

A Discrete Choice Model of Transitions to Sustainable Technologies

Paolo Zeppini*

*School of Innovation Sciences, Eindhoven University of Technology, The Netherlands
CeNDEF, Amsterdam School of Economics, University of Amsterdam, The Netherlands
Istituto di Economia, Scuola Superiore Sant'Anna, Pisa, Italy*

Abstract

We propose a discrete choice model of sustainable transitions from dirty to clean technologies. Agents can adopt one technology or the other, under the influence of social interactions and network externalities. Sustainable transitions are addressed as a multiple equilibria problem. A pollution tax can trigger a sudden transition as a bifurcation event, at the expenses of large policy efforts. Alternatively, periodic dynamics can arise. Technological progress introduced in the form of endogenous learning curves stands as a fundamental factor of sustainable transitions. For this to work, the positive feedback of network externalities and social interaction should be reduced initially, for instance by promoting niche markets of clean technologies and making technological standards and infrastructure more open. Traditional policy channels such as pollution tax and feed-in-tariffs have an auxiliary - yet important - role in our model. Compared to feed-in-tariffs, a pollution tax promotes smoother and faster transitions.

Key words: bounded rationality, environmental policy, learning curves, multiple equilibria, network externalities, social interactions.

JEL classification: C62, D62, O33, Q55

1 Introduction

Resource scarcity, climate change and environmental justice are among the major challenges faced by human mankind in present times. These challenges require profound changes of industrial and agricultural sectors, but also involve behaviours, institutions and more generally the organization of society. In particular environmental challenges call to reform energy, housing, and transportation, and pose new targets for technological progress towards sustainable solutions (van den Bergh, 2012).

There is currently little evidence that major changes occur in energy solutions, and in particular no evidence of relevant transitions towards sustainable power generation.

*Address: Technische Universiteit Eindhoven, P.O. Box 513, 5600 MB Eindhoven, The Netherlands.
Email: paolo.zeppini@gmail.com. Telephone: +31 40-247 2854.

Fig. 1 contains the time series of different sources of energy production in the United States. The data show little change from 1972 until 2008: the aggregate amount of

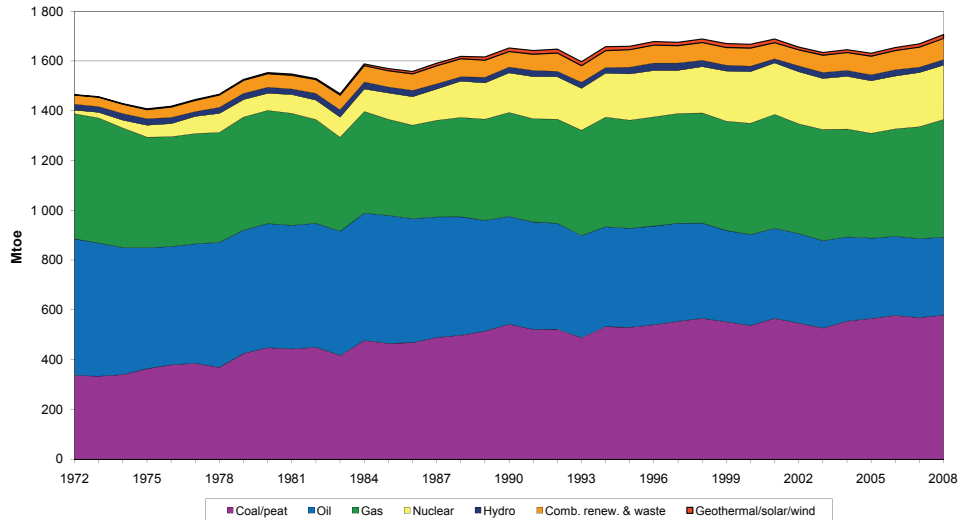


Figure 1: Energy production in US: time series of different sources (source: OECD/IEA).

fossil fuels (coal, oil and gas) maintains its leadership almost untouched, and renewable energy is not able to score any appreciable gain of market shares. All this suggests that the economy and the whole society are stuck into an equilibrium where fossil fuels are the dominant technology for energy production. Why this is so, despite substantial technological progress in renewable technologies, and environmental policy actions, at least in some developed countries? Power generation is just one, yet important, example of industrial sectors causing major damages to the environment and contributing to climate change. Other examples are transportation systems, which also heavily rely on fossil fuels.

Technology plays a primary role in the interplay between the economy and the natural environment, which is strongly relevant to a model of climate change mitigation. However, this role has been recognized only recently. In the economic literature, notable examples are models of endogenous growth theory, such as Acemoglu et al. (2012) and integrated assessment modeling, as Popp (2004), for instance. However these models pose little attention to the heterogeneity of economic agents and their decision process, neither to the dynamics of competition between multiple technological options. To address these issues face to the problem of sustainable transitions is the scope of our paper.

The issue of sustainability has become central in innovation studies and environmental economics, and led to the concept of “sustainability transitions” (Kemp, 1994; Köhler et al., 2009; Markard et al., 2012). A transition path of climate change mitigation is quite different from a gradual and linear path, with strong implications for macroeconomic theory and environmental policy (van der Ploeg, 2011). Moreover, the intrinsic dynamic nature of a transition event finds a natural conceptual framework in evolutionary mod-

elling (Foxon, 2011). In this paper we propose an analytical framework for the study of sustainability transitions, based on discrete choice dynamics, bounded rationality and switching behaviour (Golman, 2012).

Sustainability transitions often imply a regime shift from an established technology to an innovative technology. The idea of technological regime is central to transition thinking and to evolutionary economics (Nelson and Winter, 1982). A technological regime has often the connotation of “lock-in” (Arthur, 1989). A technological lock-in is a state in which one technology is dominant in a particular application domain or industrial sector, and competing alternatives find it hard if not impossible to enter the market, even if they are socially desirable (David, 1985).

Technological lock-in is the result of increasing returns to adoption: a technology tends to be more attractive the more it is adopted. Several factors give place to this positive externality in adoption decisions: learning effects among producers and users, the advantages of common standards and infrastructure, and the provision of complementary goods, services and institutions. These factors add to the utility of using a technology and in economics are often referred to as “network externalities” (Katz and Shapiro, 1985).

Network externalities give rise to barriers which are strong to be broken. This scenario translates into multiple equilibria, and once the economy is stuck in one of those, with one technology dominating the market (technological lock-in), it is hard for alternative technologies to gain market shares, let alone to overcome the dominant technology. In the energy sector, a shift from the equilibrium represented by fossil fuels is very hard to achieve, due to the large scale of infrastructures and amount of investments, a fact that suggested the notion of “carbon lock-in” (Unruh, 2000; Könnölä et al., 2006). A possible way to escape carbon lock-in has been analysed by Zeppini and van den Bergh (2011) with the concept of “recombinant innovation”.

Beside the tangible effects of network externalities, there are other sources of positive feedback in all kinds of discrete choice decisions, which stem from social interactions in the form of contagion effects, imitation and social learning (Young, 2009). In some cases positive feedback of social interactions regard the informational content of actions, where one agent makes a decision based not only on her own knowledge but also trying to infer information from the decisions of others, as for instance in financial markets (Banerjee, 1992). A different mechanism is the advent of fads and fashions, which is mainly connected to imitation and peer-effects (Bikhchandani et al., 1992). In our context it is important to stress the relevance of decision externalities for environmental problems and sustainability issues due to the role played by social interactions in collective behaviour.

In this paper we propose to integrate the concepts and approaches outlined above in a simple model of competing technologies and sustainable transitions based on the discrete

choice and social interactions framework of Brock and Durlauf (2001). We frame the problem of a transition to sustainable technologies as a transition from one to another of two alternative equilibria. Clean technologies represent the ultimate goal of sustainability transitions in our model. Multiple equilibria reflect a coordination problem, where economic agents face dirty and clean technologies competing with each other. We make the assumption of myopic behaviour of adopting agents, who base their decision on past experience, and consequently focus on the dynamics of technology market shares. This focus is much in line with evolutionary models of financial markets, which are based on bounded rationality and heterogeneous agents (Hommes, 2006). Brock and Durlauf are interested in the conditions for rational equilibrium consistency, while our focus on transitions call for developing a dynamic model.

With our model we take the discrete choice framework to the realm of sustainable transitions. By making technology explicit, we can introduce different channels for environmental policy intervention, such as *R&D* subsidies to stimulate sustainable choices beside taxes on polluting technologies. We address a simple scenario with the competition between a “clean” and a “dirty” technology, and an environmental policy attempting to reduce the overall level of pollution. In this article we show how such policy can trigger a transition to clean technologies by affecting the dynamics of the system and its equilibria.

We study two types of environmental policy: one linked to technology shares, and one that tries to close the technological gap between “clean” and “dirty” technologies. The model gives the following indications: a static policy, such as a pollution tax, that misses to focus on technological progress, can only reduce marginally the share of a dirty technology, and can only trigger a major transition as an equilibrium shift, at the expense of relatively large efforts. A policy that favours technological progress for the clean solution can foster smooth and continuous transitions. However, in a scenario where the dirty technology is initially dominant the clean technology is strongly opposed by the positive feedback of network externalities and social interactions. The most efficient intervention is the combined action of technological progress and an environmental policy such as a pollution tax or subsidies linked to the technological gap that deploy their effect in the initial phase, and then are adaptively reduced as the clean technology gains momentum.

The structure of this article is as follows. Section 2 presents a basic version of the model. Section 3 introduces the environmental policy. Section 4 focuses on technological progress. Section 5 brings together environmental policy and technological progress. Section 6 concludes.

