Thresholds Models of Technological Transitions

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1. Introduction

The question how technological transitions occur is an old one (Schumpeter, 1943). Nevertheless, it is only since the turn of the century that the study of transitions has gained momentum (Grübler, 1998; Rip and Kemp, 1998; Geels, 2002). The increased attention can be understood in the light of the pressing need to reform energy, housing, transportation, agriculture and health sectors given resource scarcity, climate change and environmental justice. It is commonly agreed that such reforms necessitate fundamental changes in the socio-technical systems that are currently dominant in these sectors. In this context, one speaks of the need for sustainability transitions (Grin et al., 2010; Markard et al., 2012).

A common notion underlying transition thinking is that of "technological regime" (Nelson and Winter, 1977) and "lock-in" (Arthur, 1989). A lock-in into a technological regime can be defined as a state in which one technology is dominant in a particular application domain, and resistant to competing alternatives, even if the latter can be considered socially desirable (David, 1985). Underlying the lock-in phenomenon are increasing returns to adoption: a technology tends to be more attractive, the more fellow users already use a technology.

To further our understanding of the mechanisms underlying technological lock-in, and the possibilities to successfully introduce alternative technologies to promote transitions, we look into various threshold models in complexity theory. Such models identify "tipping points" that lead a system to transit from one state (here one dominant technological regime) to another state (here, an alternative technological regime). Understanding the nature of such tipping points is important as it may be informative regarding transition policies at the level of individual actors, groups of actors, and government.

In the past two decades, several complexity-theoretic models of technological transitions have been proposed. Reviewing these contributions, it becomes clear that the sources of technological lock-in may vary, and that the possible mechanisms leading towards technological transitions are multiple. In the built up of a substantively interpretable theory of technological transitions, we find it helpful to clarify the various assumptions of different models and how these models are related. Hence, a systematic review of elementary models of technological transitions is useful in order to discern the various mechanisms underlying causing transitions or the absence thereof in empirical work. What is more, our review also serves as a "menu" for future modelling exercises that can take one or more elementary models as a basis, and elaborate on these to fit more specific contexts.

Our paper is structured around seven core models of technological transitions. Each of these addresses the same question (the conditions under which a population of agents switches from a technology to an alternative technology) but from different angles. We start in *Section 2* with the hyperselection model, which includes the classic Fisher-Pry substitution model as a special case. The hyperselection model contains a tipping point that specifies the critical mass required for a new technology to successfully replace the old. One can also derive such tipping points using a modified Arthur-model of increasing returns to adoption (*Section 3*), or using an informational cascade model (*Section 4*), or else a coordination game model (*Section 5*). The widespread notion of technological transitions as a co-evolutionary process between various interdependent technologies is taken up in *Section 6* where we discuss the NK-model, which in turn bears resemblances with game theory. In *Section 7* we go into transitions as percolation processes in social networks. We finally go into sociologically-inspired transition models in *Section 8*. We end with a comparison of the various models and discuss the usefulness in probing the complex phenomenon on technological transitions theoretically and empirically and discuss their relevance for the study of technological transitions in general and sustainability transitions in particular.

2. Hyperselection

Bruckner et al. (1996) developed a general model of substitution, considering the case of an already existing technology 1 with N_1 users, and an innovative technology that enters the market with N_2 early adopters. The model assumes a constant number of adopters $N = N_1 + N_2$, which suggests that the two technologies are perfect substitutes. Because of this assumption the innovative technology can succeed only by substituting the old one. The dynamics of substitution, then, follows from the differential equation:

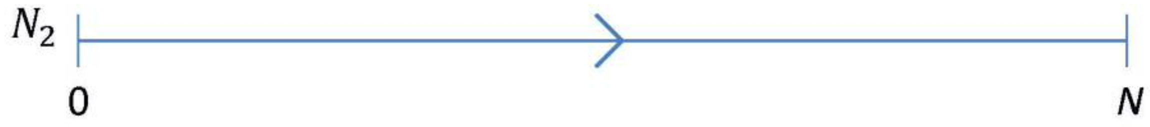
$$\frac{dN_i}{dt} = (E_i + B_i N_i)N_i - k_0 N_i \ , \ \ i = 1,2$$

Here the coefficients E_i and B_i set the growth rate of each technology, and, hence, reflect the quality of each technology. To assure that *N* is constant, the decay rate must fulfil the condition:

$$k_0 = \frac{(E_1 + B_1 N_1)N_1 + (E_2 + B_2 N_2)N_2}{N}$$

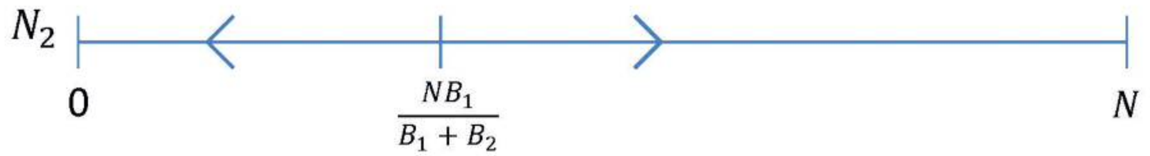
There are three stationary points $\left(\frac{dN_i}{dt} = 0\right)$ for the population of adopters (N_1, N_2), which are (0,1), (1,0) and $\left(\frac{NB_2+E_2-E_1}{B_1+B_2}, \frac{NB_1+E_1-E_2}{B_1+B_2}\right)$. The model is a general model as it can distinguish between the case of linear growth ($B_1 = B_2 = 0$) and non-linear growth ($E_1 = E_2 = 0$). The linear model corresponds to the classic selection model of substitution (Fisher and Pry, 1971), while the non-linear case captures self-reinforcing growth rates reflecting increasing returns to adoption where a technology becomes more attractive the more it is already used (Arthur, 1989). In the latter case, one speaks of hyperselection.

In the case of linear growth there are only two stationary points, $(0, N)$ or $(N, 0)$, one stable and one unstable, depending on whether E_1 is smaller or larger than E_2, respectively. Whenever the new technology is a better one than the old technology, meaning that $E_2 > E_1$, it will always substitute the old technology, since the only stable equilibrium is $(0, N)$, as it is shown in the phase diagram:



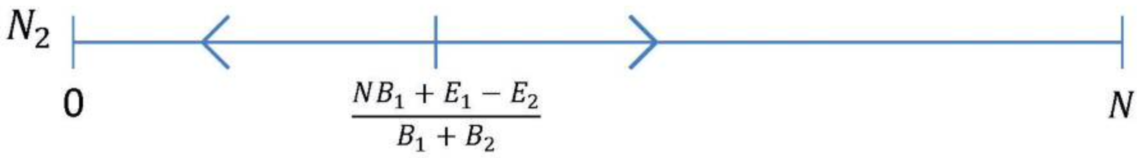
As shown by Bruckner et al. (1996), the case of linear growth is equivalent to the classic Fisher-Pry model (Fisher and Pry, 1971; Grübler, 1998). The only difference between the two models holds that the Fisher-Pry model is expressed in the shares of two technologies rather than in absolute numbers.

In the case of exponential growth ($E_1 = E_2 = 0$), we have three stationary points: $(0, N)$, $(N, 0)$ and $\left(\frac{NB_2}{B_1+B_2}, \frac{NB_1}{B_1+B_2}\right)$, with the latter being unstable. The phase diagram becomes:



In this case, we have a threshold value specifying the minimum number of adopters of technology 2 that is required to 'unlock' society from technology 1 and cause a transition to technology 2. This threshold value, or critical mass, will be smaller for larger differences in quality between the new B_2 and the old technology B_1, and will be larger for larger values of *N*. The model shows that a superior technology will not automatically substitute an inferior technology. Rather, the problem underlying transitions is a problem of coordination, that is, the problem to have a critical mass of agents adopting the new technology simultaneously. This coordination problem, then, becomes more difficult, the more agents are present in a population.

