Modeling Technology Adoptions for Sustainable Development

under Increasing Returns, Uncertainty, and Heterogeneous Agents

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Abstract

This paper presents a stylized model of technology adoptions for sustainable development under the three potentially most important "stylized facts": increasing returns to adoption, uncertainty, and heterogeneous agents following diverse technology development and adoption strategies. The stylized model deals with three technologies and two heterogeneous agents: a risk-taking one and a risk-averse one. Interactions between the two agents include trade in resources and goods, and technological spillover (free riding and technology trade). With the two heterogeneous agents, we run optimizations to minimize their aggregated costs in order to find out what rational behaviors are under different assumptions if the two agents are somehow cooperative. By considering uncertain carbon taxes, the model also addresses environmental issues as potential driving forces for technology adoptions.

1. Introduction

It has been widely recognized that the development and diffusion of new technologies is the most important source of economic growth (e.g., Metcalfe, 1987; Freeman, 1994) and sustainable development (e.g., World Bank, 2000). But new technologies do not fall like "manna from heaven." They frequently need high investment in research and development (R&D) and the establishment of demonstration projects at an early stage of development. Moreover, as experience in new technologies accumulates, the cost of using them tends to decrease—so-called technological learning. Historical evidence of technological learning includes reduced investment in photovoltaic cells, gas turbines, and windmills as the cumulative installed capacities of these technologies increase (Nakicenovic and Rogner, 1996; Nakicenovic et al., 1998; Watanabe, 1995). As costs decrease, new technologies become more widely adopted, making technological learning a classic example of increasing returns (Arthur, 1989). Technological change or technological learning is highly uncertain, as evidenced by investment cost distributions for biomass, nuclear, and solar electricity generation in numerous engineering studies (e.g., IIASA–WEC, 1995). The importance of technological uncertainty has been recognized and explored since the earliest days of global environmental modeling (e.g., Nordhaus, 1973; Starr and Rudman, 1973).

To date, technological change has been treated in most traditional models as largely exogenous (i.e., technological change is a free good and can also be known with perfect foresight within a given scenario of technological "expectations"). Technological change is either reduced to an aggregate exogenous trend parameter (the "residual" of the growth accounts) or introduced in the form of numerous (exogenous) assumptions on the costs and performance of future technologies. Common to both modeling traditions is that the only endogenous mechanism of technological change is that of progressive resource depletion and the resultant cost increases, which also explains the inevitable outcome of additional (e.g., environmental) constraints having to be placed on the model: rising costs due to the forced adoption of more costly capital vintages that remain unaffected by endogenous policy variables in the model. Such constraints, which are at odds with historical experience (Barnett and Morse, 1967), trigger both substitutions of factor inputs and the penetration of otherwise uneconomical technologies. These are either represented generically as aggregates in form of so-called backstops (Nordhaus, 1973) or through detailed assumptions on numerous technologies individually.

Traditional, deterministic, social planner models have been criticized (e.g., Grübler and Messner, 1998) for being overly naive and "optimistic" regarding the feasibility of meeting constraints, as agent heterogeneity and uncertainty will make the availability and adoption of new technologies much slower and more discontinuous than is suggested by traditional policy models. However, traditional models can also be technologically too "pessimistic," as they miss out not only on important spillover effects but also on adaptive, innovative behavior that arises precisely because of agent heterogeneity and interaction.