2 Social interactions and network externalities

In this section we present the basic version of the model, modelling the effect of social interactions and network externalities in technology competition. Network externalities are a source of self-reinforcement due to increasing returns to adoption: the utility from one technology increases with the number of fellow adopters (Arthur, 1989), because of technological standards and infrastructure. Social interactions in technology adoption convey all (usually positive) decision externalities induced by imitation, “word of mouth” or social learning (Young, 2009), conformity effects and habit formation (Alessie and Kapteyn, 1991), or even forms of recruitment (Kirman, 1993). The main difference in these two sources of positive feedback is that network externalities stem from measurable contributions to utility with the diffusion of a technology (a network of users), while social interactions imply social contacts and do not give any tangible benefit in terms of technological performance. For example, the adoption of an electric car or a fuel cell car bears a positive marginal contribution to utility if there are many similar cars around, due to the realization of infrastructure such as refueling stations. Similarly, a larger sales volume brings a positive effect in terms of repairing skills and costs. But at the same time the decision to adopt one such car is also positively affected by seeing an increasing number of them around, or knowing that a friend has bought one, even if these facts do not affect the utility from using the car.

Social interactions and network externalities are important to a different extent in different technology sectors. For instance, computer software packages present strong network externalities, due to standards and compatibility barriers. On the other hand, web browsers are perfectly compatible, and their competition is likely to be characterized only by social interactions. There may also be cases where social interactions give place to a negative feedback, as with conspicuous consumption aiming at social status. We discard this possibility, and we model social interactions and network externalities together as a unique source of self-reinforcement in technology decisions.

Consider M technologies competing in the market for adoption or for $R\&D$ investment by N agents ($N \gg M$). The utility, or profitability, from technology c in period t is

$$u_{c,t} = \lambda_c + \rho_c x_{c,t}, \tag{1}$$

where λ_c is the profitability of technology c , and $x_{c,t}$ is the fraction of agents that choose technology c in period t . For the moment we assume λ_c to be constant, that is we discard technological progress. In Section 4 we relax this assumption. The parameter $\rho_c > 0$ expresses the intensity of positive externalities in agents’ decisions. The term $\rho_c x_{c,t}$ describes the self-reinforcing effect of decision externalities.

We model agents’ choices about technology by the discrete choice framework of Brock

and Durlauf (2001). The general case with M choice options is addressed in Brock and Durlauf (2002) and in Brock and Durlauf (2006). According to this model, each agent i experiences a random utility $\tilde{u}_{i,t} = u_{i,t} + \epsilon_{i,t}$, where the noise $\epsilon_{i,t}$ is *iid* across agents, and it is known to an agent at the decision time t . What the agent does not know with infinite precision is the decision of other agents, that is the social term $\rho_c x_{c,t}$ of Eq. (1). In the limit of an infinite number of agents, when the noise $\epsilon_{i,t}$ has a double exponential distribution, the probability of adoption of technology c converges to the Gibbs probability of the multinomial logit model:

$$x_{c,t} = \frac{e^{\beta u_{c,t-1}}}{\sum_{j=1}^M e^{\beta u_{j,t-1}}}. \quad (2)$$

The parameter β is the *intensity of choice* and it is inversely related to the variance of the noise $\epsilon_{i,t}$ (Hommes, 2006). In the limit $\beta \rightarrow 0$ the different technologies tend to an equal share $1/M$. The limit $\beta \rightarrow \infty$ represents the “rational agent” limit, where everybody chooses the optimal technology. The main difference of our model with respect to Brock and Durlauf (2001) is in the timing of utility computation entering Eq. (2): their model is based on rational expectations, so as to have the utility of time t dictating the agents’ fraction $x_{c,t}$. In our model instead an agent’s decision is based on *past experience*, either involving technological network externalities or social interactions. Our focus is on technology competition dynamics, which calls for modelling the decision dynamics like in Brock and Hommes (1997), instead of the decision rule (2) as a condition for equilibrium consistency, like in Brock and Durlauf (2001). Of all the possible learning heuristics we adopt the most simple one, naive expectations, according to which agents at time t make a decision based on the technological utility (profitability) experienced at time $t - 1$. A model proposed by Smallwood and Conlisk (1979) considers a similar switching mechanism where consumers take into account the market share of products, beside their quality. The main difference of our model is that we make explicit the dynamics of choices.

Consider the simplest scenario with two competing technologies, labelled c and d . This model is one-dimensional: one state variable, the fraction of technology c , $x_c \equiv x$, is enough for knowing the state of the system at a given time ($x_d = 1 - x$). Assume for simplicity an equal increasing return on adoption $\rho_c = \rho_d \equiv \rho$ for the two technologies. The difference of utilities is central in this model:

$$u_{d,t} - u_{c,t} = \lambda + \rho(1 - 2x_t), \quad (3)$$

where $\lambda \equiv \lambda_d - \lambda_c$ is the difference in profitability between the two technologies. The probability of adoption (and the market share) of technology c in period t is:

$$x_t = \frac{e^{\beta(\lambda_c + \rho x_{t-1})}}{e^{\beta(\lambda_c + \rho x_{t-1})} + e^{\beta[\lambda_d + \rho(1 - x_{t-1})]}} = \frac{1}{1 + e^{\beta[\lambda + \rho(1 - 2x_{t-1})]}} \equiv f(x_{t-1}). \quad (4)$$

Analytical results regarding the dynamics of the system (4) are in line with Brock and Durlauf (2001). The fixed points of the map f give the equilibrium values for x_t .

Proposition 1 *The system (4) has either one stable steady state or an unstable steady state x^* and two stable steady states x_1^* and x_2^* such that $x_1^* \leq x^* \leq x_2^*$.*

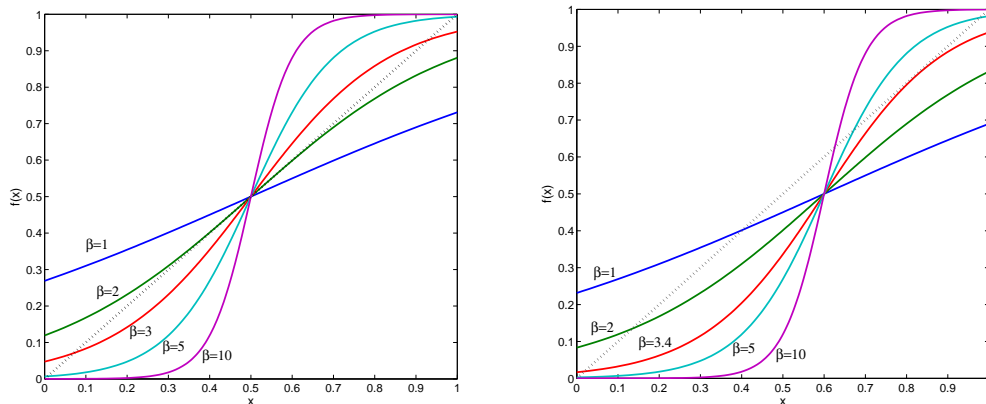


Figure 2: Map f for different values of β ($\rho = 1$). Left: $\lambda = 0$. Right: $\lambda = 0.2$.

A first observation is that $x = 0$ and $x = 1$ (technological monopoly) are equilibria only for $\beta = \infty$, which represents the limit of perfect rationality in agents' decision. For finite β the technology with lower profitability never disappears. Fig. 2 shows some examples with different values of β for $\lambda = 0$ and $\lambda = 0.2$ (with $\rho = 1$). In the symmetric case $\lambda = 0$ (left panel) the steady state $x = 1/2$ is stable if $f'(1/2) \leq 1$, which is true if $\beta \leq 2$. Whenever the intensity of choice is smaller than 2, the adoption process will converge to equal shares of technologies c and d . Conversely, for $\beta > 2$ the system converges to one of two alternative steady states, where one technology is dominant. Such qualitative change in the dynamics of a model due to a change in one parameter is called a *bifurcation*. The critical value ($\beta = 2$) is the bifurcation value. Symmetry of the two technologies ($\lambda = 0$) gives place to a “pitchfork bifurcation” for $\beta = 2$, where the steady state $x = \frac{1}{2}$ loses stability and two new stable steady states are created. This is the case in the example of the left panel of Fig. 2, for a value of β between 2 and 3. When one technology is more profitable than the other one ($\lambda \neq 0$) additional steady states are created by a “tangent bifurcation”. The right panel of Fig. 2 shows a tangent bifurcation for $\beta \simeq 3.4$, in which two steady states are created, one stable and one unstable. Fig. 3 (left panel) describes the qualitative changes in dynamics brought by changes in the differential profitability λ . No pitchfork bifurcations take place for this parameter, but tangent bifurcations are possible if ρ or β are large enough. The left panel of Fig. 3 indicates that such a bifurcation occurs for λ slightly larger than 2 in absolute value.

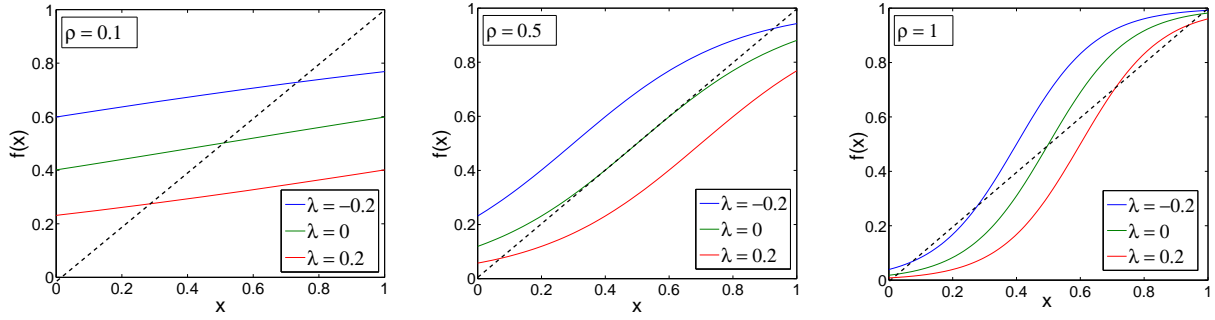


Figure 3: Map of the model (Eq. 4) for different values of the difference in profitability λ and the intensity of externalities ρ . Left: $\rho = 0.1$. Centre: $\rho = 0.5$. Right: $\rho = 0.5$. Here $\beta = 4$.

Whenever one technology is more profitable than the other, $\lambda \neq 0$, the worse technology may still attain a larger share in equilibrium. A positive value of λ (technology d better than c), for instance, shifts the map to the right, with an unstable steady state $x^* > 1/2$. If the initial condition $x_0 > x^* > \frac{1}{2}$, the system converges to x_2^* , with a larger share of technology c , despite this one being worse than technology d .

