



ELSEVIER

Contents lists available at SciVerse ScienceDirect

Environmental Innovation and Societal Transitions

journal homepage: www.elsevier.com/locate/eist



Branching innovation, recombinant innovation, and endogenous technological transitions

Koen Frenken^a, Luis R. Izquierdo^b, Paolo Zeppini^{a,c,*}

^a School of Innovation Sciences, Eindhoven University of Technology, The Netherlands

^b University of Burgos, Spain

^c CeNDEF, Faculty of Economics and Business, University of Amsterdam, The Netherlands

ARTICLE INFO

Article history:

Received 20 February 2012

Received in revised form 17 May 2012

Accepted 4 June 2012

Available online 12 July 2012

JEL classification:

C15

O33

Keywords:

Lock-in

Network externalities

Punctuated change

Switching costs

Variety

ABSTRACT

We propose a model of technological transitions based on two different types of innovations. Branching innovations refer to technological improvements along a particular path, while recombinant innovations represent fusions of multiple paths. Recombinant innovations create “short-cuts” which reduce switching costs allowing agents to escape a technological lock-in. As a result, recombinant innovations speed up technological progress allowing transitions that are impossible with only branching innovations. Our model replicates some stylised facts of technological change, such as technological lock-in, experimental failure, punctuated change and irreversibility. Furthermore, an extensive simulation experiment suggests that there is an optimal rate of innovation, which is strongly correlated with the number of recombination innovations. This underlines the pivotal role of technological variety as a seed for recombinant innovation leading to technological transitions.

© 2012 Elsevier B.V. All rights reserved.

1. Introduction

Among the most challenging questions in the social sciences is the question how one can explain societal transitions. Transitions range from transitions in norms, in opinions, in preferences, and in technology use. It is the latter case we will refer to in the following though we reckon that some elements of the model developed below may be more generally applicable.

* Corresponding author at: IPO Building, P.O. Box 513, 5600 MB Eindhoven, The Netherlands. Tel.: +31 040 2472854; fax: +31 040 2474646.

E-mail address: p.zeppini@tue.nl (P. Zeppini).

We characterise transitions as large-scale changes that occur suddenly yet endogenously. This implies that the time-scale at which a transition takes place in a particular context is considerably smaller than the time-scale at which such transitions are absent, which is characteristic of a pattern of punctuated change. Our approach also implies that we do not invoke an external cause (shock) to explain transitions.

Understanding the endogenous forces of technological transitions is particularly important in the design of policies, as for instance innovation policy or environmental policy. In this view, a policy can attempt to render transitions more likely given the underlying endogenous dynamics of technological change at hand, rather than to force a transition through exogenous policy shocks. Deepening our theoretical understanding of the dynamics of technological transitions is particularly relevant given the current challenge to promote sustainable technologies in energy, transportation and agriculture sectors alike.

A salient feature of technology concerns the network externalities that adopters enjoy from using the same technology. Previous models of network externalities (David, 1985; Arthur, 1989; Bruckner et al., 1996) only explain how a technology becomes dominant in a population, and do not explain the emergence of new technological paths. Put differently, while we have a good theoretical understanding of the dynamics of path dependence, we still lack models of path creation. The call for models that combine path creation and path dependence is thus legitimate (Garud and Karnøe, 2001; Garud et al., 2010), as they are fundamental aspects of transitions to sustainable technologies.

To explain the dynamics of technological transitions, we develop a model where agents enjoy positive network externalities from using the same technology, while some agents, called innovators, ignore these externalities and introduce new technologies. After a new technology has been created, the remaining agents make decisions about technology adoption. Adopting agents only adopt a new technology if it gives higher returns net of the switching costs. In the event that all agents switch to a better technology, we speak of a technological transition.

We assume that technologies form a graph, as in Vega-Redondo (1994) and Carayol and Dalle (2007). In these two models the graph is a tree, while a specific feature of our model holds that technologies can be recombined. Models of recombinant innovation proposed hitherto are rare, both theoretical (Silverberg and Verspagen, 2005; van den Bergh, 2008; Zeppini and van den Bergh, 2011; Enquist et al., 2011) and empirical (Fleming, 2001; Fleming and Sorenson, 2001; Schilling and Green, 2011). Recombinant innovations create short-cuts which speed up technological progress, allowing transitions that are impossible otherwise. Different from previous models, our network of technologies is endogenously evolving through the actions of agents, which means that we do not need to make any *a priori* assumptions about the nature of the technology graphs that agents are exploring.

Our model replicates some stylised facts of technological transitions, such as technological lock-in, experimental failure, punctuated change and irreversibility. Lock-in and experimental failure are a consequence of new innovations developed by entrepreneurs being rejected by adopters because of the strong network externalities associated with the old technology (Bruckner et al., 1996). Recombinant innovation underscores the importance of technological diversity as a key feature of technological transitions. Punctuated change is reflected by rare occurrence of transitions, which are irreversible in nature.

