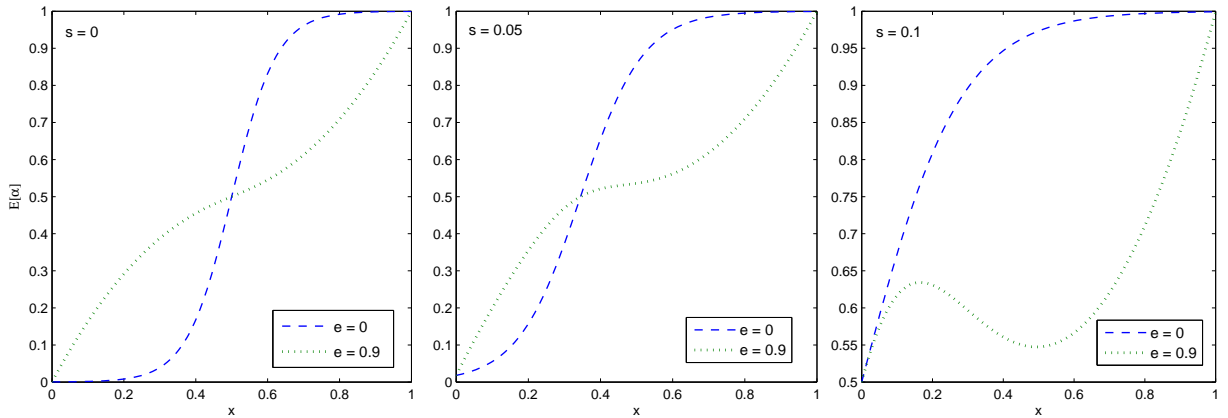

Figure 5: Plots of the expected value of investment $E[\alpha(x)]$, with and without recombinant innovation. Left: without policy (s=0). Centre: with s=0.05. Right: with $s = 0.1$.

3.2 Simulation of the model with environmental policy

In the following we simulate the model for different levels of policy stringency s and recombination effectiveness e. As before, we assume the dirty technology has emission intensity ten

times larger than the clean technology ($e_d = 10$, $e_c = 1$), and the last one is much less diffused, with a share $x_0 = 10\%$. All other parameters are set with the same value of the simulations without policy. Let us first consider the case without recombinant innovation, evaluating the model for three different levels of policy stringency. In the case with $s = 0.05$ (figure 6))
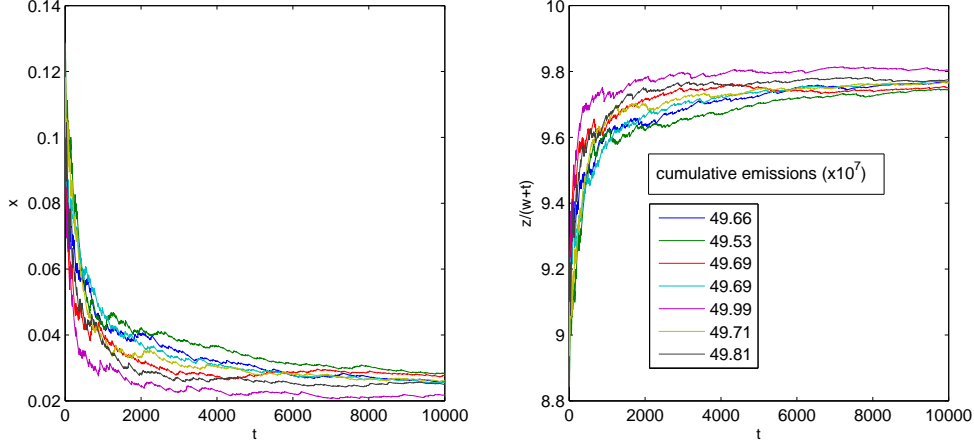