A bifurcation diagram gives a broader picture of the qualitative dynamics of this system, consisting of the long run value(s) of the state variable x_t in a given range of parameter values. Fig. 4 reports the bifurcation diagram of λ for three different values of ρ . When externalities are weak (left panel) the transition from one to the other technology

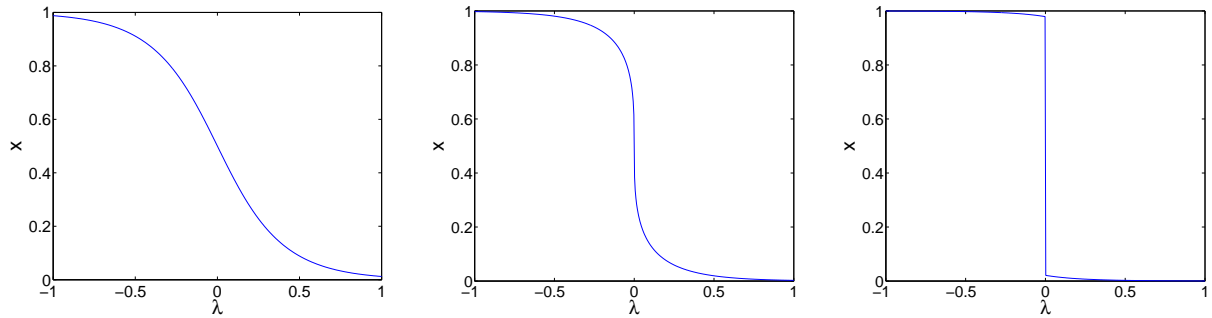


Figure 4: Bifurcation diagram of the difference in profitability λ for three different values of the intensity of externalities ρ . Left: $\rho = 0.1$. Centre: $\rho = 0.5$. Right: $\rho = 0.5$. Here $\beta = 4$.

driven by a change in the difference of profitability values is smooth. As the intensity of externalities becomes larger, the transition becomes more abrupt, but it is still continuous. Above a certain a level of ρ (pitchfork bifurcation) the transition takes the connotation of a jump (right panel). In this scenario there is not one equilibrium anymore, but two alternative equilibria. As the difference in profitability turns in favour of one technology, agents jump massively from one equilibrium to the other.

The values of β , ρ and λ together determine the steady states of the system and its dynamics. In particular, these parameters set the conditions for multiple equilibria. The following two necessary conditions hold true:

Proposition 2 $\rho\beta > 2$ and $-\rho < \lambda < \rho$ are necessary conditions for multiple equilibria.

The proof is based on the position of the inflection point $\hat{x} = \frac{\lambda+\rho}{2\rho}$ of the map f and on the maximum derivative $f'(\hat{x}) = \frac{\beta\rho}{2}$ (see Appendix A).

The intensity of choice regulates the shape of the map (4): the larger is β , the more f is similar to a step function, with a discontinuity in $\hat{x} = \frac{\lambda+\rho}{2\rho}$. The following holds true:

Proposition 3 Consider map (4):

- when $\beta \approx 0$, there is a unique equilibrium, and it is stable.
- when $\beta \approx \infty$, there may be three cases:
 1. if $\lambda < -\rho$ the equilibrium $x_2^* = 1$ is unique and stable,
 2. if $\lambda > \rho$ the equilibrium $x_1^* = 0$ is unique and stable,
 3. if $-\rho < \lambda < \rho$, $x^* = \hat{x} = \frac{\lambda+\rho}{2\rho}$ is unstable, while $x_1^* = 0$ and $x_2^* = 1$ are stable.

The proof of Proposition 3 relies on the fact that when $\beta = \infty$, the two conditions of Proposition 2 are also sufficient for multiple equilibria, because the system depends only on the position of the inflection point \hat{x} ; in the third case, \hat{x} falls inside the interval $[0, 1]$, and both $x = 0$ and $x = 1$ are stable equilibria. In this case the market will be completely taken by one or the other technology, depending on the initial condition.¹

3 Competing technologies and environmental policy

We now move to the realm of sustainability transitions, and consider technologies that have a direct impact on the natural environment which can be described by a measure of pollution emission intensity. Environmental policies favour less polluting technologies. The actual economy is characterized by many instances of dirty incumbent technologies and innovative clean technologies that find it hard to break through and gain substantial market shares. One example is power generation, where fossil-fuels are dominant, and renewable energy is still marginal (Fig. 1). A sustainable transition in this case would be a shift from fossil fuels to renewables. Without policy intervention, this is unlikely to happen, due to the larger profitability of the former. In this section we study the conditions for an environmental policy to trigger such a transition.

Let d be a “dirty” technology, with high pollution intensity (e.g. fossil fuels) and c a “clean” technology, with low pollution intensity (e.g. solar Photo-Voltaic). Let’s assume the clean technology has higher production costs (or lower performance), which

¹If we add an arbitrarily small noise term to the state variable x , our model replicates results in Arthur et al. (1987), as shown in Zeppini (2011), Chapter 4.

translates into a profitability gap $\lambda = \lambda_d - \lambda_c > 0$. The goal of an environmental policy is to make λ low enough, so as to eliminate the less desirable equilibrium, or to promote the coordination of decision makers in the alternative desirable equilibrium (Fig. 3).

In the case of power generation, environmental policies aim at the “grid parity”, where clean energy (solar, wind) reaches the cost (and the profitability) of traditional energy sources (fossil fuels). Different policies have been implemented in different countries (Fischer and Newell, 2008), which either impose taxes on pollution or provide market subsidies for the clean(er) technology. Taxes make the dirty technology more expensive, by internalizing the pollution externality. Subsidies make the clean technology less expensive. Both measures result in an attempt to lower the profitability gap λ . Here we extend the model of competing technologies with a pollution tax.

Environmental policies tend to be endogenous to technology competition, because their effort usually decreases as the share of the clean technology increases. If we assume constant installed capacity of production from clean and the dirty technologies together, and we assume constant pollution intensity for the dirty technology, we can model the pollution tax with a term $\tau(1 - x)$, with τ the marginal tax on a 1% increase in the share of dirty technology. In order to enforce this policy a government needs to know the market shares of competing technologies. The profitability gap is reduced by $\tau(1 - x)$, and the difference of utility from dirty and clean technologies becomes:

$$u_{d,t} - u_{c,t} = \lambda_0 + \rho(1 - 2x_t) - \tau(1 - x), \quad (5)$$

where $\lambda_0 = \lambda_d - \lambda_c$ is the profitability gap without policy. The map of the system is:

$$f_\tau(x) = \frac{1}{1 + e^{\beta[\lambda_0 + \rho(1 - 2x) - \tau(1 - x)]}}. \quad (6)$$

The dynamics of the share of clean technology is given by $x_t = f_\tau(x_{t-1})$. Without policy ($\tau = 0$) one is back to the basic model (4). The pollution tax introduces a negative feedback that counters the positive feedback of network externalities in agents’ adoption decisions. Notice that a pollution tax is formally equivalent to a subsidy for the clean technology in a model such as ours, which limits its scope of analysis to the relative shares dynamics of a system of competing technologies.²

The pollution tax is a static policy, because it can only change the equilibrium structure of the system by changing (once for all) one parameter, and does not ‘drive’ the system to another equilibrium. It may well be the case that a pollution tax renders the basin of attraction of the “dirty” equilibrium smaller than the basin of the “clean” equilibrium, but nevertheless only the former remains populated. A transition does not occur, due to

²In general taxes and subsidies have substantially different impacts on the economy. For instances, taxes limit overall consumption, while subsidies foster it.

the lack of coordination. A pollution tax can only gradually increase the share of the clean technology by continuously re-setting a higher tax rate τ , or cause an abrupt shift to the “clean” equilibrium, if the τ reaches a threshold value where the “dirty” equilibrium ceases to exist (bifurcation), and agents are forced to coordinate on the “clean” equilibrium. This means that a transition to clean technologies with such a policy may only occur with an ever increasing (and socially expensive) stringency, and in some cases only occur through an abrupt (and dramatic) shift. Both features are unattractive and unfeasible. A solution requires a dynamically changing factor, such as technological progress, and possibly a dynamic environmental policy, as we will see in Section 4 and in Section 5.

A change in the number of stable equilibria is not the only qualitative effect of a pollution tax. In particular, it can lead to cyclical dynamics. The following lemma holds:

Lemma 1 *A necessary condition for cyclical dynamics is $\tau > 2\rho$.*

The proof of Lemma 1 is in Appendix A. The inequality $\tau > 2\rho$ is a condition for a downward sloping map. In order to have cyclical dynamics the initial profitability gap plays a role, as stated by the following proposition:

Proposition 4 *There are six cases:*

1. *the map f^τ is upward sloping ($\tau < 2\rho$):*
 - (a) $\lambda_0 < \rho$: *a larger τ increases the share of clean technology in equilibrium, and leads to a tangent bifurcation. The inflection point is $\hat{x} < 1$.*
 - (b) $\lambda_0 = \rho$: *there is only one steady state, which is stable. The inflection point is $\hat{x} = 1$.*
 - (c) $\lambda_0 > \rho$: *there is only one steady state, which is stable. The inflection point is $\hat{x} > 1$.*
2. *the map f^τ is downward sloping ($\tau > 2\rho$):*
 - (a) $\lambda_0 < \rho$: *there is only one steady state, which is stable. A larger τ increases the equilibrium share. The inflection point is $\hat{x} > 1$.*
 - (b) $\lambda_0 = \rho$: *there is only one steady state, which becomes unstable for τ sufficiently large, giving place to a stable period 2 cycle. The inflection point is $\hat{x} = 1$.*
 - (c) $\lambda_0 > \rho$: *there is only one steady state, which becomes unstable for τ sufficiently large, giving place to a stable period 2 cycle. The inflection point is $\hat{x} < 1$.*

The proof is in Appendix A. The intuition for cyclical dynamics of technology shares is the following. An environmental policy that reduces the profitability gap as indicated by