From our model, we conclude that neither too low nor too high efforts are advisable for innovation policy. A too low innovation effort does not allow society to escape the current lock-in as all new paths creations are rejected by adopters. A too high innovation effort is wasteful as the marginal returns to an increase in innovation rate quickly approach zero. The optimal innovation effort in between is strongly correlated with the number of recombinations, which indicates how recombinant innovation is important in achieving a sustained technological progress at relatively low costs.

The paper is organised as follows. Section 2 presents the model. Section 3 provides a qualitative analysis of the model results illustrated by some exemplary simulations. In Section 4 we turn to the numerical analysis of an extensive simulation experiment. Section 5 concludes, also indicating the direction for possible extensions of the model.

2. Our model

Let there be a population of N agents ($N \geq 2$). In each period t some agents will develop a new technology while the remaining agents face an adoption decision. Given the technology set A_t of period t , agents decide based on a utility $u_{\alpha,t}$, where $\alpha \in A_t$ indicates the technology adopted. The utility from using technology α comes from an intrinsic quality level l_α and from the positive externalities that other users of α exercise on the single agent (cf. Arthur, 1989):

$$u_{\alpha,t} = l_\alpha + en_{\alpha,t} \tag{1}$$

where the parameter $e \in [0, 1]$ measures the strength of network externalities, while $n_{\alpha,t}$ indicates the number of agents using α in period t . Technologies form a directed graph of which they represent the nodes, while the links express the genealogical relationships.

2.1. Innovation

In each period any agent can innovate with probability p , introducing one new technology that represents a quality improvement with respect to the technology previously used. In case more than one agent innovates in the same time period, they will do so jointly. This means that each period only one new technology is created provided that one or more agents innovate. There are two types of innovation: *branching* and *recombination*. In the first case, one or more agents previously adopting the same technology innovate and create a new technology that “branches” from the old one. In the second case, agents previously adopting different technologies join to create the recombinant innovation. In the technology graph a recombinant technology has at least two incoming links from different parent technologies, while with branching the incoming link is always one (Fig. 1).

We assume that quality improvements are always equal to one, reflecting the incremental nature of technological progress. This assumption is also chosen as to avoid any spurious explanation of transitions as stemming from single innovations creating a jump in quality improvement. In the case of branching the quality improvement is a unitary step up over the parent technology. If β is an innovation that branches from technology α , we have:

$$l_\beta = l_\alpha + 1 \quad \text{branching} \tag{2}$$

For recombinant innovation, the quality of the innovation is assumed to be a unit higher than the maximum quality of recombinant technologies. If α , γ and more technologies recombine to give the innovative technology β , we write:

$$l_\beta = \max\{l_\alpha, l_\gamma, \dots\} + 1 \quad \text{recombination} \tag{3}$$

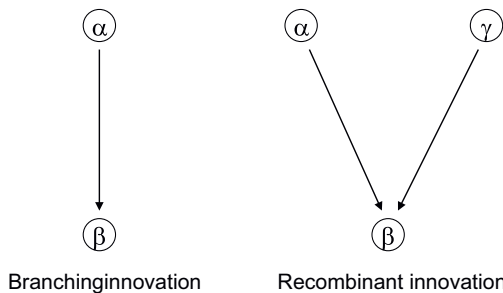


Fig. 1. Representation of possible innovation events in one period.

Thus, if m technologies recombine the quality of the innovation will be one unit higher than the quality of the best among these m technologies.¹ By assumption the innovators stick to their newly developed technology at least for one period. This means that the set of adopting agents at time t consists of the agents who have not been involved in an innovation at time t .

2.2. Adoption decision

In every period t an agent may be drawn as innovator with some probability p . If an agent is not an innovator, it evaluates and compares the utility from adopting each available technology in the set A_t . All non-innovating agents decide synchronously which technology to adopt. The decision is actually about whether to stay with the technology they currently use, or to switch to a more attractive technology. Such decision involves a third factor, switching costs, which we derive from the distance between the used and the new technology in the technology graph. Let all technologies be part of a connected graph with the technological distance between α and β given by the geodesic distance $d_{\alpha\beta}$ (with $d_{\alpha\alpha} = 0$). We assume that the switching costs from one to the other technology equal the geodesic distance $d_{\alpha\beta}$. This means that switching from technology α to technology β takes place as soon as the following condition realises:

$$u_{\beta,t} - d_{\alpha\beta} > u_{\alpha,t} \quad (4)$$

Thus, if the difference $\Delta u_{\alpha\beta} = u_{\beta,t} - u_{\alpha,t} - d_{\alpha\beta}$ is positive, agents will migrate from α to β , otherwise the old technology is maintained. Since more than two technologies are present in the network in general, agents search for the best one. If two technologies β and γ present the same benefits from switching, that is if $\Delta u_{\alpha\beta} = \Delta u_{\alpha\gamma}$, a random decision is taken.