Figure 6: Seven simulation of the model with $e = 0$ and $s = 0.05$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.
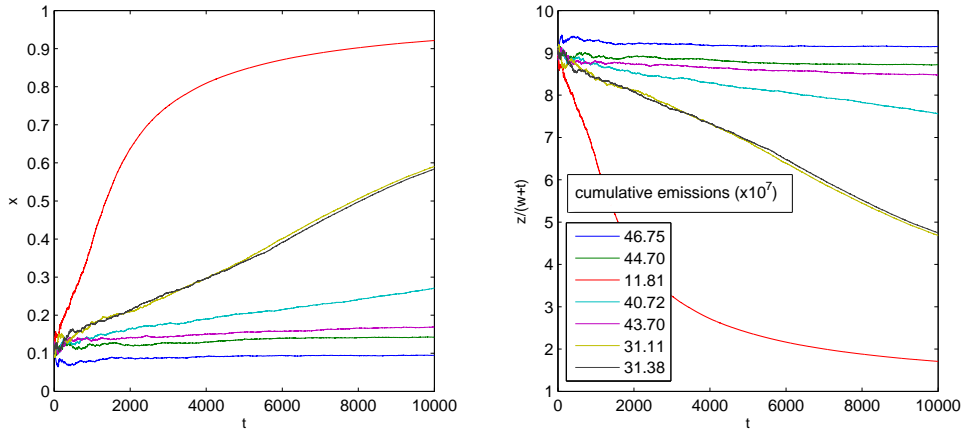
Figure 7: Seven simulation of the model with $e = 0$ and $s = 0.06$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

the system converges to the dominance of the dirty technology, with consequent increase of the pollution intensity. This indicates that such policy stringency is inadequate to mitigate pollution in the situation considered. A slightly more stringent policy ($s = 0.06$, figure 7) may lead to very different outcomes: in some cases the system remains locked-in into the dirty technology, while in other cases the clean technology overcomes eventually the dirty one, with consequent large abatement of the total pollution intensity. Such a high variability is testified also by the values of the cumulative emissions in the seven simulation (left part of figure 7). With $s = 0.07$ the system always escapes lock-in, converging to the dominance of the clean
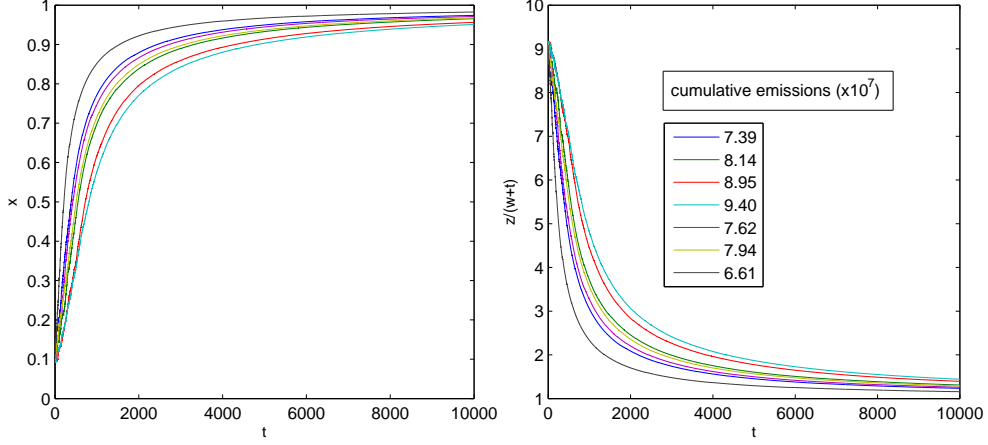
Figure 8: Seven simulation of the model with $e = 0$ and $s = 0.07$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

technology (figure 8). These simulations show that an environmental policy can unlock the system from the dirty technology. This happens if the negative externality from pollution weights more in agents decisions than the initial network externalities advantage of the dirty technology. The case $s = 0.06$ is one where the two forces are comparable. The final outcomes present a high variability depending strongly on early decisions by agents. This mechanisms explains the path dependency of the technology shares dynamics ((Arthur, 1989)).