Finally, one can also consider the general case, where the growth rate is a mix of linear and quadratic growth, with again two stable stationary states $(0, N)$ and $(N, 0)$, and one unstable stationary state $\left(\frac{NB_2+E_2-E_1}{B_1+B_2}, \frac{NB_1+E_1-E_2}{B_1+B_2}\right)$. As for the case of non-linear growth, the unstable equilibrium gives the critical mass that adopters of technology 2 must reach in order for this technology to be selected, as evidenced by the phase diagram:



Whenever the population of adopters of the new technology is above the threshold, a transition takes place. The speed of transition can be derived from the differential equation. For a given size of the population, the better the new technology is with respect to the old one (the larger the coefficients E_2 and B_2 with respect to E_1 and B_1) the faster the transition will take place.

Bruckner et al. (1996) also go into a stochastic version of the model, which can be studied analytically using a Master equation approach. In the stochastic version, the results remain intact in that the probability of a transition depends on the difference in quality and the total size of the population.

3. Adoption

Arthur (1989) proposed a model of competing technologies under increasing returns. Increasing returns to adoption is a salient feature of technology, since the value of using a technology generally increases with the number of fellow adopters. This positive externality is due to learning effects, both among producers and users, the advantages of using common standards and infrastructure, and the provision of complementary goods, services and institutions supporting the dominant technology. This model is similar to the hyperselection model in that both address increasing returns to adoption. But Arthur models individual adoption decisions explicitly, while in the hyperselection model decisions are captured directly on the macroscopic scale in a single differential equation.

In Arthur's model there are two technologies A and B competing for adoption. Adopters exist in two types (R or S) that have an equal share in the population. Type R prefer technology A, while type S prefer technology B. Returns from adoption of technologies A and B are a_R and b_R respectively, for type R, while a_S and b_S are the returns for type S. Preferences are such that $a_R > b_R$, and $a_S < b_S$. Beside preferences, a feedback mechanism makes the return to depend also on previous adoptions. If N_A and N_B are the number of previous adopters the two technologies, the overall returns are given in Table 1.

	Technology A	Technology B
R-agent	$a_R + rN_A$	$b_R + rN_B$
S-agent	$a_S + sN_A$	$b_S + sN_B$

$a_R > b_R, a_S < b_S,\ a_R = b_S, a_S = b_R, r = s, r > 0, s > 0$

Table 1. Payoff function for Arthur's model of competing technologies

When coefficients *r* and *s* are positive, the more one technology is adopted, the higher its return to any agent. This is a mechanism of positive feedback. In this model R-agents and S-agents arrive in random order, and *R*-agents switch to technology B choosing against their own preference for A once the dominance of technology B passes the following threshold:

$$N_B - N_A > (a_R - b_R)/r$$

while *S*-agents switch to technology A instead of following their preference for B when the dominance of technology A passes the following threshold:

$$N_A - N_B > (b_S - a_S)/s$$

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Arthur's model explains well why a process of competing technologies tends to end in a state where one of the technologies is dominant, even if agents differ in their preferences regarding technologies. This is a direct consequence of increasing returns. If returns would be decreasing with the number of previous adopters, technologies would always share the market as agents would always follow their own preferences and a 50-50 distribution of market shares will result.[i]

The lock-in model is often invoked in the study of technological transitions, but the model is not about transitions *in stricto sensu* (Frenken and Verbart, 1998). It models competing technologies among agents that did not adopt a technology before, while in the case of technological transitions, we start with a state in which all agents already have adopted the same technology in the past (Technology 1), and a new, and superior, technology becomes available (Technology 2). We can re-formulate Arthur's model as a model of transitions in the following way. We assume that all agents have the preferences, and that new technology 2 is preferred over old technology 1. We get payoffs as in Table 2.

	Technology 1	Technology 2
any agent	$a + rN_1$	$b + rN_2$

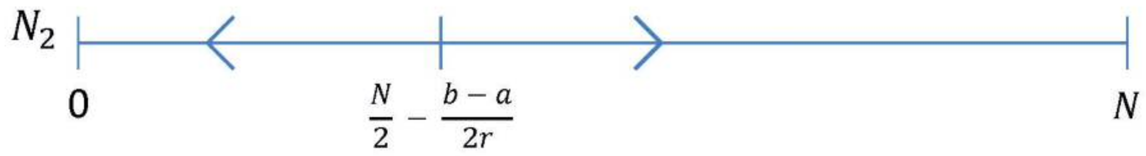
$b > a, r > 0$

Table 2. Modified Arthur-model of technological transitions

There are *N* agents in the population. We can now consider the question of technological transition as the question under what conditions agents using technology 1 all switch to technology 2. Hence, the starting point in the analysis of a technological transition is the state $N_1 = N$. The question becomes how many agents have to switch simultaneously from technology 1 to 2 such that all remaining agents using technology 1 will follow suit, and also switch to technology 2. This will happen once the payoff of using technology 2 will be greater than the payoff of using technology 1, that is, when $b + rN_2 > a + rN_1$. Given that $N_1 = N - N_2$, we get, as tipping point:

$$N_2 > \frac{N}{2} - (b-a)/2r$$

And the phase diagram becomes:



The tipping point specifies the critical mass of users of the new technology 2, which is required to cause a full technological transition. Once this critical mass of users is achieved, all other users will follow suit. We can derive a number of properties of the tipping point:

1. If $(b-a)$ is positive and infinitesimally small, half of the agents must switch from 1 to 2 for a full transition to occur
2. If the sensitivity for increasing returns (r) is very large, just more than half of the agents must switch from 1 to 2 for a full transition to occur
3. The more the quality of the new technology 2 exceeds the quality of the old technology 1, the fewer agents needed to switch from 1 to 2 for a full transition to occur
4. For "an entrepreneur", that is a single agent, to cause a transition, she must introduce a new technology b with sufficiently high quality such that one agent is already sufficient as a critical mass. The threshold is given by: $b > a + r(N-2)$.

This modified Arthur-model has also been the basis for a recent model by Frenken et al. (2012). In their model, agents adopt a technology by maximizing utility according to Table 2. That is, at each moment in time they compute the payoff for each technology given the number of fellow adopters and choose the one with the highest payoff. An additional feature of the model holds that at each moment in time, a fraction of agents engage in the development of a new technology, with higher quality. New technologies start a new branch of incremental innovations. Later on, branches can be recombined through recombinant innovation, which occurs when agents occupying different branches develop a joint invention through collaboration.[ii] A second additional feature in the model are switching costs, that agents have to pay when they change technology, and that are proportional to the technological distance between two technologies. The distance between technologies is determined by the genealogy of their ancestors. Then, 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. Their model replicates some stylised facts of technological change, such as persistent technological lock-in, experimental failure with new branches and occasional punctuated change ("transitions").

4. Coordination game

Game theory refers to a class of economic models of strategic interaction where players choose between strategies, and the payoff they receive from each strategy depends on the strategies chosen by others. At an abstract level, there is an immediate connection between game theory and technological transitions: agents tend to remain locked into inferior technologies, since the payoff of adopting a new technology is too low, given that others will continue using the old technology.

One way of representing this coordination problem underlying technological transitions is as a coordination game between two players. Imagine that there are two alternative technologies. The technologies are only useful when both players adopt the same technology due to compatibility requirements. Think, for example, of telecommunication equipment that only functions if both players use a technology adhering to the same technical standard. Or think of a car producer and a fuel company facing the choice between gasoline and hydrogen to fuel car engines. Hence, increasing returns exist from adopting the same technology. However, the coordination game model is different from the other models of increasing returns to adoption already discussed (Bruckner et al., 1996; Arthur, 1989), in that the advantages of using the same technology stem from bilateral interaction only. In this sense, increasing returns in coordination games are local, rather than global in nature.