3. Qualitative analysis

3.1. The effect of recombinant innovations

We implemented the model in NetLogo. A qualitative analysis is conducted here from observations of single simulation runs, while in the next section we turn to batch simulations. We show a number of single runs for different values of p where p stands for the probability in each period that an agent is drawn as an innovator. This parameter thus reflects the rate of innovation in society. Hence, p can be regarded as the crucial policy parameter that a government can tune through subsidies.

Some properties of the model can be readily derived. Parameter p directly determines the expected number of innovating and non-innovating agents. For example, if we have $N = 50$ agents and $p = 0.1$ we will have, on average, 5 innovating agents and 45 adopting agents in each period. Generally, the expected number of innovators in each period is given by pN and the expected number of non-innovators by $(1 - p)N$.

Network externalities are expressed by parameter e which we put to 0.5 in the qualitative analysis. Given that externalities are positive, agents thus profit a lot from adopting the same technology. For a population again of 50 agents, adopting the same technology adds no less than 25 to each agent's utility. One can thus readily understand that if p is low, say 0.1, a population of 50 agents will find it hard to escape from a lock-in. With only a small minority of agents developing a new

¹ This specification is crucial, but alternative specifications do not affect the behaviour of the model and its messages. Alternative specifications have been studied, such as the *mean* of the quality levels of parent technologies and the *min* of quality levels. Simulation results do not change qualitatively. Quantitatively, these two alternative specifications require a higher innovation probability p to achieve a given level of technological quality. As a matter of fact, the choice of specification for the quality of a recombinant innovation is an empirical issue, where different industrial sectors and/or technologies call for different specifications. We model technology competition in a broad sense, meaning that technologies are mainly substitutes and compete for scarce resources (capital and labour). In this context, two or more firms co-innovate only if the recombinant innovation makes better off each one of them. To this case the specification adopted (Eq. (3)) fits the best. We reckon that whenever interacting technologies present some degree of complementarity, a different specification as one of the two mentioned above or even one based on the weighted average of parent technologies can be more suitable.

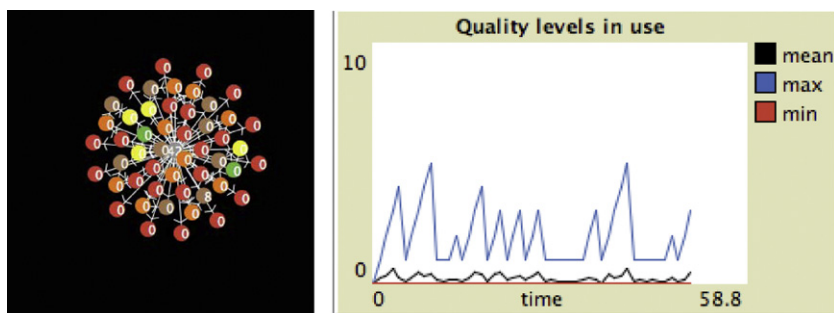


Fig. 2. Simulation with $p = 0.1$ ($N = 50$, $e = 0.5$, $T = 50$). *Left:* technology graph (the colours of the nodes represent the quality of a technology. The grey colour is assigned to the first technology that all agents adopt at the start of each simulation, with quality level $l = 0$. Red nodes are technologies with quality level $l = 1$, orange nodes have $l = 2$, etc. The label on each node refers to the number of adopters at the end of the simulation run). *Right:* quality levels (minimum quality is red, maximum quality is blue and mean quality is black). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

technology, which represents only an incremental quality improvement over the old technology, the remaining adopting agents will choose to stick to the old technology to profit from the strong network externalities associated with using the same technology.

Fig. 2 reports an example with $p = 0.1$. The graphs show that despite the many attempts to create new technologies (all nodes with a colour different from grey), the population has remained stuck in the old technology with quality level $l = 0$ (the splitting of the population with 42 agents using the old technology and 8 agents in an innovative technology, is temporary, since the 8 innovators have to use their innovation for one period by assumption). This is also apparent from the right panel of the figure, where we observe that the minimum quality level of all technologies in use is $l = 0$. Defining a transition as an event that leads the whole population to a better technology – meaning that the minimum quality level of all technologies in use raises – we observe that for $p = 0.1$ no transitions could take place within the simulation period.²

The example with $p = 0.2$ (Fig. 3) presents two transitions: in the right panel we see two jumps in the time series of the minimum quality, that is, two technological transitions. Such transitions occur suddenly once a sufficient number of agents developed a sufficiently superior technology as to attract all remaining agents to switch. This will happen more often if the final event leading up to a transition is a recombinant innovation involving agents using the old technology, so that the geodesic distance between the old and the new technology is reduced to 1 and, hence, switching costs are minimum. Fig. 3 illustrates this phenomenon: both transition events originated from a recombinant innovation. Also note that transitions are irreversible: once all agents adopt a technology such that the minimum quality of technologies in use increases, they will never switch back to a technology with lower quality, since these are all unoccupied. These jumps are reflected in the out-degree distribution of the technology graph in the left panel of Fig. 3, where the out-degree of a node stands for the number of arcs starting from a node. In the simulations, nodes with high out-degree are temporarily locked-in technologies with many failed innovation attempts. Here there are three nodes with high out-degree. The first one corresponds to the initial technology. A second one represents the first technological transition. The third one comes from a second transition, and it is the one that is populated at the final time of the simulation run ($T = 50$).