Recombinant innovation may or may not work in the same direction as environmental policy. It helps to abate pollution when the policy is weak (figure 9). In the case of figure 10
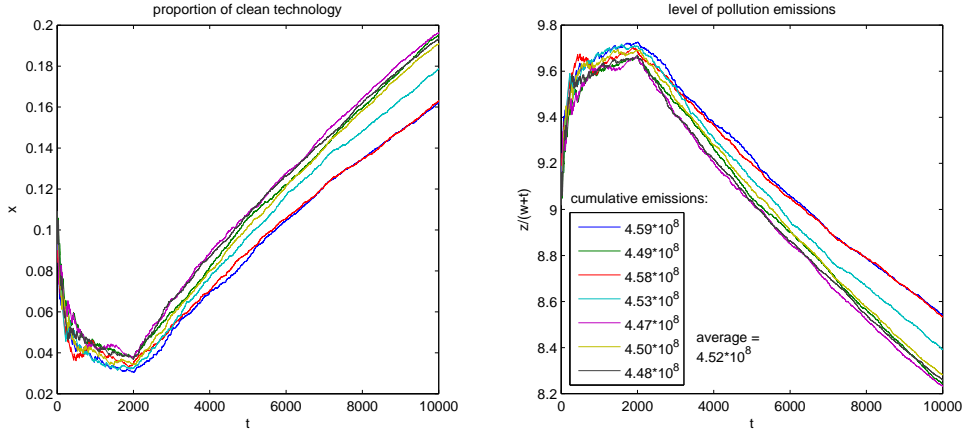

Figure 9: Seven simulation of the model with $e = 0.9$ and $s = 0.05$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

the abatement is even larger: recombinant innovation and environmental policy work together in favour of the clean technology. If we compare this case with the corresponding case without recombinant innovation (figure 7) we see a trade off in the action of recombinant innovation: on the one hand it limits the abatement of pollution, excluding the possibility that the clean technology overcomes the dirty one, on the other hand it reduces strongly the variability of
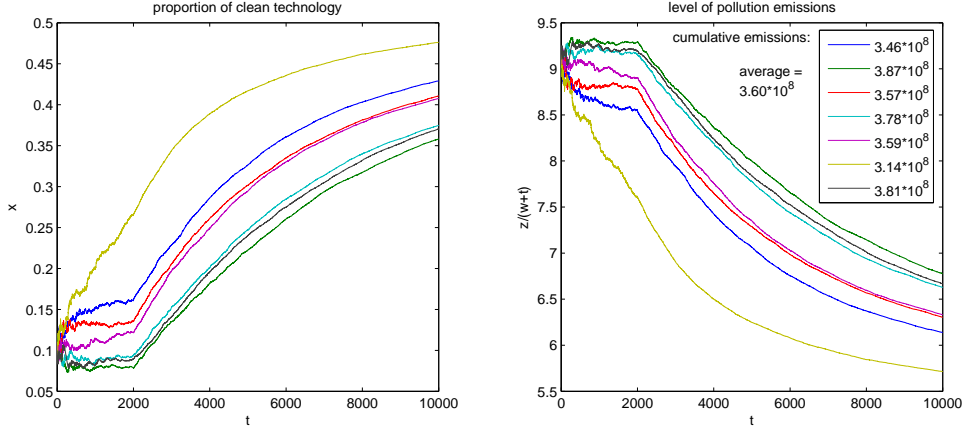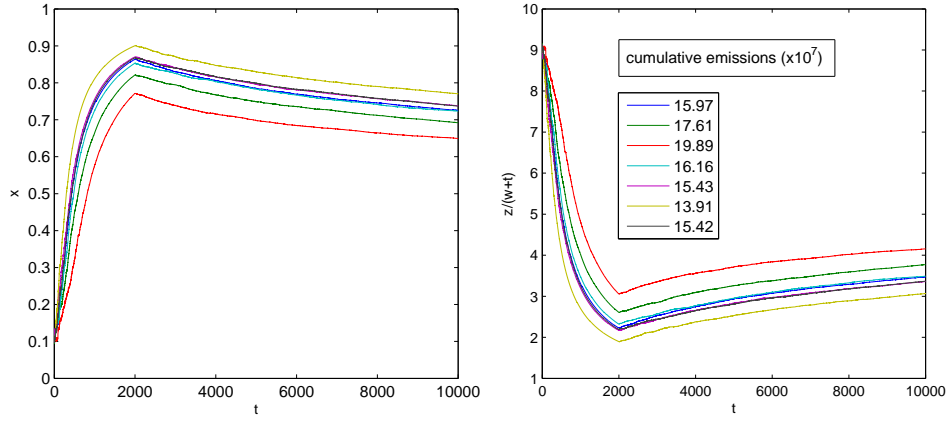
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Figure 10: Seven simulation of the model with $e = 0.9$ and $s = 0.06$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

Figure 11: Seven simulation of the model with $e = 0.9$ and $s = 0.05$. Left: share of the clean technology. Right: total pollution intensity. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

final outcomes. The negative effect of recombinant innovation is more evident with a strong environmental policy ($s = 0.07$, figure 11): initially the clean technology outperforms the dirty one, thanks to the environmental policy, but later it loses ground, due to the takeoff of recombinant innovation.