Eq. (5) introduces a negative feedback, which opposes the positive feedback of network externalities. These two forces can balance each other leading to a stable equilibrium. But if the tax rate is too high, the negative feedback of environmental policy overcomes the positive feedback of network externalities. As soon as the profitability gap is reduced, the policy intervention for the next period is reduced accordingly (Eq. 5). The profitability gap widens again, calling for the policy to be re-enforced, and the story repeats. Fig. 5 illustrates the different cases of Proposition 4 with a number of examples. A tougher policy

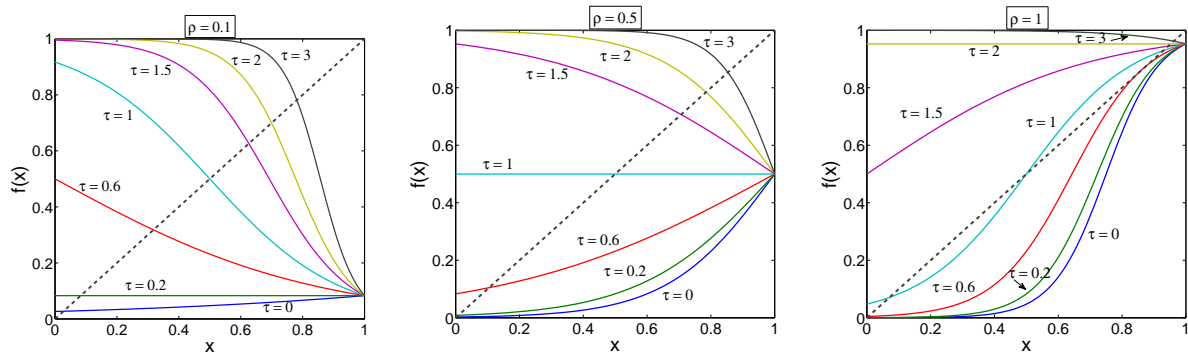


Figure 5: Competing technologies and environmental policy. Map f_τ for seven different values of pollution tax τ and three levels of network externalities ρ . (Here $\lambda_0 = 0.5$ and $\beta = 6$)

(larger τ) generally leads to a larger share of clean technology, as one may expect. Beyond a threshold value of τ cyclical dynamics occur. Both effects are clear in the left and middle panels of Fig. 5. In the left panel ($\lambda_0 > \rho$, cases (1c) and (2c) of Proposition 4) there is always a unique steady state, and an increasing effort shifts the inflection point \hat{x} to the right. In the middle panel ($\lambda = \rho$, cases (1b) and (2b)) there is still only one steady state, but the inflection point position $\hat{x} = 1$ is unaffected. In the right panel ($\lambda_0 < \rho$, cases (1a) and (2a)), rising τ leads to a tangent bifurcation for $\tau \simeq 0.6$, with the appearance of two additional steady states, one of which stable. Another tangent bifurcation above $\tau = 1$ reduces the number of steady states again to only one. We can resume the effect of the environmental policy in the condition of the right panel as follows: for low effort values the marginal effect of the policy on the market share of the clean technology is very small, and the system is stuck into the only stable equilibrium where the dirty technology is dominant. For middle values of the effort, the environmental policy creates an alternative stable equilibrium where the clean technology is dominant. This is the socially desirable, yet not populated, equilibrium. Higher efforts lead to a sudden shift, eliminating the suboptimal equilibrium. If the economy is locked-in into a dirty technology, this event tips the market towards the clean technology. Concluding, the positive feedback of network externalities and social interactions gives multiple equilibria and technological lock-in. When this positive feedback is relatively weak, an environmental policy can increase the share of the clean technology. But if the policy effort is too strong it destabilizes the

market with cyclical dynamics.

Fig. 6 on the left reports a simulated time series of the share x_t that converges to a period 2 cycle. The right panel of Fig. 6 is a bifurcation diagram of the tax rate τ . By

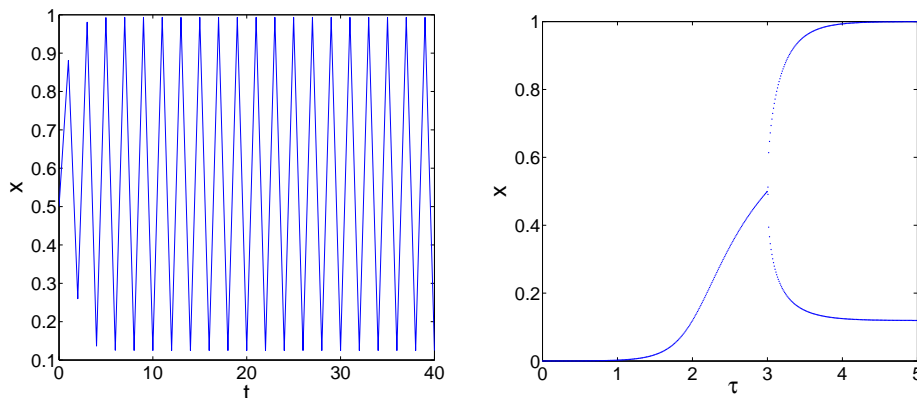


Figure 6: Competing technologies and environmental policy. Left: time series of the share of clean technology. Right: bifurcation diagram of τ . $\lambda_0 = 1.5$, $\rho = 1$, $\beta = 4$ and $\tau = 4$ (left).

comparing the left and right panels of Fig. 5 we see that a lower intensity of positive feedback from network externalities and social interactions makes it more likely for an environmental policy to fall into cyclical dynamics.

The switching behaviour of the discrete choice framework may be unrealistic in cases where large sunk costs cause stickiness in the decision process. The power generation sector is an example, where the choice of energy resource is limited. The discrete choice framework allows to introduce persistence of behaviours through asynchronous updating. This extension of the model responds to the idea that not all agents update their strategy in every period. The discrete choice model with asynchronous updating is given by

$$x_{i,t} = \alpha x_{i,t-1} + (1 - \alpha) \frac{e^{\beta u_{i,t-1}}}{\sum_{j=1}^M e^{\beta u_{j,t-1}}}, \quad (7)$$

where α is the portion of agents that stick to their previous strategy, while a fraction $1 - \alpha$ chooses a strategy based on the discrete choice mechanism (2). A larger α gives more persistence of strategies.

Although asynchronous updating has a stabilizing effect, it may lead to chaotic dynamics. If the map f_τ is downward sloping due to a high pollution tax (Fig. 5), the map of the model with asynchronous updating is a convex combination of an upward and a downward function, which may result in a non-monotonic map. A system with a non-monotonic map may present chaotic dynamics (Hommes, 1994). In our case we have:

$$f_{\sigma,\alpha}(x) = \alpha x + (1 - \alpha) \frac{1}{1 + e^{\beta[\lambda_0 + \rho(1-2x) - \sigma(1-x)]}}. \quad (8)$$

The left part of Fig. 7 reports an example of chaotic dynamics, with a time series of technology shares present irregular behaviour. The right panel shows a bifurcation diagram

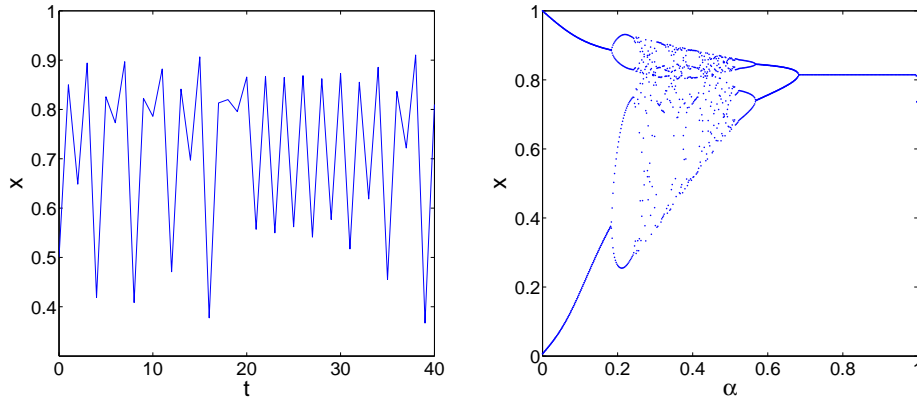


Figure 7: Environmental policy and asynchronous updating. Left: time series of x . Right: bifurcation diagram of α . Here $\lambda_0 = 2$, $\rho = 1$, $\tau = 9$, $\beta = 5$ and $\alpha = 0.3$ (left).

of the fraction α . Here the dynamics of technology shares is chaotic for α between 0.25 and 0.5, where a cascade of period doubling and period halving bifurcation occurs.

4 Competing technologies and technological progress

In this section we extend the discrete choice model of technology competition of Section 2 by introducing an endogenous mechanism of technological progress. The stream of research that goes under the name of “endogenous growth theory” addresses the mutual relationship between economic growth and technological progress (Romer, 1990; Aghion and Howitt, 1998). The main feature of this approach to economic growth is the recognition of mutual effects between the economy and technological change, going beyond the traditional one-way relationship from science to technology to the economy. Although these models are generally claimed to have micro-foundations, relatively little attention is given to the decision of agents concerning which technology to adopt. Here we propose a behavioural approach, and study the decision process that underlies the interplay of technological competition and technological progress. Building on the discrete choice mechanism of the basic model, we can study in particular how network externalities and social interactions shape technological progress.