There have been increasing concerns in recent years about modeling endogenous uncertain technological change (e.g., Nordhaus, 2002), with Grübler and Gritsvskyi's (1998; 2002) work being a typical example. Grübler and Gritsvskyi (1998) introduced a model of endogenous technological change through uncertain returns on learning with a deliberately simplified 3-technology system, and they applied the model to study a multi-region and multi-actor energy system by considering more technological details (Grübler and Gritsvskyi, 2002). The purpose of this paper is to explore the result if an assumption in the original model -- perfect markets both in terms of spillovers for technological learning and trade -- is relaxed. As such the paper constitutes a first step to subsequent model extension where the risk attitudes of agents and eventually their behavior changes evolutionary as the implications of spillover[1] and trade restrictions become apparent. To make this as transparent as possible this paper uses the simple 3-technology version of the model (Grübler and Gritsvskyi, 1998) and extends it by considering explicit agent heterogeneity. Following the tradition of agent-based modeling (Ma and Nakamori, 2005), which studies macro-level complexities from the interactions at the micro level -- combined here with the field of optimization modeling under uncertainty—agent heterogeneity is represented by the different risk attitudes and weights of each. The interaction between agents is represented via trade in resources and goods as well as

[1] Grübler and Gritsvskyi (2002) introduced technological spillover among different (but similar or what they called "family") technologies, e.g., different types of gas turbines, while this paper includes technological spillover effect between a pioneer agent and a follower agent.

through technological spillover. Using two heterogeneous agents, we run an optimization to minimize their aggregated costs in order to discover the rational behaviors for technology adoptions under different assumptions if the two agents are somehow cooperative. The global optimal solutions of the two-agent model are of Pareto optimality in the sense that neither could be made better off without the other being made worse-off.

As technological change has the potential to impact human society, some social issues can act as drivers of, or brakes on, technological change. This paper addresses environmental issues as possible drivers of technological change, with uncertain carbon taxes being introduced in the model.

The resultant mathematical problems are non-convex stochastic optimization problems. To solve the optimization problems, Matlab's Optimization Toolbox (version 3.0), which applies a sequential quadratic programming (SQP) method, was used. In this method, the function solves a quadratic programming (QP) subproblem at each iteration. An estimate of the Hessian of the Lagrangian is updated at each iteration using the BFGS formula. A line search is performed using a merit function. More details of the method can be found in the user's guide to Mathworks (2004). Global optimality of solutions was checked by using different starting points.

The model presented here is not intended by any means to be a "realistic" model in the sense of showing technological or sectoral detail. Rather, the model is mainly intended to be used for exploratory modeling purposes and as a heuristic research device to examine in depth the impacts of alternative model formulations on the dynamics of endogenous technology transition.

The rest of this paper is organized as follows. Section 2 introduces Grübler and Gritsvskyi's (1998) model of endogenous technological change through uncertain returns on R&D investment with one decision agent and provides an analysis of simulation results. Section 3 extends the model by considering two heterogeneous agents and analyzes various simulation results with trade and technological spillover between the two agents. Section 4 plots and analyzes emission paths that result from different technological change processes. Section 5 concludes.

2. A Stylized Model of Endogenous Technological Change with One Decision Agent

Grübler and Gritsvskyi's (1998) model

Grübler and Gritsevskyi's (1998) model of endogenous technological change through uncertain returns on learning is deliberately highly stylized. The model supposes one primary resource (e.g., coal), the extraction costs of which increase over time as a function of resource depletion. The economic system demands one homogeneous good (e.g., electricity) and the exogenous demand increases over time. There are three kinds of technologies, namely, "existing," "incremental," and "revolutionary" that can be used to produce the good. The "existing" and "incremental" technologies need primary resources to be consumed for the good to be produced, while the "revolutionary" technology needs hardly any resource input.

- The "existing" technology is assumed to be entirely mature, its investment cost and efficiency do not change over time, and the emissions caused by using it are a little high. An example is coal power plants.
- The "incremental" technology has a slight efficiency advantage. With a higher initial investment cost than that of the "existing" technology (a factor of 2 higher), it has potential for technological learning (we assume a mean learning rate of 10%), and its emissions are lower than those of the "existing" technology. An example is gas turbines.
- The "revolutionary" technology's initial investment cost is much higher than that of the "incremental" technology (and by a factor of 40 higher than the "existing" technology), but its learning potential is also higher (we assume a mean rate of 30%). It has little in the way of emissions. An example is photovoltaic cells.