To illustrate the coordination game as a model of technological transitions, consider the example of Table 3 where the payoff associated with the old technology is 1 when used collectively and the payoff from using the new technology is 4 when used collectively. If an agent decides to switch from the old to the new technology, she will have to incur switching costs equal to 2. Hence, the net payoff for each player if both adopt the new technology is equal to 2. If only one player adopts the new technology, this player will receive no payoff while still incurring the switching costs of 2 resulting in a net payoff of -2. The other player still using of the old technology, then, will receive no reward but does not incur any cost either, resulting in a payoff of 0. The payoff matrix becomes:

	Technology 2	Technology 1
Technology 2	(2, 2)	(-2, 0)
Technology 1	(0,-2)	(1, 1)

Table 3. The coordination game; an example

There are two Nash equilibria for which no player has an incentive to change strategy once this equilibrium is attained: both adopting technology 1 and both adopting technology 2. Obviously, both adopting the new technology 2 is socially optimal. Nevertheless, as long as both players still use the old technology, neither of them has an incentive to change strategy individually since such unilateral switch from using the old to using the new technology would entail a utility loss from 1 to -2. This is a classic “coordination problem”.[iii]

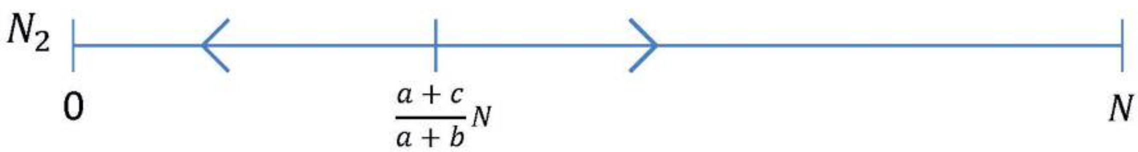
The classic two-player setting in game theory is a highly stylized model, since players are many in most empirically relevant settings. Then, players' interactions are better described with a population approach and assuming an evolutionary selection dynamic (Maynard Smith and Price, 1973). In evolutionary game theory players are matched randomly, play a bilateral game, and are matched again randomly, play a bilateral game etc. Each player is identified by a strategy, and better strategies reproduce faster (e.g., through imitation), depending on the payoff they generate, which in turn depends on the relative abundance of other strategies.

In such a population setting, the best strategy for each player depends on the distribution of strategies among other players. If there are N agents in the population, we can write the fraction of agents using the technology 2 as n and the fraction of agents using the old technology 1 as $(1\text{-}n)$. The expected payoff adopting the new technology becomes $n(2) + (1\text{-}n)(\text{-}2) = 4n\text{-}2$, while the expected payoff from adopting the old technology equals $n(0) + (1\text{-}n)1 = 1\text{-}n$. Hence, the tipping point is given by the equality of the two payoffs, which yields n=0.6. This is also the mixed strategy equilibrium of the 2x2 stage game.

	Technology 2	Technology 1
Technology 2	(b-c, b-c)	(-c, 0)
Technology 1	(0,-c)	(a, a)

Table 4. The coordination game; general respresentation

In general the coordination game for technological transitions can be expressed by the payoffs matrix in Table 4, where b and c are the reward and cost of the new technology 2, respectively, while a is the payoff from coordination on the old technology 1. The expected payoff adopting the new technology 2 becomes n(b-c) + (1-n)(-c) = nb-c, while the expected payoff from adopting the old technology 1 equals n(0) + (1-n)a = (1-n)a. Hence, the tipping point (or mixed strategy equilibrium) is given by the equality of the two payoffs, which is $n = \frac{a+c}{a+b}$. This means that, for a population with N agents, $\left(\frac{a+c}{a+b}N\right)$ agents have to adopt the technology 2 in order for the others to follow suit. The phase diagram becomes:



Again, as in the models by Arthur (1989) and Bruckner et al. (1996), we have a tipping point defining the minimal number of agents required to move from the old inferior technology to the new superior technology for a full technological transition to occur. Notice that lower costs c and/or higher rewards b from the new technology make easier to reach the transition threshold. In order to analyse the exact transition dynamics, and the speed at which a transition takes place, the model must be equipped with a full evolutionary framework, meaning an explicit specification of the mechanism describing how strategies reproduce. In Evolutionary Game Theory this is called the *revision protocol*. Common examples are Replicator dynamics, Best Response dynamics, and Logit dynamics (Samuelson, 1997).

Kandori et al. (1993) explain how a population can transit from the old technology to the new technology without any explicit coordination of adoption decisions. Their evolutionary game theory model assumes that players can adjust their choice according to some payoff-dependent learning mechanism, and also assume that learning is in turn subject to perturbations ("mutations"). That is, agents occasionally mutate their strategy by adopting the other technology. Then, it can happen by chance that multiple agents mutate in a row such that the population of agents transits from one equilibrium to the other. Hence, in an evolutionary setting the population perpetually fluctuates between all using the old technology and the new technology. Yet, overall more time is spent with using the new, superior technology compared to the old, inferior technology.

5. Informational cascades

A social phenomenon known as informational cascades can be relevant to the understanding of technological transitions. Informational cascades refer to the dynamics of expectations where each potential adopter forms expectation based on decisions of previous adopters. Indeed, the dynamics of expectations regarding the promise of new technologies has been studied widely in transition studies (Borup et al., 2006; Van Lente et al., 2013). Informational cascades are at the basis of phenomena of herding behaviour, when people act following what others do. It is evident how herding in general and informational cascades in particular presents a positive feedback mechanism. Although herding sounds like myopic or even irrational behaviour, it may well result out of the aggregation of perfectly rational individual actions. The point is that it may be perfectly rational for an individual to make a decision (adoption of a new technology) following the actions of other agents, disregarding one's own information. This intuition was first developed in two different but equivalently insightful models, Banerjee (1992) and Bikhchandani et al. (1992), the latter being an adoption model most relevant to the study of technological transitions.

The model by Bikhchandani et al. (1992) is as follows. Adoption of a certain behaviour leads to a future gain V. This may be either 0 or 1 with prior probability 0.5. Adoption bears a cost C, with $0<C<1$. Agents chose sequentially and are privately informed about the future value of the payoff from adoption. Agents do not have an exact information but only a signal telling with some positive probability whether this value will be 1 (signal H) or 0 (signal L). For each individual the probability of observing a H signal is $p_i > 0.5$ if the future gain is $V=1$, and $1 - p_i$ if the value is $V=0$. The authors consider the special case of identically distributed signals, where $p_i = p$. On top of their private information agents also observe choices of previous agents and use the information they extract when making their decision on adoption.

The following example gives the intuition of the mechanism behind the occurrence of an informational cascade. Say the first agent of the sequence gets a H signal. Then she adopts, since $p>0.5$. The second agent gets again a H signal. Without hesitating she will adopt as well, since the probability that the signal is right is even larger than p. The third agent gets a L signal, instead. Based on her information she would refuse adoption. But the action (adoption) by the first and the second agent speaks very loud: they must have got two H signals or maybe the first got a H signal and the second a L signal. But in this last case the second agent was adopting only with probability 0.5. Based on this reasoning the third agent correctly assigns more likelihood to the occurrence of a signal sequence *(H,H,L)* than to the signal sequence *(H,L,L)* and she rationally adopts. This adoption by the third agent is an instance of herding, since she disregards her private information. In this way an *up* cascade takes place, and all subsequent agents will adopt irrespective of their signals. A *down* cascade occurs in the same way with just H and L signals reversed. Also note that it is not necessary that only the third agent initiates the cascade: if an even number of agents initially receive alternatively H and L signals, a neutral situation perpetuates and the agent coming after this homogeneous sequence find herself exactly in the same situation as the third agent of the example above.