Consider again two competing technologies c and d with utility given by (1). Now we relax the hypothesis of constant profitabilities λ_c and λ_d . Assume that technological progress for c and d depends on the cumulative investment in the two technologies, for instance $R\&D$ investment, and in every period the invested amounts are proportional to market shares, with a constant coefficient of proportionality. Growth is concave in investments (Barlevy, 2004), and a concave function is used also to describe endogenous technological progress (Aghion and Howitt, 1998). Resuming, we model technological

progress with the following learning curves:

$$\lambda_{c,t} = \lambda_{c0} + \psi_c \left(\sum_{j=1}^t x_j \right)^\zeta, \quad \lambda_{d,t} = \lambda_{d0} + \psi_d \left(\sum_{j=1}^t (1 - x_j) \right)^\zeta, \quad (9)$$

with λ_{c0} and λ_{d0} the profitabilities without technological progress. The sum series represent the cumulation of each period investments, from $j = 1$ to the present time $j = t$. The difference in profitability values is now a *technological gap*:

$$\lambda_t = \lambda_{d,t} - \lambda_{c,t} = \lambda_0 + \psi_d \left(\sum_{j=1}^t (1 - x_j) \right)^\zeta - \psi_c \left(\sum_{j=1}^t x_j \right)^\zeta, \quad (10)$$

where λ_0 is the technological gap without progress. ψ_c, ψ_d measure how investment translates into technological progress. $\zeta \in [0, 1]$ dictates the curvature of the learning function. This parameter is very likely to be different for different technologies, but in a first order approximation we assume the same value for the two competing technologies.

The difference in utility between technology d and technology c equipped with the learning curves above becomes:

$$u_{d,t} - u_{c,t} = \lambda_t + \rho(1 - 2x_t), \quad (11)$$

Here technology competition is driven both by externalities (the second term of the right hand side) and technological progress (the first term): the share of technology c according to (2) is now given by:

$$x_t = \frac{1}{1 + e^{\beta[\lambda_t + \rho(1 - 2x_{t-1})]}} \equiv f_t(x_{t-1}). \quad (12)$$

The map f_t depends on time. It is identical to the map f of the basic model (4) after substituting the static parameter λ with the time varying technological gap of Eq. (10). Endogenous technological progress as expressed by the dynamic technological difference λ_t is a slowly changing parameter that modifies the flow map of the competing technology system as shown in Fig. 3. The long run equilibrium, or long run dynamic of this system is known only by looking at the limit map given by the limit value $\lim_{t \rightarrow \infty} \lambda_t \equiv \lambda_\infty$. The technology gap λ does not modify the curvature of the map, but it may affect the number of stable equilibria by shifting it. There can be two cases: 1) if the steady state x^* of Proposition 1 is stable, a change in λ changes gradually the equilibrium market shares as one technology slowly catches up, or 2) if x^* is unstable, a change in λ can cause a change from one to two stable equilibria (or the other way around) through a tangent bifurcation (Fig. 3). In this second case, a less adopted technology may suddenly overcome the other, unlocking the economy from the previous dominant technology.

The convergence of the series λ_t plays a key role in the dynamics of technology market shares, and in particular in setting the long run equilibrium. Whenever one technology

has a faster pace (due to larger values of ψ), we have $\lambda_t \rightarrow \pm\infty$, that is a lock-in into technology c ($\lambda_t \rightarrow -\infty$) or d ($\lambda_t \rightarrow +\infty$).

The linear case $\zeta = 1$ allows to derive some analytical results on the dynamics of λ_t , that we report in appendix B. For the general case $\zeta < 1$, we can only rely on numerical observations by simulating the model (12) in a number of different conditions. Together with technology market shares x_t and differential profitability λ_t we also look at a measure of the overall technological progress given by the weighted sum of profitability values of the two competing technologies, $\Lambda_t = x_t\lambda_c + (1 - x_t)\lambda_d$. If we make explicit the learning curves of the two competing technologies, the weighted sum of profitability values has the following expression:

$$\Lambda_t = x_t \left[\lambda_{c0} + \psi_c \left(\sum_{j=1}^t x_j \right)^\zeta \right] + (1 - x_t) \left[\lambda_{d0} + \psi_d \left(\sum_{j=1}^t (1 - x_j) \right)^\zeta \right]. \quad (13)$$

We rely on numerical observations in order to study if and how technological progress can promote sustainable transitions. Clean technologies tend to have steeper learning curves than incumbent dirty technologies (McNerney et al., 2011), and then a faster rate of technological progress. In our model we set $\psi_c = 1.8$ for the clean technology and $\psi_d = 1$ for the dirty technology, in face of initial profitability values equal to $\lambda_{c0} = 1$ and $\lambda_{d0} = 2$. Assume a 70% market share for the incumbent dirty technology, with $x_0 = 0.3$. In words, the dirty technology, with about two thirds of the market, is presently more profitable than the clean technology, but this one has more technological upside. The other parameters are $\zeta = 0.5$ and $\beta = 1$. Fig. 8 reports the simulated time series of the share x_t , the technology gap λ_t and the total technological level Λ_t , for three different intensity of decision externalities, $\rho = 0.1$, $\rho = 0.5$ and $\rho = 1$. This example gives two main messages: first, network externalities strongly affect technology competition: when they are too strong, the clean technology can not make it to the market, despite its appealing high rate of technological investments, and a transition fails (bottom panels). On the technological dimension, the profitability gap constantly widens, making a transition more and more difficult (costly) to achieve. The second message is that decision externalities are also relevant for the overall technological progress. The weighted sum of profitability values (right panels) grows much faster with low intensity externalities. The reason is that lower externalities allow the clean technology, which is potentially more profitable, to gain market shares.

The example of Fig. 8 basically addresses a trade-off between today and tomorrow, with a dirty technology which is more profitable today and a clean technology that has more potential for being more profitable in the future. Notice that here we do not discount the future. If we would introduce a discounting factor, the scenario would be even worse for the clean technology.

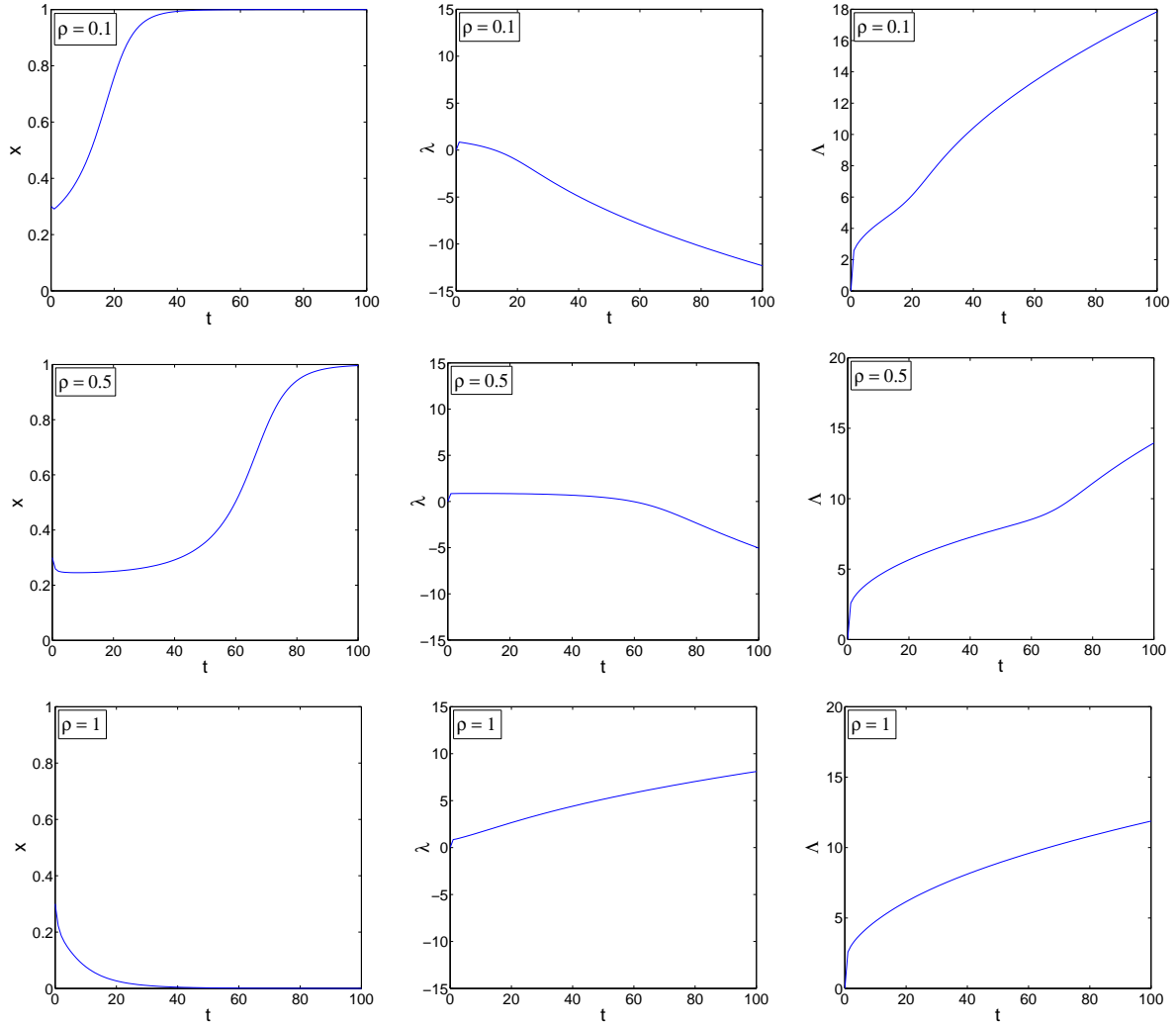


Figure 8: Time series of technology share x_t (left), technological gap λ_t (centre) and total technological level Λ_t (right), with low externalities, $\rho = 0.1$ (top), $\rho = 0.5$ (centre) and $\rho = 1$ (bottom). Initial conditions are $x_0 = 0.3$, $\lambda_{c0} = 1$ and $\lambda_{d0} = 2$. Parameters are $\psi_c = 1.8$, $\psi_d = 1$, $\zeta = 0.5$ and $\beta = 1$.

There are conditions where decision externalities and technological progress fairly balance each other. In such a scenario it may take a long while for the clean technology to take-off, and a transition takes place only following a relatively long period of sluggish market performance (middle panels). The market share time series of the clean (more innovative) technology is an S-shaped curve (middle-left panel). This pattern of transition dynamics is consistent with empirically observed adoption curves (Griliches, 1957). In our model there is not a diffusion process, and the S-shaped pattern of market penetration for the clean (innovative) technology results from slow changes in the equilibrium structure of competing technologies with positive feedback. Technological progress works as a slowly changing parameter that affects the equilibria of the system (Eq. 12). In particular, the basin of attraction of the “dirty” equilibrium shrinks, while the basin of the “clean” equilibrium enlarges, and possibly only the latter remains (Section 2). This gradual and structural effect on the dynamics of the system makes technological change a

fundamental factor to address in environmental policies aiming at sustainable transitions, as we will show in Section 5. The effectiveness of technological progress and the likelihood of sustainable transitions crucially depend on the ability of governments and consumers to look ahead without discounting too much the future.