Increasing further the probability of innovation we obtain more transitions and faster growth. Already with $p = 0.5$ (Fig. 4) the minimum level of quality increases almost continuously, with a transition in every time step. The variability of the system decreases substantially, and the model

² Note that this does not imply that transitions cannot take place. As long as p is positive, a transition will take place since there is a positive probability that more than half of the agents are drawn as innovators creating a technology that subsequently will be adopted by the remaining agents.

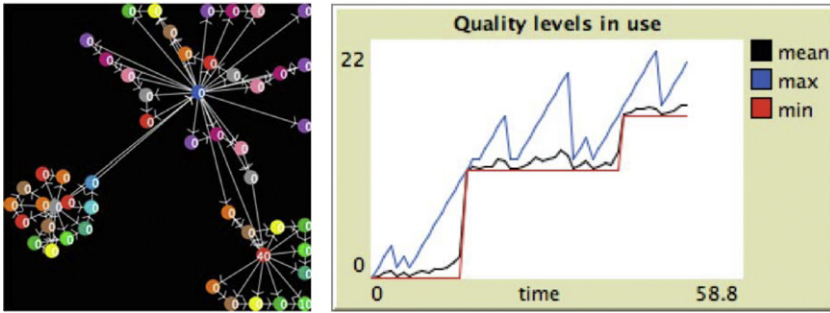


Fig. 3. Simulation with $p=0.2$ ($N=50$, $e=0.5$, $T=50$). *Left:* technology graph (the colours of the nodes represent the quality of a technology. The grey colour is assigned to the first technology that all agents adopt at the start of each simulation, with quality level $l=0$. Red nodes are technologies with quality level $l=1$, orange nodes have $l=2$, etc. Notice that we have a limited set of colours, so that after a given number of innovation a technology gets an already used colour. The label on each node refers to the number of adopters at the end of the simulation run). *Right:* quality levels (minimum quality is red, maximum quality is blue and mean quality is black). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

acquires more and more a deterministic character. The technology graph on its turn assumes the form of a chain with a few instances of recombinant innovation and without nodes with high out-degree.

Summarising the qualitative analysis of the model, we can distinguish between three regimes of innovation effort (p) reflecting qualitatively different technology dynamics:

- (i) a regime with low levels of innovation effort corresponding to a regime of “lock-in” where almost all innovation attempts fail;
- (ii) a second regime with intermediate levels of innovation effort corresponding the regime of punctuated “technological transitions” with only some innovation succeeding as being part of a series of innovation leading up to a transition; and
- (iii) a third regime with high levels of innovation effort leading to a pattern of “linear growth” where almost all innovation attempts succeed.

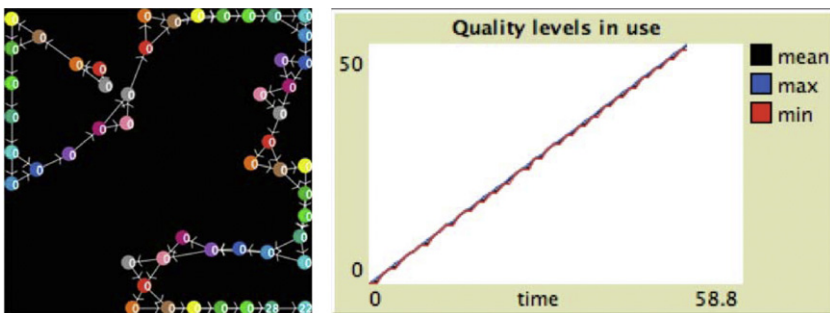


Fig. 4. Simulation with $p=0.5$ ($N=50$, $e=0.5$, $T=50$). *Left:* technology graph (the colours of the nodes represent the quality of a technology. The grey colour is assigned to the first technology that all agents adopt at the start of each simulation, with quality level $l=0$. Red nodes are technologies with quality level $l=1$, orange nodes have $l=2$, etc. Notice that we have a limited set of colours, so that after a given number of innovation a technology gets an already used colour. The label on each node refers to the number of adopters at the end of the simulation run). *Right:* quality levels (minimum quality is red, maximum quality is blue and mean quality is black). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