Now we study the distribution of many simulations of the model with environmental policy. Figure 12 contains the result for $s = 0.05$. The three different histograms indicate that recombinant innovation reduces pollution, with lower dispersion of final outcome the larger its effectiveness. With a stronger environmental policy we obtain the results in figure 13. The variability is lower with respect to a weaker policy. What is more important, recombinant innovation limits the effect of a strong environmental policy in terms of abatement of pollution. Figure 14 considers the effect of a different stringency s of environmental policy, for a given effectiveness of recombinant innovation. The mean pollution level goes down 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
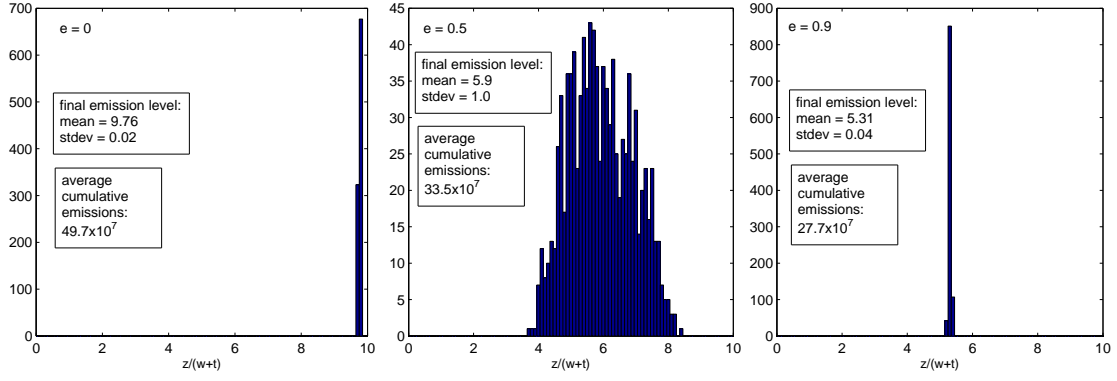
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Figure 12: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ for $M = 1000$ simulation runs. Environmental policy has $s = 0.05$. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.
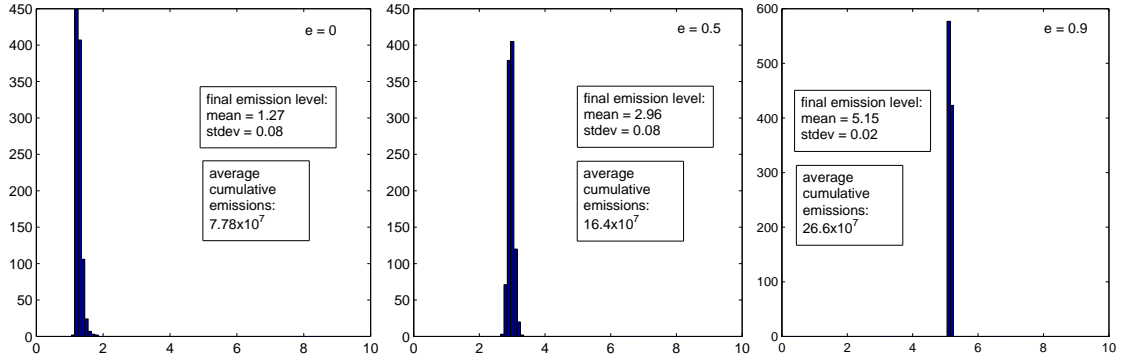