The final message of this section is the relevance of decision externalities for sustainability transitions. An environmental policy that aims at a transition to sustainable technologies should not only focus on traditional means of intervention such as a pollution tax or subsidies for clean technologies. All factors that affect the positive feedback of network externalities and social interactions represent an additional channel of environmental policy intervention. Regarding network externalities, these factors are technology standards and infrastructures, in the first place. When also social interactions are important, if decisions are taken based on what the majority of agents do, an incumbent more profitable technology will always win. It is an empirical evidence that innovative technologies usually develop on “niche” markets (Hekkert and Negro, 2009). An environmental policy should promote and sustain such markets, on the one hand, and on the other hand work in order to lower the barriers raised by technological standards and infrastructures that are the main causes of technological lock-ins.

5 Technological progress and environmental policy

In Section 3 we analyze the impact of an environmental policy on technological competition, assuming a constant profitability for the competing technologies. Now we introduce technological progress, combining the models of Section 3 and Section 4. Consider again two competing technologies, a clean and a dirty one, labeled with c and d respectively. Because of technological progress, the profitabilities $\lambda_{c,t}$ and $\lambda_{d,t}$ follow the learning curve (9), and the profitability gap $\lambda_t = \lambda_{d,t} - \lambda_{c,t}$ evolves according to Eq. (10). We assume that without intervention, the clean technology has a lower profitability, with $\lambda_0 > 0$, and the system is stuck in the equilibrium where the dirty technology is dominant.

A government steps in, enforcing an environmental policy which goal is to foster the market share of the clean technology by reducing the profitability gap λ . The model with technological progress is prone to accommodate two types of environmental policy: a pollution tax, linked to the state variable x_t , and a subsidies scheme linked to the technical gap λ_t . In the first case the profitability of the dirty technology is reduced by an amount proportional to its market share, $\tau(1 - x_t)$. This is exactly the environmental policy considered in Section 3. The second policy is calibrated on the value of the technology gap λ_t , with a subsidy for the clean technology which is proportional to the technical gap. This type of policy is implemented in the so-called Feed-in-Tariffs (Lipp, 2007),

where the per-kWh price of the energy produced by the clean technology (e.g. solar photovoltaic) is reduced adjusting for the higher production costs (ResAct, 2000). The idea is that subsidies have to decrease as the production costs of clean energy go down along the learning curve of the clean technology. In this section we extend the model with technological progress by incorporating both types of environmental policy.

Let us consider first a pollution tax. In each period the government charges pollution, and we assume that policy stringency is commensurate to the amount of pollution emission. Assuming constant production and constant pollution intensity, the utility from the adoption of a dirty technology is reduced by $\tau(1 - x_t)$. This translates into a reduced technological gap $\lambda_t^m(x_t)$:

$$\lambda_t^\tau(x_t) = \lambda_t - \tau(1 - x_t), \quad (14)$$

with λ_t the gap without policy, given by Eq. (10), that we rewrite here:

$$\lambda_t = \lambda_{d,t} - \lambda_{c,t} = \lambda_0 + \psi_d \left(\sum_{j=1}^t (1 - x_j) \right)^\zeta - \psi_c \left(\sum_{j=1}^t x_j \right)^\zeta. \quad (15)$$

The new technological gap $\lambda_t^\tau(x_t)$ follows both technological progress and the environmental policy, and enters the discrete choice mechanism of technology competition. The differential utility (3) becomes

$$\begin{aligned} u_{d,t} - u_{c,t} &= \lambda_t^\tau(x_t) + \rho(1 - 2x_t) \\ &= \lambda_t - \tau(1 - x_t) + \rho(1 - 2x_t), \end{aligned} \quad (16)$$

and the map for the share of clean technology x_t is

$$x_t = \frac{1}{1 + e^{\beta[\lambda_t^\tau + \rho(1 - 2x_{t-1})]}} \equiv f_t^m(x_{t-1}). \quad (17)$$

These two equations are to be compared to Eq. (3) and Eq. (4) of Section 2 (basic model), to Eq. (5) and Eq. (6) of Section 3 (environmental policy) and to Eq. (11) and Eq. (12) of Section 4 (technological progress).

Subsidies such as feed-in-tariffs increase the profitability of the clean technology by adding a term proportional to the previous period technological gap, $\sigma_t = \sigma \lambda_{t-1}$. We impose $0 < \sigma < 1$, which guarantees the stationarity of the time series and means that subsidies at most can offset the technical gap. The new technical gap λ_t^σ becomes:

$$\lambda_t^\sigma = \lambda_t - \sigma \lambda_{t-1}^\sigma, \quad (18)$$

where λ_t is again given by Eq. (10). It is convenient to re-write λ_t as $\lambda_t = \lambda_0 + \Delta\Psi_t$, with λ_0 the initial condition, and $\Delta\Psi_t$ the differential endogenous technological progress of the two technologies (second and third term of Eq. 10):

$$\Delta\psi_t = \psi_d \left(\sum_{j=1}^t (1 - x_j) \right)^\zeta - \psi_c \left(\sum_{j=1}^t x_j \right)^\zeta, \quad (19)$$

with the assumption $\Delta\psi_0 = 0$. The technological gap λ_t^σ can be expressed as follows:

$$\lambda_t^\sigma = \lambda_0 + \Delta\Psi_t - \sigma\lambda_{t-1}^\sigma. \quad (20)$$

By iterative substitution of lagged terms, we get to the following expression for λ_t^σ :

$$\lambda_t^\sigma = \lambda_0 \sum_{i=0}^t (-\sigma)^i + \sum_{j=0}^t (-\sigma)^j \Delta\Psi_{t-j}. \quad (21)$$

The first term in the right hand side is a geometric series, which is equal to $\lambda_0 \frac{1-(1-\sigma)^{t+1}}{1+\sigma}$, and for $t \rightarrow \infty$ converges to $\frac{\lambda_0}{1+\sigma}$, since $\sigma < 1$ by assumption.³ Intuitively, the autoregressive specification of this subsidies scheme leads to a “contrarian” behaviour, where successive periods bring adjustments of opposite sign (Eq. 18). In the meantime $\Delta\psi_t$ continues to evolve due to (endogenous) technological progress, as described by Eq. (19), growing positive or negative, or converging to a finite value (see Proposition 5). In all cases where the gap $\Delta\psi$ diverges, the policy intervention gets amplified by such differential technological progress, as indicated by the second term of the right hand side in Eq. (21): environmental policy and technological progress do not simply add together, but interact dynamically.

The difference of utility values (3) now is:

$$u_{d,t} - u_{c,t} = \lambda_t^\sigma + \rho(1 - 2x_t), \quad (22)$$

and according to Eq. (2) the map of the share x_t becomes

$$x_t = \frac{1}{1 + e^{\beta[\lambda_t^\sigma + \rho(1-2x_{t-1})]}} \equiv f_t^\sigma(x_{t-1}). \quad (23)$$

These can be compared to Eq. (3) and Eq. (4) of Section 2 (basic model), to Eq. (5) and Eq. (6) of Section 3 (environmental policy), and to Eq. (11) and Eq. (12) of Section 4 (technological progress).

We simulate the model and compare the effectiveness of the two environmental policy schemes just presented. Let us assume that without policy and before the positive feedback of agents decisions (network externalities), the profitability of the clean technology is half the profitability of the dirty technology, with an initial condition $\lambda_{c0} = 1$ and $\lambda_{d0} = 2$. Now the model contains three factors: the positive feedback of network externalities, an environmental policy and technological progress. With this model we address the following questions: first, what is the effect of policy subsidies schemes on the dynamics of technology competition in presence of technological progress? Which subsidies scheme is more effective in fostering a transition to the clean technology?

³If $\sigma = 1$, this term is equal to λ_0 when t is even, and zero otherwise.

We consider the realistic case where the clean technology has a higher rate of progress, which in our model can be expressed with a larger marginal contribution to profitability by each firm, $\psi_c > \psi_d$. We set the intensity of positive feedback from decision externalities to $\rho = 1$. In this condition the model with only technological progress shows no transition (Figure 8). When an environmental policy is introduced, we obtain the results reported in Fig. 9. The left panel refers to the policy scheme based on a pollution tax, while the right panel refers to subsidies for the clean technology linked to the technological gap. In both cases transitions to the clean technology do occur. Obviously, transitions are easier for

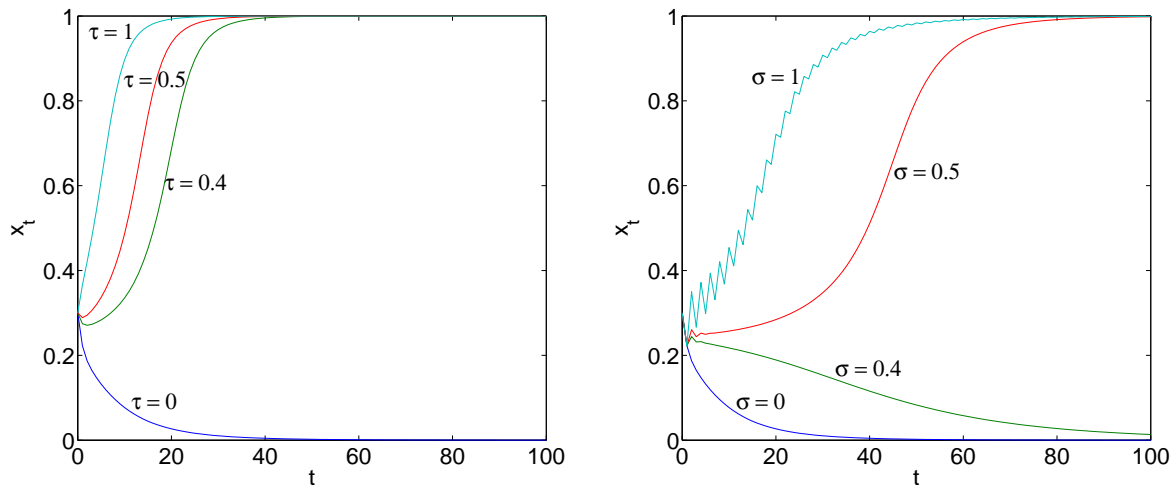


Figure 9: Model with technological progress and environmental policy. Time series of x_t (share of clean technology) with four levels of environmental policy effort. Left: pollution tax $\tau(1 - x_t)$. Right: subsidies $\sigma\lambda_{t-1}$. Intensity of network externalities $\rho = 1$. Initial conditions $x_0 = 0.3$, $\lambda_{c0} = 1$ and $\lambda_{d0} = 2$. Parameters $\psi_c = 1.8$, $\psi_d = 1$, $\zeta = 0.5$ and $\beta = 1$.