Technological learning is uncertain. An uncertain learning rate is represented by an uncertainty range around the mean value adopted, based on a lognormal distribution that is in accordance with empirical data (see Messner and Strubegger, 1991). The uncertainty was introduced into the model as an additional cost in the objective function. The stochastic model responds to a frequent criticism of traditional optimization models: the inappropriate assumption of a decision-making agent that operates under perfect foresight.

As a result of the endogenization of uncertainty, decision making in the model no longer operates under perfect foresight.

Environmental issues are addressed as possible drivers of technological change. The existence, timing, and extent of possible future environmental constraints (e.g., in the form of carbon taxes) are highly uncertain.

With the homogeneous good, three different technologies, and the uncertain carbon tax, optimization is run to minimize the total discounted cost of the economic system; thus the results denote optimized paths of technology development and diffusion.

The mathematical expressions of the model follow. The demand is exogenous and increases over time as shown in Equation (1).

$$D^t = 100(1+\alpha)^t, \quad (1)$$

where t is time period (year), D^t denotes the demand in t, and α is the annual increasing rate of demand.

Let x_i^t $(i=1,2,3)$ denote the annual production of technology i at time t, and let η_i denote the efficiency of technology i; then the annual extraction R^t is the sum of resources consumed by each technology, as shown in Equation (2)

$$R^t = \sum_{i=1}^{3} \frac{1}{\eta_i} x_i^t \quad \left(\eta_{\mathrm{i}} \le 1\right)^2. \quad (2)$$

Thus the cumulative extraction by time t is:

$$\overline{R}^t = \sum_{j=1}^{t} R^j \ . \quad (3)$$

The extraction cost of the resource increases over time as a linear function of resource depletion, as shown in Equation (4):

$$c_E^t = c_E^0 + k_E \overline{R}^t, \quad (4)$$

[2] Usually, the efficiency of a technology should be no greater than 1. But in some special cases, the efficiency of a technology could be viewed as greater than 1, for example, when viewing heating a room as a service (or goods), the efficiency of electric heat pump could be thought to has a efficiency greater than one.

where c_E^t denotes the extraction cost per resource unit at time t, c_E^0 is the initial extraction cost, $\overline{R}^t$ is the total extraction by decision time t, and k_E is a constant coefficient.

Let y_i^t $(i = 1,2,3)$ denote the annual new installation of technology i at time t; then the total installed capacity of technology i at time t, denoted by C_i^t $(i = 1,2,3)$ can be calculated according to Equation (5).

$$C_i^t = \sum_{j=t-\tau_i}^{t} y_i^j, \tag{5}$$

where τ_i denotes the plant life of technology i.

The cumulative installed capacity $\overline{C}_i^t$ of technology i by time t is calculated as:

$$\overline{C}_i^t = \sum_{j=-\infty}^{t} C_i^j = \sum_{j=1}^{t} C_i^j + \overline{C}_i^0. \tag{6}$$

where $\overline{C}_i^0$ denotes initial cumulative installed capacity of technology i, which means the cumulative experience on technology i before $t = 1$.

Technology learning is based on experience that is quantified by the cumulative installed capacity; thus future investment cost is a function of cumulative installed capacity, as shown in Equation (7)

$$c_{Fi}^{\ t} = c_{Fi}^{\ 0} \times (\overline{C}_i^t)^{-b_i}, \tag{7}$$

where $1 - 2^{-b_i}$ is technology i's learning rate which means the percentage reduction in future investment cost for every doubling of cumulative capacity, and 2^{-b_i} is called progress ratio which denotes the speed of learning, and c_{Fi}^0 is the initial cost of technology *i*.