4. Batch simulations

In this section we report on the analysis of a systematic simulation experiment (batch simulations), that aims at unveiling the effect of the innovation probability p on the model, in different conditions of agents population (N) and network decision externalities (e). In this simulation experiment we considered a time horizon of $T = 50$ steps, and averaged results over 50 repetitions.³ We analyse the simulation results by looking at four variables: the minimum quality of used technologies, the mean utility of agents, the total number of recombinations and the accumulated entropy. The first two variables are computed at the end of the simulation run (that is at time $t = T = 50$), while the second two are cumulative variables, being made of the contributions of all periods in the simulation time horizon ($T = 50$ periods). Entropy measures the variety of technologies that are in use (Frenken et al., 1999). In a given period t , the entropy of the system is defined as⁴

$$E_t = - \sum_{\alpha \in A_t} \frac{n_{\alpha,t}}{N} \log_2 \frac{n_{\alpha,t}}{N} \quad (5)$$

Simulation results are collected in Fig. 5 where we consider three different values of the externality parameter, namely $e = 0.1$, $e = 0.5$ and $e = 1$, and three different values of the population size,⁵ $N = 10$, $N = 20$ and $N = 50$. On the horizontal axis there is the value of the probability of innovation p . Entropy and number of recombinations report on the “technology dynamics”, which are reflected in the quantities that are accumulated over the whole simulation time horizon (50 periods here). On the other hand, minimum quality of technologies in use (min-quality) and the average utility of agents show the “welfare effects”, and are measured at the end of the simulation ($t = 50$). One can readily note the high correlation of quality and utility curve, which is a consequence of Eq. (1).⁶

We have the following results. First, in all simulations there is an internal maximum both for the number of recombinant innovations that occur during the time horizon considered and for the entropy of the distribution of agents over technologies. Also note that the entropy at $p = 0$ and $p = 1$ is zero. This reflects a state where all agents use the same technology. For $p = 0$ this is the initial zero-quality technology. For $p = 1$ it is the newest technology. Actually, the latter case already realises for $p = 0.9$. The internal maximum of the number recombination events does not coincide with the internal maximum of the entropy for $N = 10$, but with a larger N the maximum of entropy shifts to the right, while the maximum of the number of recombinations shifts to the left. With $N = 50$ the two curves are almost coincident. Moreover, we notice that entropy is zero already when $p > 0.8$ for $N = 20$ and when $p > 0.7$ for $N = 50$, for any value of e : the larger the population size, the lower innovation probability is required for having all agents use the best technology, and this is quite independent on the strength of network externalities.

A second interesting result, which requires the combination of large N and large e , is the non-monotonicity of the utility curve: for low values of p , this is initially decreasing, and then increasing again. In other words, there is an internal minimum of mean utility. For low values of the probability of innovation, its marginal effect is negative. The intuition is that low p only subtracts agents to the most populated technology, giving up benefits from network externalities, without rewarding enough in terms of increased quality. This loss due to waived network externalities is more severe the larger is e .⁷

³ Increasing the number of simulation runs (50 runs in this section) lowers the standard deviation of average values. Longer time horizons ($T = 50$ in this section) do not alter qualitatively the results.

⁴ Notice that $0 \log 0 = 0$ by definition.

⁵ The population size cannot be too low due to the assumption that agents do not interact strategically as in game-theoretical models.

⁶ In particular, when p is high the value of minimum quality coincides with the number of periods in the time horizon considered T , because innovation becomes almost deterministic. The mean utility, in this limit, is equal to the minimum quality plus eN .

⁷ Notice the irregular shape of the utility for mid values of p when e and N are relatively large. This is a technical effect from the definition of the model: when $p = 0.5$, half the agents are innovators, on average. With half agents in the old technology and half in the new, the utility from switching and the utility from remaining are equal, because the unitary increase in quality is offset by the unitary switching cost. We assume that in case of tie between old and new technology agents go for the former, which creates a bias resulting in a relatively lower utility for $p = 0.5$.