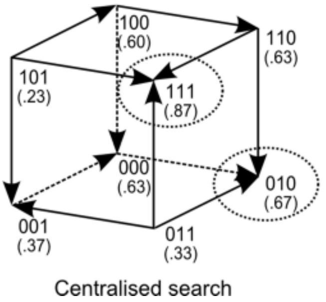
Bikhchandani et al. also show how informational cascades may be fragile and eventually vanish. The idea is that in a herding mechanism positive feedback vanishes as further adoptions are less and less informative. The authors show how the release of a small amount of public information is enough to end an informational cascade and leave place for a new one to start. They further show that the probability of a correct cascade increases as the signal becomes more precise and conversely how the probability of a wrong cascade decreases instead. Nevertheless, what is instructive is to note that a positive probability of a wrong cascade always remains.

The last result suggests a conclusive consideration about the relevance of information cascade models for the issue of technological adoption in general and technological transitions in particular. In the context of innovation, private signals may reflect the in-house R&D carried out by each individual firms. A firm, then, may adopt a new technology after a critical number of other firms already adopted the technology before, even if its own R&D results – as a private signal – would suggest the firm not to do so. Hence, a transition towards a new technologies may occur even if the new technology is inferior to an existing technology.

6. Co-evolution

A characteristic feature of many technologies is that they are composed of several components that interact in complex ways to produce particular functionalities. The challenge for designers is to put together components in a system such that they “fit” together, meaning that the components work in complementary, instead of conflicting ways. This design problem has been addressed using Kauffman’s NK-model (Kauffman, 1993; Frenken and Nuvolari, 2004; Frenken, 2006). NK refers to systems with N components each affected by K other components. In the NK-model, K is thus the complexity parameter which indicates the extent to which the functioning of each component is dependent on other components.

In case of minimum complexity (K=0), each component functioned independently from other components. Hence, each component can be optimized independently and in parallel as the system if fully "decomposable" (Simon, 1969, 2002; Frenken, 2006). By contrast, in the case of maximum complexity (K=N-1), the fitness of a component depends upon the choice of design of all other components. It follows that the fitness value of a component is different for different configurations of other components. Hence, to simulate the fitness landscape of such a complex system, one can simply draw a random fitness value w_i if for each component i for each possible design configuration (Figure 1).



	w_1	w_2	w_3	W
111	0.9	0.8	0.9	0.87
110	0.7	0.4	0.8	0.63
101	0.2	0.1	0.4	0.23
100	0.3	0.8	0.7	0.60
011	0.1	0.3	0.6	0.33
010	0.6	0.7	0.7	0.67
001	0.3	0.6	0.2	0.37
000	0.2	0.9	0.8	0.63

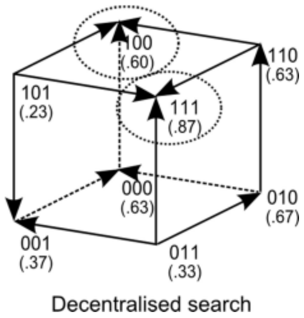


Figure 1. Simulation of a fitness landscape of a N=3 system with K=2.

Two types of search strategies can be distinguished on fitness landscapes: centralized and decentralized search. Centralised search represents a single agent, such as a firm (Frenken and Nuvolari 2004) or a government (Alkemade et al., 2009) who experiments with different design configurations which are evaluated on the basis of the global fitness *W*. Decentralised search refers to the co-evolutionary case where multiple actors are innovating, each being responsible for one of the *N* elements. In this case, each actor evaluates an innovation on the basis of its own element fitness (w_i). The co-evolutionary nature of this process stems from the fact that a mutation by one actor affects the fitness of other actors and *vice versa* (Kauffman and Johnson 1991; Caminati, 2006). Such interdependencies typically exist in value chains where the payoff of a technology depends on the choices made by other firms in the value chain (Press, 2008; Adner, 2012) as well as in large firms where departments exerts high levels of autonomy (Kauffman and Macready, 1995; Siggelkow and Levinthal 2003; Rivkin and Levinthal, 2003).

If we assume local search (i.e., a mutation occurs only in one element at the same time), local optima are those design configurations with global fitness superior to neighbouring designs. In the example of Figure 1, the local optima are 010 and 111. Centralized search can end up in different local optima depending on the starting point in the landscape and the particular sequence of mutations that follow. Search is "path-dependent" on the initial starting point of search and the sequence of searches that follow. Considering decentralized search, however, local optima correspond to Nash equilibria, i.e. design configurations with element fitness values that cannot be improved through unilateral mutation. In figure 1, these equilibria are 100 and 111. For such configurations, it holds that no actor has an incentive to switch its own technology.

As a model of technological transition – that is a move from one local optimum to a better local optimum – the fitness landscape model highlights that to 'unlock' a technological system, a change in governance may by itself already be sufficient. Consider a centralized governance system (*left*) currently locked into in the suboptimal state 010. Changing the governance into a decentralized system (*right*) would mean that the superior technology 111 suddenly becomes accessible via 110. However, success is not warranted, since any other transition path leads to the sub-optimum 100. Reversely, if a decentralized system is lock into the sub-optimum 100, changing the governance system into centralized search would open up a transition path to 111 via 110. Again, success is not warranted as other paths lead to the sub-optimum 010.

The more general lesson holds that there is no *ex ante* optimal governance structure to support technological transitions. Adner (2012) calls this a 'ecosystem perspective' to innovation strategy, where the innovating firm should recognize that they are part of a complex technological system. A go-alone strategy often fails when complementary innovations by other parties fail to occur. Among Adner's (2012) empirical examples is the famous case of Nokia's 3G handset, which failed as content providers did not come up with the necessary complementary innovations such as video streaming, location based services, and automated payment systems.

7. Percolation

A generic model of diffusion is the percolation model. Percolation is the diffusion of a liquid through a porous material layer. The density of the material regulates porosity, and this regulates diffusion. If one increases the density, porosity decreases, and eventually percolation stops. This process shows a phase transition, whit a sudden passage from diffusion to a no-diffusion regime. A typical percolation process occurs in making coffee. But several other natural phenomena can be described as percolation, like the spread of fire in a wood. In the context of technology diffusion, the percolation model represents the *word-of-mouth* process in social networks accompanying the diffusion most new technologies (Solomon et al., 2000; Hohnisch et al., 2008; Cantono and Silverberg, 2009; Campbell, 2012). Word-of-mouth here means that an agent who adopts a new technology will recommend the new technology to its acquaintances in the social network.

Imagine N agents and each agent being part of a social network. Two agents that are connected in the social network are called *neighbours*. Word-of-mouth means that when an agent adopts a new technology at time t, it will tell to its neighbours in the social network about the technology. Then, at time $t+1$, each neighbour will consider whether to adopt the technology, and if it does so, it will tell its neighbours, and so on.

Of course, if all agents are willing to adopt the technology, the technology will automatically diffuse throughout the whole (connected) population. Instead, if only some fraction of agents is willing to adopt the technology, once informed about it by a neighbour, a percolation threshold exists. In economic terms, the willingness to pay for a technology is expressed by an agent's reservation price p_r which denotes the maximum price the agent is willing to pay. Hence, an agent adopts if $p_r > p$.