The following intertemporal optimization will be used to minimize the total cost.

$$\begin{aligned} \text{Min} \quad & \sum_{i=1}^{3}\sum_{t=1}^{T}(\frac{1}{1+\delta})^t c_{Fi}^{\ t} y_i^t + \sum_{t=1}^{T}(\frac{1}{1+\delta})^t c_E^t R^t + \sum_{i=1}^{3}\sum_{t=1}^{T}(\frac{1}{1+\delta})^t c_{OMi} x_i^t + \\ & \rho\left\{\mathrm{E}\left\{\sum_{t=1}^{T}\max\left\{0,\sum_{i=2}^{3}\left\{[c_{Fi}^{\ t}(\psi)-c_{Fi}^{\ t}]y_i^t\right\}\right\}\right\}\right\}+ \\ & p^{tax}\left\{p^{t_0}\left\{\sum_{t=t_0}^{T}\sum_{i=1}^{3}c_C\frac{\lambda_i}{\eta_i}x_i^t+\rho\left\{\mathrm{E}\left\{\sum_{t=t_0}^{T}\max\left\{0,\sum_{i=1}^{3}\left\{[c_C(\omega)-c_C]\frac{\lambda_i}{\eta_i}x_i^t\right\}\right\}\right\}\right\}\right\}\right\} \end{aligned} \tag{8}$$

subject to

$$\begin{cases} D^t \le \sum_{i=1}^{3} x_i^t \quad (t=1,\cdots T) & (9) \\ x_i^t \le C_i^t \quad (t=1,\cdots T) \quad (i=1,\cdots 3) & (10) \\ x_i^t \ge 0 \quad (t=1,\cdots T) \quad (i=1,\cdots 3) & (11) \\ y_i^t \ge 0 \quad (t=1,\cdots T) \quad (i=1,\cdots 3) & (12) \end{cases}$$

where:

T denotes the scale of the problem;

δ denotes the discount rate;

c_{OMi} denotes the operating and maintenance (O+M) cost of technology i ;

ρ denotes the decision maker's risk attitude (a small ρ denotes a risk-taking attitude, and a big ρ denotes a risk-averse attitude);

$c_{Fi}^{\ t}(\psi)$ is a random variable with ψ denoting an element from a probability space that is characterized by a lognormal distribution, and $c_{Fi}^{\ t}$ is the mean of the distribution;

E denotes expectation;

p^{tax} is the probability that the tax will ever be established;

p^{t_0} is the probability that, if established, the tax will be introduced before time t_0;

c_C is the mean of uncertain carbon tax value;

λ_i denotes the carbon emissions caused by producing and consuming every unit of the good by technology i;

and $c_C(\omega)$ is a random variable, with ω denoting an element from a probability space that is characterized by a Weibull distribution.

Table 1. Initial values of parameters

Parameters related to the three technologies			
	Existing Tech.	Incremental Tech.	Revolutionary Tech.
Initial investment cost (US$/kW)	$c_{F1}^{0} = 1000$	$c_{F2}^{0} = 2000$	$c_{F3}^{0} = 40000$
Efficiency	$\eta_1 = 30\%$	$\eta_2 = 40\%$	$\eta_3 = 90\%$
Plant life (year)	$\tau_1 = 30$	$\tau_2 = 30$	$\tau_3 = 30$
Initial total installed capacity (kW)	$C_1^0 = 100$	$C_2^0 = 0$	$C_3^0 = 0$
Initial cumulative installed capacity (kW)	$\bar{C}_1^0 = 1000$	$\bar{C}_2^0 = 1$	$\bar{C}_3^0 = 1$
O+M cost (US$/kW)	$c_{OM1} = 30$	$c_{OM2} = 50$	$c_{OM3} = 50$
Carbon emission coefficient	$\lambda_1 = 0.8$	$\lambda_2 = 0.8$	$\lambda_3 = 0.1$
Mean learning rate[3]	$b_1 = 0$ $(1-2^{-b_1} = 0)$	$b_2 = 0.1520$ $(1-2^{-b_2} = 10\%)$	$b_3 = 0.5146$ $(1-2^{-b_3} = 30\%)$
Other parameters			
Probability of carbon tax[4]	$p^{tax} = 0.33$	Mean carbon tax[5] (US$/t)	$c_c = 75$
Increasing rate of annual demand		$\alpha = 2.6\%$	
Initial extraction cost (US$/kW)	$c_E^0 = 200$	Extraction cost coefficient	$K_E^0 = 0.01$
Scale of the problem		$T = 100$, decision interval is 10 years	
Discount rate		$\delta = 5\%$	
Risk factor		$\rho = 1$	