Figure 13: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ for $M = 1000$ simulation runs. Environmental policy has $s = 0.07$. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.
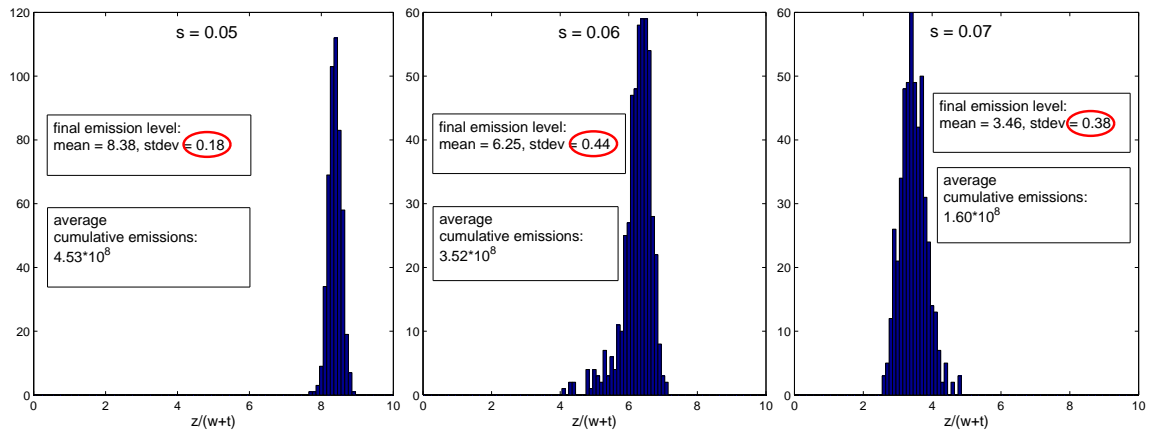

Figure 14: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ for $M = 1000$ simulation runs. Recombination effectiveness is $e = 0.09$. Left: $s = 0.05$. Centre: $s = 0.06$. Right: $s = 0.07$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

the period considered ($T = 10000$) is much reduced with a more stringent policy.

Summarizing the results, recombinant innovation helps to escape from the lock-in of the dirty technology, notably if policy stringency is not too high. When recombinant innovation is strong enough, the outcome is a 50/50 scenario, with limited abatement of pollution. This means that recombinant innovation is harmful when the environmental policy is very stringent. 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.

3.3 Cost of environmental policy

As a final extension of the model we include the cost of the environmental policy, and study how this affects technology diffusion and pollution. The cost of an environmental policy may be modeled through a factor that lowers the growth rate, meaning that both investments in clean and dirty technology have a lower return. Formally, we define a cost factor $r \in [0, 1]$ which enters the sequential decision equations (1) in the following way:

$$
\begin{aligned}
n_{d,t} &= n_{d,t-1} + r\alpha_t \\
n_{c,t} &= n_{c,t-1} + r(1 - \alpha_t)
\end{aligned}
$$
(14)

Consequently, the difference equation of the stochastic process x_t for the share of clean technology (7) becomes

$$
x_{t+1} = x_t + \frac{1}{w + t} \Big[r\alpha(x_t) - x_t \Big]
$$
(15)

One way to link the cost factor to the stringency of the environmental policy s is by defining $r \equiv \frac{1}{1+s}$: the more stringent is the policy, the higher is the cost. Let see how policy costs affect the distribution of final outcomes of the model. We consider first a policy with stringency $s = 0.05$ (figure 15). If we compare the distributions of final pollution levels with the distributions
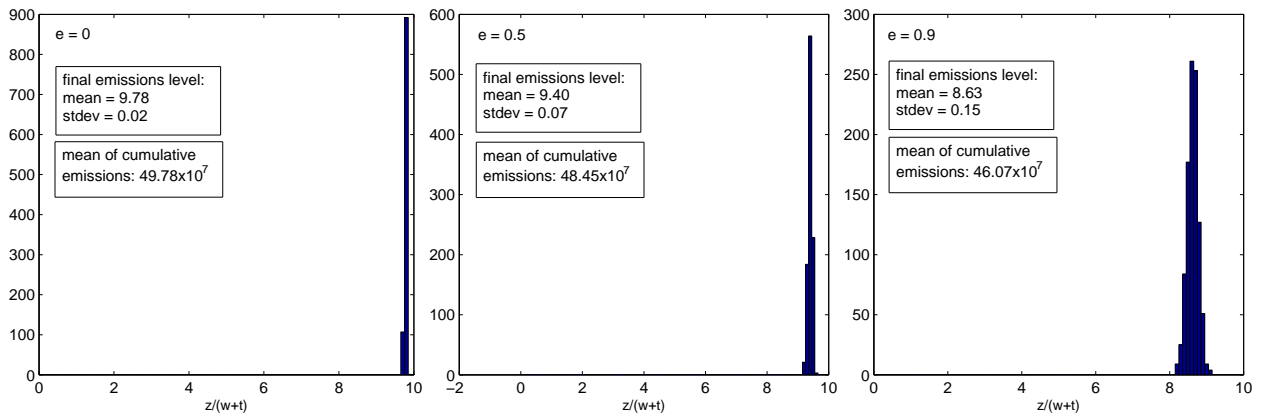