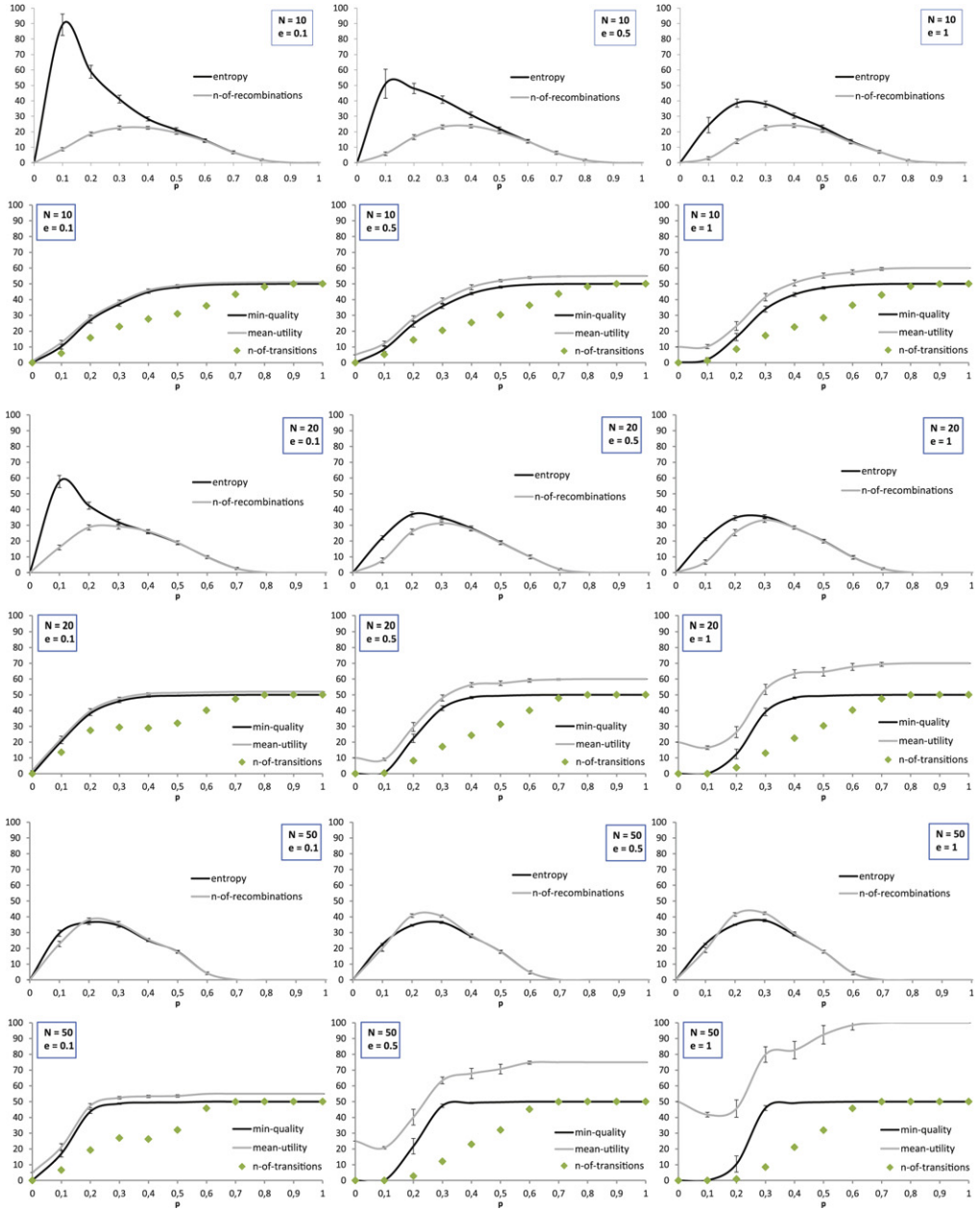


Fig. 5. Batch simulations with 50 runs: cases $e = 0.1$, $e = 0.5$, $e = 1$ and $N = 10$, $N = 20$, $N = 50$. Entropy, number of recombinations and number of transitions are cumulative quantities over 50 periods. Minimum quality of used technologies and mean utility across agents are measured at $T = 50$. Graph values are averages of 50 simulation runs, while error bars are the standard deviation. Lines are a polynomial fit.

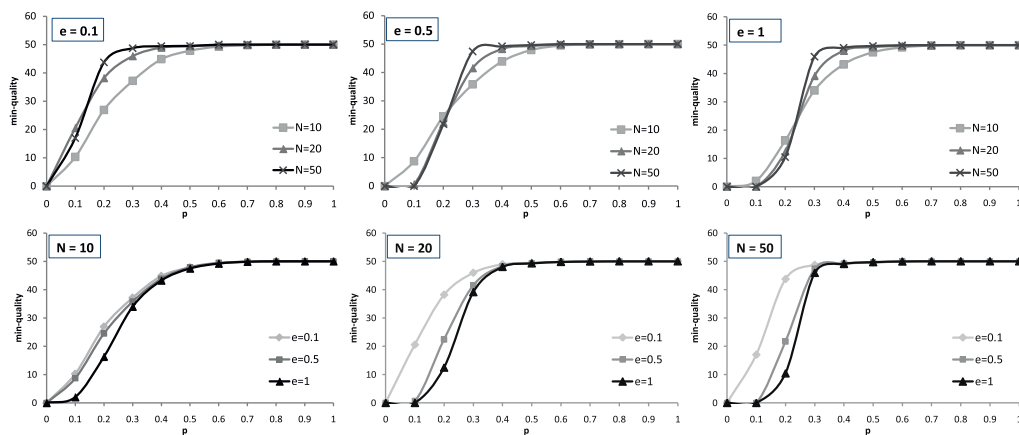


Fig. 6. Minimum quality at $T = 50$. Top: effect of N for a given e . Bottom: effect of e for a given N .