The objective function is made up of three parts. The first part (/the first line) of Equation (8) is the cost with deterministic (or mean) learning rates; the second part (/the

[3] The lognormal PDF (probability distribution function) is $y = f(x \mid \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-(\ln x - \mu)^2}{2\sigma^2}}$. For the learning rate of the "incremental" technology, we set $\mu = \ln 0.1$ and $\sigma^2 = 0.1$; and for the learning rate of the "revolutionary" technology, we set $\mu = \ln 0.3$ and $\sigma^2 = 0.1$.

[4] The establishment of the tax is uncertain with a given occurrence probability of 0.33. The introduction time (in case the tax is established) is also unknown with an expected cumulative distribution function that goes from 0 in the first decision time to 99% in the final decision time.

[5] The mathematic formulation of the Weibull distribution $y = f(x|a,b) = ba^{-b}x^{b-1}e^{-\left(\frac{x}{a}\right)^b}$ $(x \geq 0)$, where a is called the scale parameter and b is called the shape parameter. For the uncertain carbon tax, we set $a = 75$ and $b = 1$.

second line) is the expected cost resulting from overestimating learning rates; and the third part (/the third line) is the expected cost of carbon tax. The constraint function Equation (9) denotes that the total annual production of all three technologies must satisfy given demand; the constraint function Equation (10) denotes that annual production for each technology does not exceed its total installed capacity; the constraint functions Equation (11) and Equation (12) denote that decision variables cannot be negative.

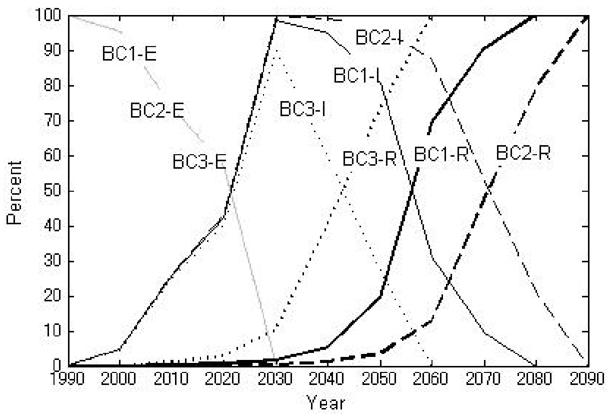
The scale of the problem is assumed to be 100 years (e.g., from 1990 to 2090) with 10-year decision intervals. The model is solved for a sufficiently large sample N, where the size of N has been determined through successive experiments. Several successive model runs with the same sample size N are compared. If no major changes in the solution structure and the objective function can be observed, then N is considered sufficient large (for more detail, see Messner et al., 1996).

Table 1 summarizes the initial values of all the parameters that will be used in simulations introduced in the next subsection. We will introduce simulations with those initial parameter values and sensitivity analysis.

2.2 Simulations and Sensitivity Analysis

To show how uncertainty in learning and the uncertain carbon tax affect technological change processes, we carried out simulations in three stages. In the first stage, simulations were carried out with deterministic learning and without considering the carbon tax; that is, the second and third part of the objective function (/the second and the third line) of Equation (8) did not appear. In the second stage, uncertainty in learning was considered, but not carbon tax; that is, the third part (/the third line) of Equation (8) did not appear. In the third stage, both uncertainty in learning and the uncertain carbon tax were considered. In Table 1, we assume a basic case with those initial values at each stage. The three basic cases for the three stages are called BC1, BC2, and BC3, respectively. Figure 1 shows the results of the three basic case simulations, from which we can see that the uncertainty in the learning rate is a factor that will postpone R&D investment in the “revolutionary” technology, while the uncertain carbon tax will encourage earlier investment in the “revolutionary” technology.