Consider the case that agents form a random network as in Figure 2. Further imagine that a technology is introduced with p=p* with 0<p*<1. Reservation prices are randomly drawn from a uniform distribution between 0 and 1. This means that for a price equal to p* (say, 20 cents), a percentage of (1-p*) agents is willing to buy (here, 80 percent). Since reservation prices are randomly distributed among agents, the reservation price of an agent is uncorrelated with the reservation prices of its neighbours. Drawing reservation prices, then, amounts to "removing" nodes randomly, in that consumers with a too low reservation price are unwilling to buy, do not convey information to their neighbours. Hence, they can be removed from the network, and the agents that remain will form the "operational" network.

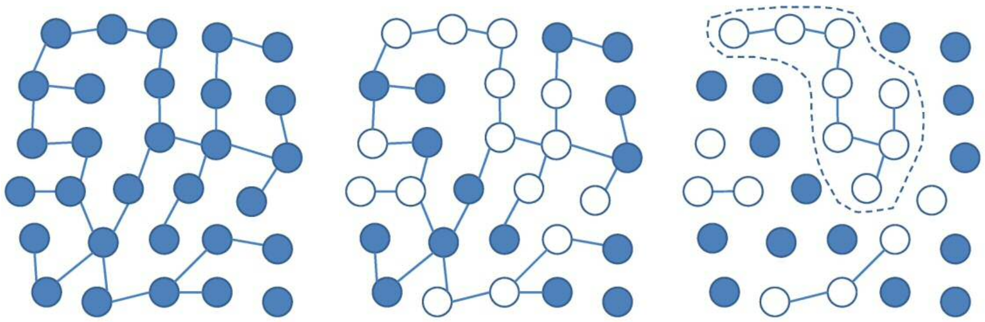


Figure 2. Percolation. In a random network (*left*), white nodes are willing to buy ($p_r > p$) and filled nodes are unwilling to buy ($p_r < p$) (*middle*). Widespread diffusion happens if an initial adopter is part of a giant connected component (surrounded by dotted lines) in the resulting "operational network" (*right*).

In the approximation of a large number of nodes, the percolation threshold can be computed for a number of special network structures. For instance, a Poisson random network (Erdös and Rényi, 1960) with average connectivity of neighbours of 4 has percolation threshold $p^* \simeq 0.67$, In the case of a regular lattice with connectivity of 4 for all agents, the threshold is $p^* \simeq 0.407$. As long as the price is below this threshold, almost everyone will be informed about the existence of the technology. That is, the information fully "percolates" through the social network. This means that all those who are willing to buy, will actually buy the new technology. However, if the price exceeds the critical threshold, there will be many agents that remain uninformed, who would have been willing to buy. In those cases, diffusion is less than what is socially desirable. Notice how the network structure is important: even with the same average connectivity, the Poisson random network allows percolation to occur at substantially higher prices than the regular lattice, due to the positive variance of connectivity in random networks.

Figure 3 simulates percolation for different prices in a regular lattice of 10,000 agents with connectivity 4. To get diffusion started, a seed is used of 10 randomly chosen agents who are given the product for free (that is, who adopt independently from their reservation price). As long as the price is rather low, everyone willing to buy will buy the new technology. The observations then follow the standard demand curve represented by the straight dotted line. However, for higher prices, many potential buyers remain uninformed and the technology does not take off. Already at a price of 0.6, almost no agent adopts, even though there is a potential market of no less than 40 percent of the population. Hence, the model explains that technological transitions (here defined as the event of a new technology being widely adopted by those willing to adopt it) may be difficult to predict as there is a fine line between success and failure. What is more, the probability of a transition to occur will not only depend on price, but also on the number of seeds and connectivity distribution of the network (Zeppini et al., 2013).[iv]

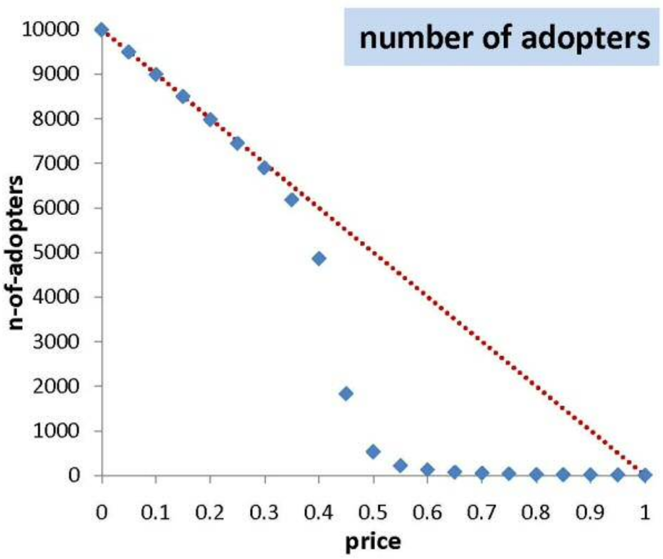


Figure 3. Percolation shows a critical transition.

The time dimension of a diffusion process governed by a percolation mechanism is rather peculiar, in that it presents the typical features of second order critical transitions. In such processes, the time required to reach the equilibrium state presents a spike at the threshold (Zeppini et al., 2013). This means that both above the threshold, in the non-diffusion regime, as well as below the threshold, in the diffusion regime, the adoption process becomes increasingly slower the closer the price is to the threshold price.

Silverberg and Verspagen (2005) developed an alternative percolation model to represent technological innovation as a long series of small innovations punctuated by occasional breakthroughs. The nodes in the network, here, represent technologies and technologies that are linked are neighbouring technologies. They also start from a lattice, but one which is bounded in the horizontal dimension (representing the technological distance between technologies) and unbounded in the vertical dimension (representing the performance of technologies). At each moment in time, a node is in one out of four possible states: 0 (technologically impossible), 1 (possible but not yet discovered), 2 (discovered but not yet viable) and 3 (discovered and viable).[v] Starting from the baseline, agents travel through the technology space by local search. As they discover technologies, nodes are switch on (changing from 1 into 2). Subsequently, a node turns from 2 into 3 if and only if there exists a contiguous path of cells in state 2 or 3 connecting it to the baseline. That is, a technology becomes operational ‘when it can draw on an unbroken chain of supporting technologies already in use’. Because of the percolation properties of the model, local search will occasionally produce avalanches of many sudden innovations, as certain sites cause chain reactions of other sites becoming viable. This result, then, can be understood as a theoretical explanation for the existence of technological transitions.

8. Social influence

Technological transitions are not solely driven by economic logics. Social processes can play a key role as well (Rip and Kemp, 1998). One such a process is mimicking, that is, the tendency of agents to imitate behaviour of others. An influential model in this context is that of Granovetter (1978) who considers binary individual decisions subject to social influence, such as the adoption of an innovation. A key feature of his model holds that individuals differ in the extent to which they are influenced by decision of others. Heterogeneity is expressed as individual thresholds that specify the number of other agents adopting the innovation that is required for an individual agent to adopt. That is, there exist different critical mass levels for each individual. Granovetter considered two settings: i. Global influence, where people thresholds refer to the total number of adopters, with no preferential influence, and ii. Social structure, where friends have higher influence than other people on individual decisions.

Granovetter main focus is how the distribution of individual thresholds influences collective behaviour, or in other words how individual decisions aggregate. The aggregation of individual decisions brings non-linear effects. In particular, small changes in the variance of the distribution of individual thresholds may lead to large changes in aggregate behaviour (bifurcations). This means that almost identical distribution of thresholds may lead to completely different adoption scenarios. The following theoretical example is instructive: consider a population of 100 individuals, where the first has threshold 0 (this is someone who adopts irrespective of social influence), the second has threshold 1, the third has threshold 2, and so on, until the last individual who adopts only of all the rest of the population (99) have adopted. With such a uniform distribution of threshold the outcome is always full adoption, since a *domino* effect occurs, starting from the early adopter and propagating through individuals of ever increasing threshold. If we now perturb slightly the distribution by changing the threshold of the second individual from 1 to 2, the outcome is that only one individual will adopt (the one with threshold 0).