lower values of network externalities ρ . In general, for relatively moderate levels of policy stringency (pollution tax) or effort (subsidies), the transition to a “clean” equilibrium (an equilibrium where the clean technology is dominant) only occurs after an initial phase of little change in market shares, with an S-shaped curve. We have seen this pattern already with only technological progress, in Section 3. Network externalities initially push the dirty technology, because its initial share is larger. If this effect is too strong, a transition may not occur with only technological progress. That is the case in the conditions of the example in Fig. 8 (bottom panels) and Fig. 9 ($\tau = 0$ and $\sigma = 0$). An environmental policy helps the profitability of the clean technology to take off, and drive down the technological gap. It does so by reducing the positive feedback of network externalities (Eq. 16) or by reducing the technological gap (Eq. 22). Putting together the numerical evidence of this section with the ones of Sections 3 and 4 we draw the message that a pollution tax is more of an auxiliary factor, and the true engine of an effective transition to clean technologies is technological progress. A pollution tax without a faster progress of the clean technology is unattractive for not allowing a gradual - and not too expensive -

transition, while technological progress alone is ineffective when network externalities are too strong. Technological progress equipped with an environmental policy can effectively drive a sustainable transition. Moreover, by favouring the clean technology with a faster rate of progress, the environmental policy also speeds up technological innovation.

The two different policy schemes are not directly comparable in terms of the simulated time series of Fig. 9, since parameters τ and σ have different units. One should also consider the terms $\tau(1 - x)$ and $\sigma\lambda_t$, which represent the inputs (effort) of policy intervention. However, the pollution tax seems to be more effective in triggering a transition path to the clean technology, while there is a delay in the action of subsidies linked to the technological gap. Moreover, subsidies may present an oscillatory dynamics of market shares (case with $\sigma = 1$). Both the delay and the oscillatory dynamics are a result of the autoregressive specification (18). Oscillations do not arise with a pollution tax, which means that a policy intervention linked to market shares (Eq. 14) gives a more stable negative feedback than a policy term linked to the technical gap. These results are particularly meaningful considering the empirical relevance of the subsidies scheme, which is implemented by feed-in-tariffs. The message from the present analysis is that a policy based on market shares can be more effective, obtain a faster and smoother transition to the clean technology.

6 Conclusion

Transitions to clean technologies are framed in our model as a coordination problem with multiple equilibria. Pollution taxes introduce a negative feedback in agents' decisions which counters the positive feedback of social interactions and network externalities. A pollution tax gradually increases the share of clean technology proportionally to its stringency. Alternatively, a sudden shift (bifurcation) from the “clean” to the “dirty” equilibrium may occur, when a (relatively high) threshold tax rate (tipping point) is reached. An overly stringent policy can also trigger periodic dynamics in technology market shares when the positive feedback of network externalities and social interaction is low. All this results from a policy that just “follows” pollution, without creating the conditions for a structural catching-up by clean technologies.

Technological progress is modeled explicitly with a learning curve that enters the profitability of each competing technology. Learning curves are endogenous through the cumulation of agents' past adoption decisions. We have considered a scenario where the dirty technology is initially dominant and more profitable. On the other hand, we have assumed a faster progress for the clean technology. The technological gap between dirty and clean technology works in the model as a slowly changing parameter that smoothly

drives the system to an equilibrium where only the clean technology is adopted. This aspect indicates technological progress as a fundamental channel of policy intervention.

Transitions driven by technological progress present an S-shaped time pattern: there is an initial critical phase where the clean technology does not gain market shares despite technological progress. The delayed take-off is due to the balanced opposition between a closing technological gap and the market advantages of dirty incumbent technologies. The latter can be limited by reducing the positive feedback of network externalities and social interactions, for instance by making technological standards and infrastructures open to innovative clean solutions, and by (initially) reducing the consumers' base (agents population) through niche markets where an innovation can develop more easily.

Endogenous technological progress and environmental policy schemes are modeled together in a policy mix for sustainable transitions. Two schemes are compared: a pollution tax, and a market subsidy linked to the technological gap (feed-in tariffs). Taxes or subsidies work as an auxiliary factor in our model, better suited for the initial phase of a sustainable transition where the main factor is technological progress. The combination of technological progress with a pollution tax is more effective than a subsidy scheme linked to the technological gap. The latter generates slower transition patterns, and may present oscillatory transitory dynamics for large policy efforts, due to an autoregressive mechanism. This result is particularly significant considering the empirical relevance of subsidy schemes such as feed-in-tariffs.

The final message of the model is that a policy aiming at sustainability transitions from incumbent dirty technologies to clean technologies should embrace a number of different yet complementary channels: first, it should reduce the positive feedback of network externalities and social interactions by lowering the barriers represented by technological standards and infrastructures, and by promoting niche markets where innovative clean technologies can develop. Second, it should focus on learning curves, fostering the technological progress of clean solutions and using traditional policy schemes such as pollution taxes as auxiliary measures. Third, a pollution tax linked directly to market shares presents itself as a more effective and stable intervention than policies linked to the technological gap, such as feed-in-tariffs, in order to work as auxiliary channels in closing the technological gap of clean technologies.

The main contribution of this model is a new theoretical framework for understanding how sustainable transitions can emerge from distributed decision making in the presence of network externalities and social interactions, technological progress and the introduction of environmental policies. There are unanswered questions and limitations in this model. First, entry of new technologies is excluded, and competition is limited to the initial pool of technologies. Second, this is a “mean-field” approach, where the population

of agents is indefinitely large and their interactions are randomly distributed. Local effects are missing, such as reference groups, institutions and large corporations that can influence agents' decisions. Finally, technologies are described in a very stylised way. For a more realistic representation of sustainable transitions, a less general but more detailed description of technologies and industrial sectors involved might be useful.

Appendix A Equilibrium stability analysis

Consider the map (4) for the basic model of Section 2:

$$f(x) = \frac{1}{1 + e^{\beta[\lambda + \rho(1-2x)]}}. \quad (24)$$

The first derivative of f is:

$$f'(x) = \frac{2\beta\rho e^{\beta[\lambda + \rho(1-2x)]}}{\{1 + e^{\beta[\lambda + \rho(1-2x)]}\}^2}. \quad (25)$$

Since f is continuous in $[0, 1]$ and $f(x) \in [0, 1] \forall x \in [0, 1]$, then f has at least one fixed point $x = f(x) \in [0, 1]$, which is proved by applying the Bolzano's theorem to the function $g(x) = f(x) - x$. This means that at least one equilibrium exists. Moreover, since $f'(x) > 0$ for all $x \in [0, 1]$, $f(x = 0) > 0$ and $f(x = 1) < 1$, there is at least one stable equilibrium, by the Mean-value theorem.

The second derivative of the map (4) is:

$$f''(x) = \frac{4\rho\beta^2 e^{\beta[\lambda + \rho(1-2x)]} [e^{\beta[\lambda + \rho(1-2x)]} - 1]}{\{1 + e^{\beta[\lambda + \rho(1-2x)]}\}^3}. \quad (26)$$

The condition $f''(x) = 0$ gives the inflection point $\hat{x} \equiv \frac{\rho + \lambda}{2\rho}$, with $f''(x) > 0$ in $[0, \hat{x}]$ and $f''(x) < 0$ in $(\hat{x}, 1]$. The inflection point \hat{x} does not depend on β . If $\lambda > \rho$, then \hat{x} is outside the interval $[0, 1]$, and there can not be more than one fixed point for f . Similarly, if $\lambda < -\rho$. This is why $-\rho < \lambda < \rho$ is a necessary condition for multiple equilibria of f .

The steepness of function f in the inflection point is $f'(\hat{x}) = \frac{\rho\beta}{2}$. Since this is the point where f' is maximum, $\rho\beta > 2$ is a necessary condition for multiple equilibria.

When a pollution tax is introduced as a term $-\tau(1-x)$ in the utility of the dirty technology, the map of the model (6) is again a function of the form:

$$f_{a,b}(x) = \frac{1}{1 + e^{a-bx}}. \quad (27)$$

The first derivative of this map is

$$f'_{a,b}(x) = \frac{be^{a-bx}}{(1 + e^{a-bx})^2}. \quad (28)$$

The sign of b determines whether the map is upward or downward sloping. In the case of the basic model we have $b = 2\beta\rho$, and the map f is always upward sloping. In the case of a pollution tax we have $b = \beta(2\rho - \tau)$. Consequently the map f^τ is downward sloping whenever $\tau > 2\rho$. There are two cases:

- weak policy effort ($b > 0$, increasing map): increasing the tax rate τ a transition occurs from three steady states, two of which are stable, to one stable steady state.
- strong policy effort ($b < 0$, decreasing map): increasing the tax rate τ is destabilizing, with a transition from a stable equilibrium to a stable period 2 cycle.

The intensity of positive feedback from decisions externalities ρ has an opposite effect to τ , because the pollution tax counters network externalities and social interactions.