Figure 15: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ with environmental policy costs, for $M = 1000$ simulation runs. Environmental policy has $s = 0.05$. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

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obtained without policy costs (figure 12), the mean level is higher, especially when recombinant innovation is present. The reason is that policy costs turn out to affect more strongly the investments in the clean technology. A stronger policy ($s = 0.06$, figure 16) increases the variability of final outcomes, making the distribution very skewed. This is more evident the
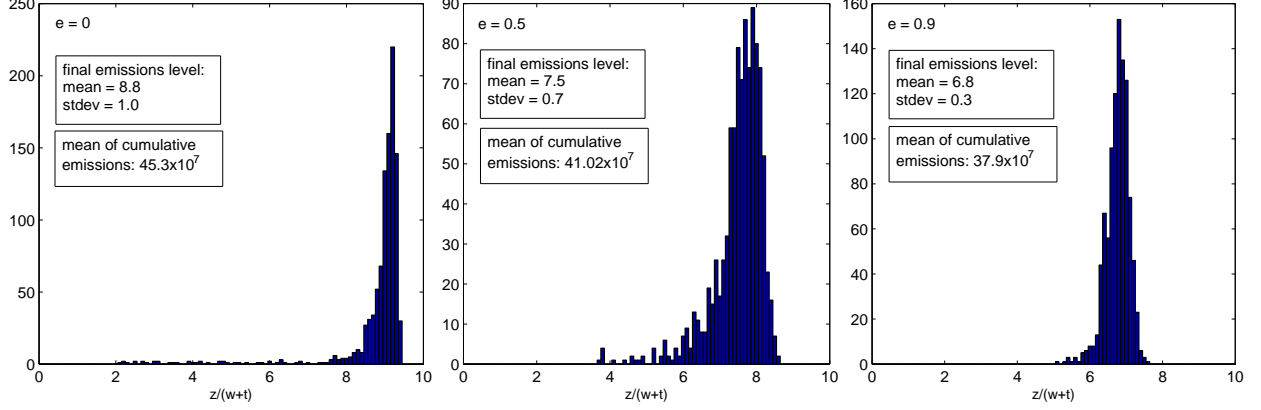

Figure 16: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ with environmental policy costs, for $M = 1000$ simulation runs. Environmental policy has $s = 0.06$. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