Granovetter (1978) extended the basic model with an explicit social structure. Here, friends have higher influence than strangers. A useful way to model this is to retain the notion of unique individual threshold for adoption, and introduce a weight for personal influence. For instance, an adopting friend may count as two adopting strangers. The model is enriched with a “sociomatrix” representing social structure, and this is equipped with weights that describe how much a friend’s action counts more than a stranger’s action. The main result is that social structure may cause a sizeable adoption outcome in cases where that would not be possible if all actions count the same.

In recent years there has been a large research effort in understanding the effect of social structure in collective behaviour, and more generally how different diffusion processes take place in social networks (for a review, see Vega-Redondo 2007). Here local effects depend on the absolute number of neighbours adopting a certain behaviour (e.g., Pastor-Satorras and Vespignani, 2001). Local threshold models provide another variant of such models, where the number of interest is the relative fraction of neighbours adopting (e.g., Lopez-Pintado, 2008). In the first case, a decision maker looks at the absolute number of adopting friends. In the second case instead the decision maker "weighs" the number of adopting friends on the size of her neighbourhood. The main message from network models of social behaviour is that a threshold exists that cause transitions, and this threshold strongly depend on the distribution of social ties of agents in a social network.

9. Discussion

The seven models all address the phenomenon of a technological transition in terms of a substitution process of an old technology being replaced by a new technology. Table 5 summarises the main features for each model. Typically, the way the models express the transition process is in terms of the number of agents adopting the one or the other technology. Thresholds, then, refer to the classic notion of the critical mass that is required to cause a transition, where critical mass stands for the minimum number of adopters of the new technology required to trigger the remaining agents to switch to the new technological as well. However, the co-evolutionary model is different, as the threshold thatneeds to be crossed is not expressed in terms of a number of agents, but in terms of the fitness of the new technology vis-à-vis the old technology. The percolation model is also different in that the critical threshold is expressed in terms of the critical price below which a transition takes place, rather than a critical number of adopters above which a transition takes place.

Further differences between the models concern the micro-foundations underlying the models. Most follow the standard economic assumption that adoption behaviour is driven by utility maximization. The hyperselection model, however, has no explicit micro-foundations at all as it expresses all adoption decisions by a single differential equation. And, the social-influence model regards agents as solely driven by their inclination to mimic other people's behaviour. Another difference between models is whether agents are assumed to be homogenous or heterogeneous. And, concerning modelling frameworks that introduce heterogeneous-agents models, the nature of heterogeneity is also different among models. In the case of informational cascades, heterogeneity stems from the differences in information that agents receive. In the case of social influence agents differ in their individual threshold (share of other agents) triggering them to adopt, while in the percolation model differences stem from preferences determining reservation prices. In the co-evolutionary model, heterogeneity stems from the different payoffs assigned to each subsystem depending on the design configuration of the technology as a whole.

The key insight from our review holds that the very same phenomenon of a technological transition can be explained by very different underlying logics ranging from typical economic explanations based on prices, increasing returns and technological complementarities or alternative explanations based on word-of-mouth recommendations in social networks convergence of expectations, or social mimicking behaviour. Hence, transitions can be caused by very different processes, and possibly combinations of processes. An empirical challenge will be to discern what kind of processes are operating and what their relative importance has been in (stages of) the transition process.

Though the elementary transition models reviewed here all address different key mechanisms that may underlie technological transition process, some key aspects of transitions have not been addressed so far, or only in very rudimentary ways (Holtz, 2011; Safarzyńska et al., 2012). For example, historical studies have shown that transitions are often generally not well understood as a simple battle between the old and the new technology. Rather, in the process of transitions, several alternatives compete, with new alternatives emerging from recombination (Sahal, 1985; Geels, 2005). Hence, recombinant innovation can be considered an important feature of transition models (Van den Bergh, 2008; Safarzyńska and Van den Bergh, 2010, Zeppini and Van den Bergh, 2011; Frenken et al., 2012). What is more, transitions may be better understood as evolutionary processes with transitions resulting from several incremental steps and intermediary technologies (Geels, 2002). This view is at odds with the typical 'revolutionary' framing of two competing technologies, though notable exceptions exist of models where more than two technologies compete (e.g., Silverberg and Verspagen, 2005; Weisbuch et al., 2008; Frenken et al., 2012).

Furthermore, it can be stressed that, often, the new technology initially does not compete with the old technology (Pistorius and Utterback, 1997; Geels, 2002). Rather, initially technologies may have a symbiotic relation in that the new technology supplements the old technology in particular niches. And, in other cases, such niches are actively created and supported, for example, by government or other powerful actors. Such strategies of niche protection is especially relevant in the analysis of sustainability transitions (Kemp et al., 1994; Schot and Geels, 2007; Raven and Smith, 2012). A particular future challenge will be to model technological transitions by specifying niches where new technologies can develop before they invade the mass market dominated by the old technology (Lopolito et al., 2013). In this context, one can think of co-evolutionary models of demand and supply (Windrum et al., 2009a, 2009b; Safarzyńska and Van den Bergh, 2010).

A further note on the modelling of sustainability transitions concerns the specification of a technology's selection environment. In the case of a sustainability transition, the key difference between the old and new technology is that the former is less sustainable than the latter. However, whether sustainability is a key determinant driving the success of new technologies will depend on the extent to which policy creates a selection environment that will reward sustainability (e.g., R&D subsidy, price subsidies, land use policy, information campaigns, *et cetera*). Hence, in modelling sustainability transitions, an additional aspect will be to model the negative externalities associated with the continued use of the old technology, and alternative policies to reward new technologies that are more sustainable.

Methodologically, the seven elementary models have in common the ability to express one particular complex dynamic causing transitions with very few parameters. One typical parameter is the extent to which the new technology is superior to the old (whether expressed in terms of quality or price). Another typical parameter is the extent to which agents profit from increasing returns to adoption. These models with few parameters allows one to derive, analytically or through simulation, the tipping point in the model that defines a threshold that is to be crossed to cause a transition to occur. This is clearly a great advantage of the canonical models of technological transitions, since it allows one to fully understand the nature of the transition process in terms of few key parameters in very generic terms.

However, models with few parameters should not be mistaken as accurate representations of real-world transitions process. Such processes are much more complex in that several of the mechanisms highlighted by the models are likely to operate at the same time. Furthermore, real-world agents are heterogeneous in many more dimensions than the ones included in the models. For one thing, real-world consumers differ in wealth (e.g., high-income vs. low-income), skills (e.g., high-skilled vs. low-skilled), and visibility (e.g., a celebrity versus any other consumer). Similarly, firms differ in size, absorptive capacity and complementary assets all affecting their adopting decisions. Contextual factors are also likely to affect transition processes, possibly in rather fundamental ways (Holtz, 2011). Think here of specific institutions, policies and regulations that differ across territories, sectors and technologies. Hence, modelling exercises that aim to study a specific transition process – often in one sectoral and national context – will have to include much more specificity into their framework. A larger parameter space, then, is unavoidable.