The third result holds that, the marginal increase in quality for increasing p is highest for positive but low values of p , generally in the range 0.2–0.3. That is, the S-shaped quality curves in Fig. 5 present three regions: for low effort p , corresponding to the lock-in regime, this marginal effect is very low, which indicates that innovation costs may likely be above its benefits. For intermediate values of p , corresponding to the technological transitions regime, the marginal quality is largest, and innovation effort is maximally productive. Finally, large values of p , corresponding to the linear growth regime, belong to a saturation region, where marginal effects are negligible: any further increase of innovation effort is wasted here. The economic intuition is that innovation effort in this model should be just large enough to overcome the lock-in effects due to network externalities.

Importantly, a regular feature of these simulation results is the location of the maximum of the number of recombinations, which occurs between the region with high slope and the saturation region of the quality curve. Between these two regions the ratio of benefits to costs is seemingly maximum. Such observation indicates that recombinant innovation is important not just in the innovation process, but especially in favouring technological transitions (increase in minimum quality among used technologies). The intuition is that recombinant innovations create short-cuts to higher level technologies for agents that are lagging behind, because their technology is in a different branch with respect to the technology with higher quality. Without recombinant innovation it would be too costly for these agents to switch to such technology, in that every link between technologies entails the payment of the unitary cost. With recombinant innovation instead they can “jump” to the leading technology with only one link in principle, whenever some of them is drawn as innovator together with some innovators from the leading technology.

Our second systematic analysis disentangles the effect of population size N and the strength e of network externalities. At first sight, one may conclude that the two effects are just two sides of the same coin, since the effect of network externalities on agents' utility is the product of N and e . Yet, to jump to this conclusion would be wrong, as N has the additional effect on the expected number of innovating agents as given by pN , while e has no effect at all on the number of innovating agents. In order to distinguish between the effects of network externalities e and population size N , we plot together the curves for different values of e first, and then for different values of N in the same graph. Let consider the curves of minimum quality levels. In Fig. 6 each panel on the top reports together different values of the population size N for a given value of network externalities e . The bottom panels of Fig. 6 show the same data with different values of e for a given value of N . From this synoptic analysis of simulation results we infer the following: both e and N are responsible of a S-shaped minimum quality curve. Stronger network externalities e always mean a lower quality for a given innovation effort p , while a larger population size N may also give a higher quality level. In particular, when e is relatively low, this is always the case. In other words, a larger e shifts the flex point of the quality

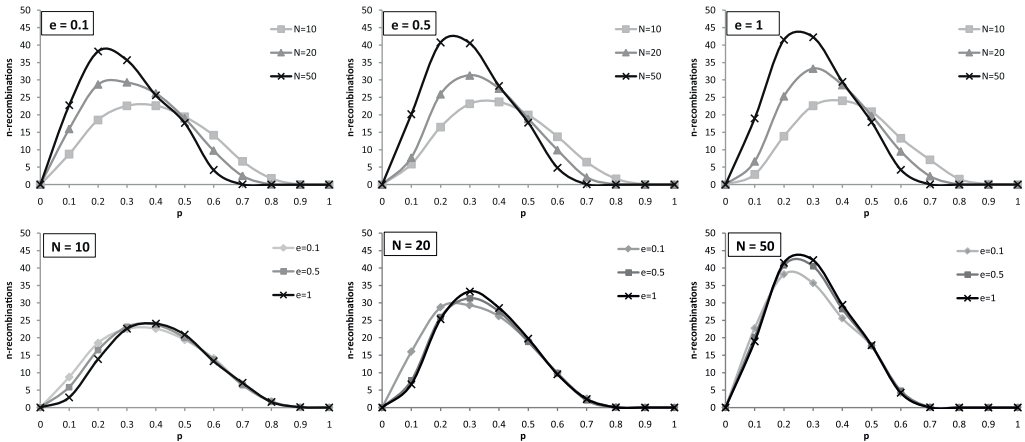


Fig. 7. Number of recombinant innovations in 50 steps. *Top:* effect of N for given e . *Bottom:* effect of e for given N .

curve to the right, while a larger N increases the steepness of the curve in the flex point, leaving this almost unmoved for $e=0.5$ and $e=1$, and shifting it to the left for $e=0.1$. This means that a larger population size can be good for technological progress, while network externalities are a limiting factor. The positive effect of the population size on technological quality can be explained through recombinant innovations. Fig. 7 reports the number of recombinant innovations for different values of e and N in the same way as the previous figure. With larger N there are more recombination events on average, and the distribution shifts to the left: less innovation effort is needed to trigger recombinant innovation. When changing N , the maximum of the number of recombinant innovations mirrors the “bump” of the S-shaped quality curve, both in location and in size, as already noticed: also the effect of population size tells the importance of the recombination process in fostering technological quality through transitions.

5. Conclusions

In this paper we have proposed a new model of technological change, which emphasises the role of recombinant innovation in processes of technological transitions. The action of innovating agents is central in the model, which is an aspect that recognises the important role of entrepreneurs in technological change (Schumpeter, 1912; Garud and Karnøe, 2001). Innovation is made by innovators but it is shaped by adopters. The model accounts for the stylised facts of technological change, such as technological lock-in, experimental failure, punctuated change and irreversibility.