Through sensitivity analysis on parameters in the model, it is found that the factors that can contribute to early R&D investment in an advanced technology and its wide application include: high learning rate of the new advanced technology, lower initial investment cost of the advanced technology, high resource extraction cost (or that the resource is becoming rare), low discount rate, low uncertainty in learning rate, low sensitivity to risk (or the decision agent is adventuring), high carbon tax, and high uncertainty in carbon tax.



R –Revolutionary, I – Incremental, E – Existing

Figure 1. Results of basic case simulations at three stages

3. Modeling with Two Heterogeneous Agents

The above model assumes one global social planner. In real world, it is most likely that there are more than one decision makers making decisions simultaneously. And those decision makers are heterogeneous and there are interactions among them. In general, this section tries to explore the impacts of relaxing the one global social planner to two decision makers, i.e., this section extends the above model by assuming there are two heterogeneous decision agents, agent 1 and agent 2, operating simultaneously for technology adoptions. For exploring the agents' different risk attitudes to uncertainty in technological learning, this section assume a deterministic carbon tax for the two agents—the carbon tax will be applied from 2060 with 50$/t for carbon emissions. Agents could be heterogonous in many senses, for example, they could face different resource depletion functions, they could have different initial status, and so on. It is beyond the capacity and not the main purpose of this paper to explore all kinds of heterogeneities. For simplicity and being comparable to the global social planner model, we assume the two agents are almost the same except they face different demand[6]. And since this paper addressed uncertain technological learning as an important factor for technology adoption, it makes sense to explore how agents' different attitudes to risk impact technology adoption, i.e., the heterogeneities of the agents considered here are the different attitudes to risk and weights of the agents. We use ρ_1 and ρ_2 to denote the risk factors for agent 1 and agent 2, respectively. We assume that agent 1 is a risk-taking one and $\rho_1 = 0.1$, and that agent 2 is a risk-averse one and $\rho_2 = 1$. With a smaller risk factor, agent 1 will be a pioneer in developing and adopting new technology, and agent 2 will be a follower. Agents' weights denote their sizes or their share in the total system. The weight for agent 1 is $w_1 \in (0,1)$, and the weight for agent 2 is $w_2 \in (0,1)$. The two weights satisfy the formulation: $w_1 + w_2 = 1$.

With two agents, it allows us to model the interactions between them. If a decision agent faces a small demand and a lot of resource, then it is not economical to invest a lot to develop the advanced technology, but it will be a different story if there is trade between it and other decision agents. Trade in goods and resource will change the demand and resource depletion functions agents face, thus it will influence technology adoption process. Another kind of interaction that has been identified by many literatures as an important factor for technological change is technological spillover. Historical observations have shown that it took shorter time for the diffusion of a new technology in a follower's market because of technological spillover from pioneers (see Nakicenovic and Grübler 1991). With the two-agent model, we will explore how technology adoption is influenced by trade in resources and goods and technological spillover.

Trade in resources and goods means that one agent can buy resources and goods from the other. In terms of minimizing the aggregated costs of the two agents, the model does not treat the price of resources and goods, but the cost of the trade. This cost can be viewed as cost for transportation, distribution, and any other additional cost caused by moving and using resources and goods from the other agent. The unit costs for the trade

[6] But their total demand is the same as that in the global social planner model.

of resources and goods are denoted as θ_1 and θ_2, respectively. The quantity of trade flow at each time step is treated as decision variables.