The elementary "canonical" models reviewed here serve as potential building blocks for more specific and elaborated models. In particular, when building models to evaluate specific policies aimed at unlocking current technological systems, contextual factors should be added concerning the specific sectoral, technological and territorial contexts at hand (Schwoon, 2006; Alkemade et al. 2009; Chappin and Dijkema, 2009; Köhler et al., 2009; Huétink et al., 2010; Van Vliet et al., 2010; Chappin and Afman, 2012; van der Vooren et al., 2012). Empirically, such "agent-based" models are rather difficult to validate (Windrum et al., 2007; Holtz, 2011). Furthermore, the exact transition threshold may be difficult to find in such models. Notwithstanding these difficulties, agent-based simulation models are extremely useful to do virtual government policy experiments. Since real-world experiments are often too risky or expensive, simulation modelling provides a unique and transparent social laboratory to evaluate alternative policies (Dawid and Fagiolo, 2008; Dawid and Neugart, 2010). Given the large scale of technological transitions, this argument applies *a fortiori* to agent-based models of technological transitions.

References

Adner, R., 2012. The Wide Lens: A new strategy for innovation. Portfolio, New York.

Alkemade, F., Frenken, K., Hekkert, M.P., Schwoon, M.A., 2009. A complex systems methodology to transition management. Journal of Evolutionary Economics 19(4), 527–543, Arthur, W.B., Ermoliev, Y.M., Kaniovsky, Y.M., 1987. Path-dependent processes and the emergence of macrostructure. European Journal of Operational Research 30, 294–303.

Arthur, W.B., 1989. Competing technologies, increasing returns and lock-in by historical events, Economic Journal, 99, 116–131.

Banerjee, A., 1992. A simple model of herd behaviour. Quarterly Journal of Economics 107, 797–817.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy 100(5), 992–1026.

Borup, M., Brown, N., Konrad, K., Van Lente, H., 2006. Expectations in science and technology. Technology Analysis and Strategic Management 18(3–4), 285–299.

Bruckner, E., Ebeling, W., Jimenez-Montano, M.A., Scharnhorst, A., 1996. Nonlinear stochastic effects of substitution: an evolutionary approach. Journal of Evolutionary Economics 6, 1–30.

Caminati, M., 2006. Knowledge growth, complexity and the returns to R&D. Journal of Evolutionary Economics 16, 207–229.

Campbell, A., 2012. Word of mouth and percolation in social networks. American Economic Review, in press.

Cantono, S., Silverberg, G., 2009. A percolation model of eco-innovation diffusion: The relationship between diffusion, learning economies and subsidies. Technological Forecasting and Social Change 76(4), 487–496.

Chappin, E.J.L., Dijkema, G.P.J., 2009. On the impact of CO2 emission-trading on power generation emissions. Technological Forecasting and Social Change 76(3), 358–370.

Chappin, E.J.L., Afman, M.R., 2013. An agent-based model of transitions in consumer lighting: Policy impacts from the EU phase-out of incandescents. Environmental Innovation and Societal Transitions 7, 16–36.

David, P., 1984. Clio and the economics of QWERTY. American Economic Review. 75(2), 332–337.

Dawid, H., Fagiolo, G., .2008 Agent-based models for economic policy design: introduction to the special issue. Journal of Economic Behavior and Organization 67, 351–354.

Dawid, H., Neugart, M., 2010. Agent-based models for economic policy design. Eastern Economic Journal 37, 44–50.

Dosi, G., Ermoliev, Y., Kaniovski, Y., 1994. Generalized urn schemes and technological dynamics. Journal of Mathematical Economics 23, 1–19.

Erdös, P., Rényi A., 1960. On the evolution of random graphs. Publications of the Mathematical Institute of the Hungarian Academy of Sciences 5, 17–61.

Fisher, J.C., Pry, R.H., 1971. A simple substitution model of technological change. Technological Forecasting and Social Change 3(1), 75–88.

Frenken, K., 2006. Innovation, Evolution and Complexity Theory, Edward Elgar.

Frenken, K., Izquierdo, L.R., Zeppini, P., 2012. Branching innovation, recombinant innovation and endogenous technological transitions. Environmental Innovation and Societal Transitions 4, 25–35.

Frenken, K., Nuvolari, A., 2004. The early development of the steam engine: an evolutionary interpretation using complexity theory. Industrial and Corporate Change 13(2), 419–450.

Frenken, K., Verbart, O., 1998. Simulating paradigm shifts using a lock-in model, in: P. Ahrweiler and N. Gilbert (eds.), Computer Simulations in Science and Technology Studies. Springer, Berlin, 117–128.

Geels, F.W., 2002. Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Research Policy 31(8–9), 1257–1274.

Geels, F.W., 2005. The dynamics of transitions in socio-technical systems: A multi-level analysis of the transition pathway from horse-drawn carriages to automobiles (1860-1930). Technology Analysis and Strategic Management 17(4), 445–476.

Granovetter, M., 1978. Threshold models of collective behavior. American Journal of Sociology 83(6), 1420–1443.

Grin, J., Rotmans, J., Schot, J., 2010. Transitions to Sustainable Development. New Directions in the Study of Long term Structural Change. Routledge, New York.

Grübler, A. 1998. Technology and Global Change. Cambridge University Press, Cambridge.

Harsanyi, J.C., Selten, R., 1988. A General Theory of Equilibrium in Games, MIT Press, Cambridge MA.

Hohnisch, M., Pittnauer, S., Stauffer, D., 2008. A percolation-based model explaining delayed takeoff in new-product diffusion. Industrial and Corporate Change 17, 1001–1017.

Holtz, G., 2011. Modelling transitions: An appraisal of experiences and suggestions for research. Environmental Innovation and Societal Transitions 1(2), 167–186.

Huétink, F.J., Van der Vooren, A., Alkemade, F., 2010. Initial infrastructure development strategies for the transition to sustainable mobility. Technological forecasting and Social Change 77(8), 1270–1281.

Kandori, M., Mailath, G.J., Rob, R., 1993. Learning, mutation, and long run equilibria in games. Econometrica 61(1), 29–56.

Kauffman, S.A., 1993. The Origins of Order. Self-Organization and Selection in Evolution. Oxford University Press, Oxford.

Kauffman, S.A., Johnson, S., 1991. Coevolution to the edge of chaos: coupled fitness landscapes, poised states, and coevolutionary avalanches. Journal of Theoretical Biology 49, 467–505.

Kauffman, S.A., Macready, W., 1995. Technological evolution and adaptive organizations. Complexity 1(2). 26–43.

Kemp, R., Schot, J.W., Hoogma, R., 1998. Regime shifts to sustainability through processes of niche formation: the approach of strategic niche management. Technology Analysis and Strategic Management 10, 175–195.

Köhler, J., Whitmarsh, L., Nykvist, B., Schilperoord, M., Bergman, N., Haxeltine, A., 2009. A transitions model for sustainable mobility. Ecological Economics 68(12), 2985–2995.

Lopez-Pintado, D., 2008. Diffusion in complex social networks. Games and Economic Behavior 62, 573–590.

Lopolito, A., Morone, P., Taylor, R., 2013. Emerging innovation niches: An agent based model. Research Policy 42, 1225–1238.

Markard, J., Raven, R.P.J.M., Truffer, B., 2012. Towards a research agenda on sustainability transitions. Introduction paper to special section on sustainability transitions. Research Policy 41, 955–967.

Nelson, R.R., Winter, S.G., 1977. In search of a useful theory of innovations. Research Policy 6, 36–76.

Nelson, R.R., Winter, S.G., 1982. An Evolutionary Theory of Economic Change. Belknap Press, Cambridge MA.

Pastor-Satorras R., Vespignani, A., 2001. Epidemic spreading in scale-free networks. Physical Review Letters 86, 3200–3203.

Pistorius, C.W.I., Utterback, J.M., 1997. Multi-mode interaction among technologies. Research Policy 26, 67–84.

Press, K., 2008. Divide to conquer? Limits to the adaptability of disintegrated, flexible specialization clusters. Journal of Economic Geography 8(4), 565–580.