The second derivative of (27) is

$$f''_{a,b}(x) = b^2 e^{a-bx} \frac{(e^{a-bx} - 1)}{(e^{a-bx} + 1)^3}. \quad (29)$$

This function is zero in the inflection point $\hat{x} = \frac{a}{b}$, where the first derivative $f'_{a,b}(\hat{x}) = \frac{b}{4}$ is maximum in absolute terms. For the basic model we have:

$$\hat{x} = \frac{\lambda_0 + \rho}{2\rho}, \quad f'(\hat{x}) = \frac{\beta\rho}{2}. \quad (30)$$

For the model with a pollution tax:

$$\hat{x}_\tau = \frac{\lambda_0 + \rho - \tau}{2\rho - \tau}, \quad f'_\tau(\hat{x}) = \frac{\beta(2\rho - \tau)}{4}. \quad (31)$$

The effect of the intensity of choice is the following:

- weak policy effort ($b > 0$, increasing map): increasing β gives an S-shaped map, leading to two stable steady states.
- strong policy effort ($b < 0$, decreasing map): increasing β gives an inversely S-shaped map, leading to period 2 cycles.

The position of the inflection point is also important for the dynamics of the system. The effect of policy effort on the inflection point is given by the following derivative:

$$\frac{d\hat{x}}{d\tau} = \frac{\lambda_0 - \rho}{(2\rho - \tau)^2}. \quad (32)$$

No matter whether the map is upward or downward sloping, a higher pollution tax rate shifts \hat{x}_τ to the right whenever $\lambda_0 > \rho$, and to the left otherwise. The effect of this shift on the stability of equilibria is ambiguous, because it depends on whether the map f_σ is upward or downward sloping.

Appendix B Technological progress: the linear case

In general technological progress is concave in investments, as expressed by the learning curve (9). Here we derive some analytical result for the linear case $\zeta = 1$. In this case the difference of profitability between the two technologies (10) becomes

$$\begin{aligned}\lambda_t &= \lambda_0 + \psi_d \sum_{j=1}^t (1 - x_j) - \psi_c \sum_{j=1}^t x_j \\ &= \lambda_0 + \psi_d t - (\psi_c + \psi_d) \sum_{j=1}^t x_j.\end{aligned}\tag{33}$$

The following proposition lists the possible outcomes in the linear case:

Proposition 5 *In the long run ($t \rightarrow \infty$) the technological gap λ_t for $\zeta = 1$ (Eq. 33) has the following limit behaviour:*

1. λ_t converges if and only if $\exists p, q$ such that $\sum_{j=1}^t x_j \sim g(t) = p + qt$, with $q = \frac{\psi_d}{\psi_c + \psi_d}$.
2. If $\sum_{j=1}^t x_j$ is slower than $g(t)$, then λ_t diverges to $+\infty$ (lock-in into b).
3. If $\sum_{j=1}^t x_j$ is faster than $g(t)$, then λ_t diverges to $-\infty$ (lock-in into a).

Condition 1 implies that $x_t = \frac{\psi_d}{\psi_c + \psi_d}$, on average, that is the (constant) rate of growth of $\sum_{j=1}^t x_j$. The intercept p can assume any value, and contributes to set the long run value of the difference in profitabilities, according to $\lambda_\infty = \lambda_0 - p(\psi_c + \psi_d)$.

Conditions 2 and 3 represent situations where one technology systematically grows faster than the other, and eventually it conquers the entire market (eq. 4). The only possibility for technological market segmentation is condition 1.

For a more extensive analytical study of technological progress in the linear case we refer to the Chapter 4 of Zeppini (2011). Whenever $\zeta < 1$, the rate of technological progress is lower, but the results above do not change as long as concavity is the same for the two technologies.

References

- ACEMOGLU, D., P. AGHION, L. BURSZTYN, AND D. HEMOUS (2012): “The environment and directed technical change,” *American Economic Review*, 102, 131–166.
- AGHION, P. AND P. HOWITT (1998): *Endogenous Growth Theory*, Cambridge, MA: MIT Press.

- ALESSIE, R. AND A. KAPTEYN (1991): “Habit formation, interdependent preferences and demographic effects in the almost ideal demand system,” *Economic Journal*, 101, 404–419.
- ARTHUR, B. (1989): “Competing technologies, increasing returns, and lock-in by historical events,” *Economic Journal*, 99, 116–131.
- ARTHUR, W., Y. ERMOLIEV, AND Y. KANIOVSKI (1987): “Path-dependent processes and the emergence of macrostructure,” *European Journal of Operation Research*, 30, 294–303.
- BANERJEE, A. V. (1992): “A Simple Model of Herd Behavior,” *Quarterly Journal of Economics*, 107, 797–817.
- BARLEVY, G. (2004): “The cost of business cycles under endogenous growth,” *American Economic Review*, 94, 964–990.
- BIKHCHANDANI, S., D. HIRSHLEIFER, AND I. WELCH (1992): “A theory of fads, fashion, custom and cultural change as informational cascades,” *Journal of Political Economy*, 100, 992–1026.
- BROCK, W. AND S. DURLAUF (2001): “Discrete choice with social interactions,” *Review of Economic Studies*, 68, 235–260.
- (2002): “A Multinomial Choice Model with Neighborhood Effects,” *American Economic Review*, 92, 298–303.
- (2006): “Multinomial Choice with Social Interactions,” 175–206.
- BROCK, W. AND C. HOMMES (1997): “A rational route to randomness,” *Econometrica*, 65, 1059–1095.
- DAVID, P. A. (1985): “Clio and the economics of QWERTY,” *American Economic Review*, 75, 332–337.
- FISCHER, C. AND R. G. NEWELL (2008): “Environmental and technology policies for climate mitigation,” *Journal of Environmental Economics and Management*, 55, 142–162.
- FOXON, T. (2011): “A coevolutionary framework for analysing a transition to a sustainable low carbon economy,” *Ecological Economics*, 70, 2258–2267.
- GOLMAN, R. (2012): “Homogeneity bias in models of discrete choice with bounded rationality,” *Journal of Economic Behavior and Organization*, 82, 1–11.

- GRILICHES, Z. (1957): “Hybrid Corn: An exploration in the economics of technological change,” *Econometrica*, 25, 501–522.
- HEKKERT, M. AND S. NEGRO (2009): “Functions of innovation systems as a framework to understand sustainable technological change: empirical evidence for earlier claims,” *Technological Forecasting and Social Change*, 76, 462–470.
- HOMMES, C. (1994): “Dynamics of the cobweb model with adaptive expectations and nonlinear supply and demand,” *Journal of Economic Behavior and Organization*, 24, 315–335.
- (2006): “Heterogeneous Agent Models in Economics and Finance,” in *Agent-based Computational Economics*, ed. by L. Tesfatsion and K. L. Judd, Amsterdam: North-Holland, vol. 2 of *Handbook of Computational Economics*, chap. 23, 1109–1186.
- KATZ, M. L. AND C. SHAPIRO (1985): “Network externalities, competition and compatibility,” *American Economic Review*, 75, 424–440.
- KEMP, R. (1994): “Technology and the transition to environmental sustainability. The problem of technological regime shifts,” *Futures*, 26, 1023–1046.
- KIRMAN, A. (1993): “Ants, rationality and recruitment,” *Quarterly Journal of Economics*, 108, 137–156.
- KÖHLER, J., L. WHITMARSH, B. NYKVIST, M. SCHILPEROORD, N. BERGMAN, AND A. HAXELTINE (2009): “A transitions model for sustainable mobility,” *Ecological Economics*, 68, 2985–2995.
- KÖNNÖLÄ, T., G. UNRUH, AND J. CARRILLO-HERMOSILLA (2006): “Prospective voluntary agreements for escaping techno-institutional lock-in,” *Ecological Economics*, 57, 239–252.
- LIPP, J. (2007): “Lessons for effective renewable electricity policy from Denmark, Germany and the United Kingdom,” *Energy Policy*, 35, 5481–5495.
- MARKARD, J., R. RAVEN, AND B. TRUFFER (2012): “Sustainability transitions: An emerging field of research and its prospects,” *Research Policy*, 41, 955–967.
- MCNERNEY, J., J. FARMER, S. REDNERA, AND J. TRANCIK (2011): “Role of design complexity in technology improvement,” *Proceedings of the National Academy of Sciences*, 108, 9008–9013.
- NELSON, R. R. AND S. G. WINTER (1982): *An Evolutionary Theory of Economic Change*, Cambridge, MA: Harvard University Press.

- POPP, D. (2004): “ENTICE: endogenous technological change in the DICE model of global warming,” *Journal of Environmental Economics and Management*, 48, 742–768.
- RESACT (2000): “Act on granting priority to renewable energy sources,” *Federal Ministry for the environment, nature conservation and nuclear safety (BMU)*, <http://www.wind-works.org/FeedLaws/Germany/GermanEEG2000.pdf>.
- ROMER, P. M. (1990): “Endogenous technological change,” *Journal of Political Economy*, 98, 71–102.
- SMALLWOOD, D. E. AND J. CONLISK (1979): “Product quality in markets where consumers are imperfectly informed,” *Quarterly Journal of Economics*, 93, 1–23.
- UNRUH, G. (2000): “Understanding carbon lock-in,” *Energy Policy*, 28, 817–830.
- VAN DEN BERGH, J. (2012): “Effective climate-energy solutions, escape routes and peak oil,” *Energy Policy*, 46, 530–536.
- VAN DER PLOEG, F. (2011): “Macroeconomics of sustainability transitions: Second-best climate policy, Green Paradox, and renewables subsidies,” *Environmental Innovation and Societal Transitions*, 1, 130–134.
- YOUNG, H. P. (2009): “Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning,” *American Economic Review*, 99, 1899–1924.
- ZEPPINI, P. (2011): *Behavioural Models of Technological Change (PhD Thesis)*, vol. 513, Tinbergen Institute.
- ZEPPINI, P. AND J. C. J. M. VAN DEN BERGH (2011): “Competing Recombinant Technologies for Environmental Innovation: Extending Arthur’s Model of Lock-In,” *Industry & Innovation*, 18, 317–334.