less effective recombinant innovation is. With $s = 0.07$ (figure 17) the skewness of emissions distribution is less pronounced than with $s = 0.06$. With respect to the model without policy costs, this time final emission levels are more dispersed, but the mean level is not much higher. Actually it is even lower when recombinant innovation is strong ($e = 0.9$). This means that policy costs affect less the location of the distribution when the policy is more stringent. These results show that policy costs do not change the main message: recombinant innovation
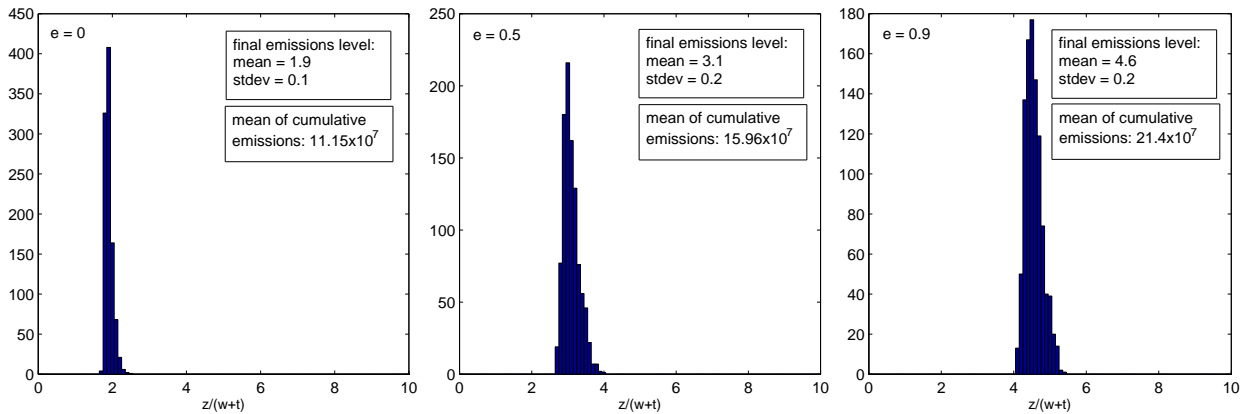

Figure 17: Distribution of total pollution level $\hat{z}_T$ at time $T = 10000$ with environmental policy costs, for $M = 1000$ simulation runs. Environmental policy has $s = 0.07$. Left: $e = 0$. Centre: $e = 0.5$. Right: $e = 0.9$. Parameters are $x_0 = 0.1$, $w = 100$, $e_d = 10$, $e_c = 1$, $\beta = 8$, $v = 10$ and $t_0 = 2000$.

helps to abate pollution emissions if environmental policy is not too strong. But the effects of recombinant innovation are weakened by policy costs: when policy is mild, recombinant

innovation does not help much, when it is strong, it does not hurt much. If policy costs are included then, the results indicate that recombinant hybrid technologies are less but still effective in contributing to the abatement of pollution.

4   Conclusions

We have studied the decision problem of investments in a dirty and a clean technology, when these are subject to increasing returns to investments and can recombine to produce a hybrid technology. Agents can choose one or the other technology, or create a diversified portfolio. We have constructed a model that extends the well-known Arthur (1989) model of competing technologies in two ways: adding (differential) pollution intensities of competing technologies, and introducing the expectation of a hybrid technology due to recombining the two competing technologies.

The diversification incentive of a hybrid technology is opposed to the specialization tendency due to the positive feedback of increasing returns that characterizes Arthur's model. If the effectiveness of recombinant innovation is large enough, lock-in of any technology is prevented. If the effectiveness is too low, the dirty technology takes advantage of its initial wider diffusion and ends up dominating the market. With a critical mass effect in the recombinant innovation learning curve we obtain a reversal of the initial path towards lock-in. The two technologies then converge to equal proportions after the reversal. Recombinant innovation can thus provoke a regime shift in the technological path and unlock the economy from an undesirable dominant dirty technology, to the advantage of the clean technology.

In a second stage we introduced environmental policy in the model in the form of a pollution charge, which causes a negative feedback from pollution to investment choices. The system becomes asymmetric given that different emission intensities enter the implicit utility function of agents. Consequently there are three forces interacting in the model, namely increasing returns, recombinant innovation and environmental policy. We find that recombinant innovation helps substantially to escape from lock-in of the dirty technology, notably if the stringency of the environmental policy is low. On the other hand, if environmental policy is stringent, recombinant innovation limits the abatement of pollution (although it reduces the uncertainty of the outcome), as the system will not entirely move away from the dirty technology. This limitation would lose relevance if the recombinant hybrid alternative emerges and enters the technology competition (which falls outside our model frame).

If we also consider the costs of the environmental policy, the role of recombinant innovation becomes less important. Nevertheless it remains effective in abating pollution. It fosters investment in the clean technology through the intermediate advantage of a diversified technological portfolio enhanced by a hybrid technology. Moreover, cumulative pollution grows less fast.

To conclude, recombinant innovation resulting from highly diversified investments in dirty and clean technologies can be seen as a second best strategy to realize a substitution of a dirty to a clean technology.

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