Rip, A., Kemp, R., 1998. Technological Change, in: S. Rayner and L. Malone (eds.) Human Choice and Climate Change, Volume 2: Resources and Technology. Batelle Press, Washington D.C., 327–399.

Rivkin, J.W., Siggelkow, N., 2003. Balancing search and stability: interdependencies among elements of organizational design. Management Science 49(3): 290–311.

Safarzyńska, K., Frenken, K., van den Bergh, J.C.J.M., 2012. Evolutionary theorizing and modelling of sustainability transitions. Research Policy 41, 1011–1024.

Safarzyńska, J. van den Bergh, 2010. Demand–supply coevolution with multiple increasing returns: policy analysis for unlocking and systems transitions. Technological Forecasting and Social Change 77, 297–317.

Safarzyńska, K., Van den Bergh, J.C.J.M., 2011a. Beyond replicator dynamics: Innovation-selection dynamics and optimal diversity. Journal of Economic Behavior and Organization 78(3), 229-245.

Sahal, D., 1985. Technological guideposts and innovation avenues. Research Policy 14(2), 61–82.

Samuelson, L., 1997. Evolutionary Games and Equilibrium Selection. MIT Press, Cambridge MA.

Schot, J.W., Geels, F.W., 2007. Niches in evolutionary theories of technical change. Journal of Evolutionary Economics 17(5), pp. 605–622.

Schumpeter, J.A., 1942. Capitalism, Socialism and Democracy. London: Routledge.

Siggelkow, N., Levinthal, D.A., 2003. Temporarily divide to conquer: centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. Organization Science 14(6): 650–669.

Silverberg, G., Verspagen, B., 2005. A percolation model of innovation in complex technology spaces. Journal of Economic Dynamics and Control 29(1–2), 225–244.

Simon, H.A., 1969. The Sciences of the Artificial. MIT Press, Cambridge MA.

Smith, A., Raven, R.P.J.M. , 2012. Towards a theory of niche protection in transitions to sustainability. Research Policy 41(6), 1025–1036.

Solomon S., Weisbuch, G., de Arcangelis, L., Jan, N., Stauffer, D. 2000. Social percolation models. Physica A 277, 239–247.

Schwoon, M., 2006. Simulating the adoption of fuel cell vehicles. Journal of Evolutionary Economics 16(4), 435–472.

Van den Bergh, J.C.J.M., 2008. Optimal diversity: increasing returns versus recombinant innovation. Journal of Economic Behavior and Organization 68(3–4), 565–580.

Van Lente, H., Spitters, C., Peine, A., 2013. Comparing technological hype cycles: Towards a theory, Technological Forecasting and Social Change, in press.

Van Vliet, O., De Vries, B., Faaij, A., Turkenburg, W., Jager, W., 2010. Multi-agent simulation of adoption of alternative fuels, Transportation Research Part D: Transport and Environment 15(6), 326–342

Vega-Redondo F., 2007. Complex Social Networks, Cambridge University Press.

Vooren, A. van der, Alkemade, F., Hekkert, M.P., 2012. Effective public resource allocation to escape lock-in: the case of infrastructure-dependent vehicle technologies. Environmental Innovation and Societal Transitions 2, 98–117.

Weisbuch, G., Buskens, V., Vuong, L., 2008. Heterogeneity and increasing returns may drive socio-economic transitions. Computational and Mathematical Organization Theory 14, 376–390.

Windrum, P., Fagiolo, G., Moneta, A. 2007. Empirical validation of agent-based models: Alternatives and prospects, Journal of Artificial Societies and Social Simulation, 10(2)8 <http://jasss.soc.surrey.ac.uk/10/2/8.html>.

Windrum, P., Ciarli, T., Birchenhall, C., 2009. Environmental impact, quality, and price: consumer trade-offs and the development of environmentally friendly technologies. Technological Forecasting and Social Change 76, 552–566.

Windrum, P., Ciarli, T., Birchenhall, C. 2009. Consumer heterogeneity and the development of environmentally friendly technologies. Technological Forecasting and Social Change 76, 533–551.

Zeppini, P. Frenken, K., Izquierdo, L.R., 2013. Innovation diffusion in networks: the microeconomics of percolation, ECIS working paper series 13-02, Eindhoven.

Zeppini, P., and J.C.J.M. van den Bergh, 2011. Competing recombinant technologies for environmental innovation. Industry and Innovation 18(3), 317–334.

Model *Key reference*	**Section**	**Origin**	**Threshold**	**Micro-foundations**	**Heterogeneity**	**Key explanation**	**Transition**
Hyperselection *Bruckner et al. 1996*	2	Biology	Critical mass	None	No	Increasing returns	Fully
Increasing returns *Arthur 1989*	3	Economics	Critical mass	Utility maximization	No	Increasing returns	Fully
Informational cascades *Bikhchandani et al. 1992*	4	Economics	Critical mass	Utility maximization	Yes	Convergent expectations	Majority
Coordination game *Kandori et al. 1993*	5	Economics	Critical mass	Utility maximization	No	Increasing returns	Fully
Co-evolution *Kauffman-Johnson 1991*	6	Biology	Fitness value	Utility maximization	Yes	Complementarities	Fully
Percolation *Solomon et al. 2000*	7	Physics	Critical price	Utility maximization	Yes	Word-of-mouth	Majority
Social influence *Granovetter 1978*	8	Sociology	Critical mass	Imitation	Yes	Mimicking	Majority

Table 5. Overview and comparison of various modelling approaches to technological transitions

[i] A more subtle approach to technology competition is to have decisions made probabilistically, otherwise known as the Polya urn model (Arthur et al., 1987; Dosi et al., 1994). The basic model considers an urn which contains an equal (positive) number of black and white balls, with the probability of extracting any ball being the same. Whenever one extracts a ball of a particular colour (an adoption of a particular technology), this is put back in the urn together with a new ball of the same colour. This procedure introduces a positive feedback in the process, because the probability of extracting a particular colour increases the probability it will happen again.

[ii] Van den Bergh (2008) developed a related model of recombinant innovation reasoning from a single actor that needs to decide whether to invest in a single technology to maximize scale economies or two spread investments across to technologies to maximize the chance of creating a third superior technology through recombination.

[iii] Another way for players to evaluate their strategies is to look at risk dominance (Harsanyi and Selten, 1988). Without any clue about the other player's action, a player places a probability of 50 percent on both technologies. This gives an expected payoff from adopting the new technology of ½(2) + ½(-2) = 0, while the expected payoff from adopting the old technology equals ½(0) + ½(1) = 0.5, which exceeds the expected payoff from adopting the new technology. Following this evaluation, a player has no incentive to switch unilaterally from the old to the new technology.

[iv] Solomon et al. (2000) developed an interesting extension of the basic percolation model. They addressed the issues of product sequels common in industries like the movie industry and videogame industry. Rather than reasoning from price (with more consumers adopting products with lower prices), they reason from product quality (with more consumers adopting products with higher quality). A sequels follows from a successful product, that is, a product with a sufficiently high quality such that diffusion has been complete. After such a product success producers have to introduce a sequel, but with lower quality as to save on costs. Consumers, by contrast, will become more demanding in the future, since they look for novelty. The authors show that under certain conditions, the market automatically evolves to products and preferences close to the critical threshold (a case of self-organisation). This model thus explains why many cultural products are just below or above the critical threshold, and, thus, are almost equally likely to become hits as to become flops.

[v] The share of nodes with value 0, indicating impossible technologies, can also be introduced as a parameter to tune the difficulty of search. Note that the presence of sites with value 0 comes close to the idea of valleys of low fitness in NK fitness landscape models.