By running an extensive simulation experiment we have analysed the role of the innovation effort in different conditions of population size and network externalities. The main conclusion that can be drawn from the model holds that the innovation effort in a society has the biggest impact on technological progress when it is just large enough to create new varieties that subsequently can be fused through recombinant innovation triggering a technological transition. Government policy should then subsidise innovation up to this optimal level.

The model can be extended in a number of directions. First, rather than assuming that innovating agents who previously used different technologies would automatically recombine, one can also allow for branching innovation events in parallel. Thus, one can introduce a parameter that governs the decision to recombine or branch in parallel. A second extension of the model would be to relax the assumption of unitary switching costs as to assess the impact of switching costs on dynamics of technological transitions. Finally, we can assume that agents are not perfectly informed about the utility of technologies, but choose probabilistically based on the technology's relative utility.

Our observations indicate that recombinant innovations are a key factor of technological progress in this model. The intuition is that recombinant innovations create “short-cuts” to higher quality in

the technology graph at low switching costs, allowing technological transitions that would be hard to realise otherwise. The policy lessons are twofold. First, subsidising innovation is a balancing act between the risk of under-spending unable to lock-out a population from existing technologies and the risk of over-spending wasting resources on redundant efforts. Second, innovation policy aimed at fostering technological transitions should not only promote the development of new varieties, but also the recombination of these varieties with elements of the old locked-in technology, as to trigger lagging agents to switch to new technologies.

These conclusions hold *a fortiori* for environmental innovation. In the case of clean energy technology, for example, quite a large number of alternatives have been developed. At the present time, recombinant innovations may well make it more likely a process of un-locking of the economy from the dominance of undesired technologies as for instance fossil fuels. Ideally, such recombinant innovations make ample use of elements of existing technologies such as to reduce the switching costs for society as a whole. More generally, emphasis in transition research and transition policy alike should not only lie on the development of new innovations, but also on recombinant innovation and switching costs, which underlie the large-scale adoption processes that ultimately drives transitions.

References

- Arthur, B., 1989. Competing technologies, increasing returns, and lock-in by historical events. *Economic Journal* 99, 116–131.
- Bruckner, E., Ebeling, W., Jimenez-Montano, M.A., Scharnhorst, A., 1996. Nonlinear effects of substitution. An evolutionary approach. *Journal of Evolutionary Economics* 6 (1), 1–30.
- Carayol, N., Dalle, J.M., 2007. Sequential problem choice and the reward system in Open Science. *Structural Change and Economic Dynamics* 18 (2), 167–191.
- David, P.A., 1985. The economics of QWERTY. *American Economic Review (Papers and Proceedings)* 75, 332–337.
- Enquist, M., Ghirlanda, S., Eriksson, K., 2011. Modeling evolution and diversity of complex cumulative culture. *Philosophical Transactions of Royal Society B* 366, 412–423.
- Fleming, L., 2001. Recombinant uncertainty in technological search. *Management Science* 47 (1), 117–132.
- Fleming, L., Sorenson, O., 2001. Technology as a Complex Adaptive System: evidence from patent data. *Research Policy* 30 (7), 1019–1039.
- Frenken, K., Saviotti, P.P., Trommetter, M., 1999. Variety and niche creation in aircraft, helicopters, motorcycles and microcomputers. *Research Policy* 28, 469–488.
- Garud, R., Karnø, P., 2001. Path creation as a process of mindful deviation. In: Garud, R., Karnø, P. (Eds.), *Path Dependence and Path Creation*. Lawrence Erlbaum, Mahwah, NJ, pp. 1–38.
- Garud, R., Kumaraswamy, A., Karnø, P., 2010. Path dependence or path creation. *Journal of Management Studies* 47, 760–774.
- Schilling, M.A., Green, E., 2011. Recombinant search and breakthrough idea generation: an analysis of high impact papers in the social sciences. *Research Policy* 40 (10), 1321–1331.
- Schumpeter, J.A., 1912. *Theorie der wirtschaftlichen Entwicklung*. Leipzig: Duncker & Humblot. English Translation Published in 1934 as “The Theory of Economic Development”. Harvard University Press, Cambridge, MA.
- Silverberg, G., Verspagen, B., 2005. A percolation model of innovation in complex technology spaces. *Journal of Economic Dynamics and Control* 29, 225–244.
- van den Bergh, J.C.J.M., 2008. Optimal diversity: increasing returns versus recombinant innovation. *Journal of Economic Behavior and Organization* 68, 565–580.
- Vega-Redondo, F., 1994. Technological change and path dependence: a co-evolutionary model on a directed graph. *Journal of Evolutionary Economics* 4 (1), 59–80.
- Zeppini, P., van den Bergh, J.C.J.M., 2011. Competing recombinant technologies for environmental innovation: extending Arthur's model of lock-in. *Industry and Innovation* 18 (3), 317–334.