Technological spillover can be through various ways, such as scientific publications, moving of scientists and engineers, trade of product lines, trade of patents, and so on. In our model, various technological spillover ways are reduced to two formats: technological "free riding" and technology trade. Technological free riding means that one agent can benefit from the other's learning effect without cost, but most of time with some delay. There are no additional decision variables for free riding. Technology trade means that one agent can benefit from the other's experience (quantified by cumulative installed capacity) with some cost, with θ_3 denoting the unit cost of buying experience. Again, the model does not treat the price of technology, and the quantities of technology trade at each time step are decision variables.

The objective function of the optimization can be simply denoted as:

$$\begin{aligned} \min \quad & A^1 + A^2 \\ & + \sum_{t=1}^{T} \left[\left(\frac{1}{1+\delta}\right)^t \left(\theta_1 \left|r^t\right| + \theta_2 \left|g^t\right|\right) \right], \\ & + \sum_{t=1}^{T} \left[\left(\frac{1}{1+\delta}\right)^t \left(\theta_3 \left|s^t\right|\right) \right] \end{aligned} \tag{13}$$

where

A^1 and A^2 denotes the costs of agent 1 and agent 2, respectively, as introduced in Equation (8), but with a deterministic carbon tax;

T denotes the scale of the problem;

δ denotes the discount rate;

θ_1, θ_2, and θ_3 denote the unit costs of trade in resources, goods, and technology, respectively;

r^t, g^t, and s^t denotes the quantity of resources, goods, and technology being traded at time t, respectively.

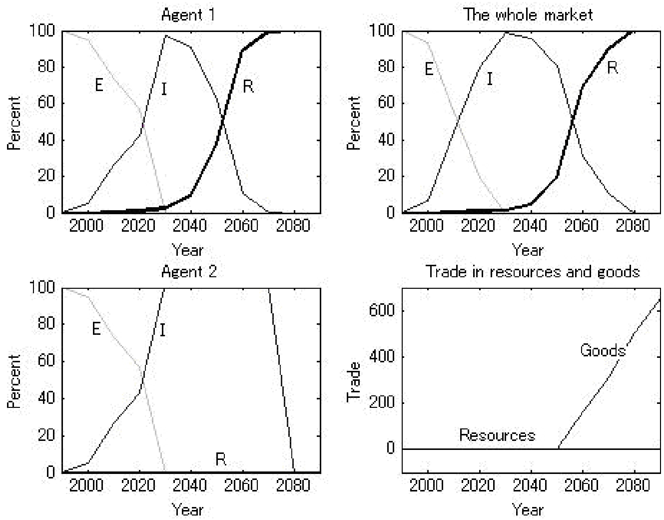
In Equation (13), the first part (/the first line) includes all the costs mentioned in Section 2, but with a deterministic carbon tax for both agent 1 and agent 2; the second part (/the second line) is the cost of trade in resources and goods; and the third part (/the third line) is the cost of technology trade. The two agents' weights do not appear in the objective function but in constraints related to demand. Suppose D^t is the demand in the whole market at time step *t*, then the demand of agent 1 at time step *t* is $D_1^t = w_1 D^t$, and the demand of agent 2 at time step *t* is $D_2^t = w_2 D^t = (1-w_1)D^t$. The r^t, g^t ,and s^t can be negative, depending on the direction of the trade, and we assume that the flow from agent 1 to agent 2 is positive.

The model can be used to generate infinite future scenarios and stories with different combinations of those parameters. Moreover, with some specific initial values for parameters, the model can be used for certain practical analyses. For example, when we want to analyze the development of energy technology in China, we can roughly divide China into two parts: western part which is abundant in resource but laggard in economy, and eastern part which is advanced in economy and technology but lack of natural resources such as coal. There is resource and goods trade and also technological spillover between the two parts. By identifying initial values for the parameters, the model can generate results which can enhance decision makers' insight. The main purpose of this paper is to explore the behaviors of the model with the two agents.

3.1 Optimization without Technological Spillover

A simulation called BC4 was run with $w_1 = 0.5$, $w_2 = 0.5$, $\rho_1 = 0.1$, $\rho_2 = 1$, $\theta_1 = \theta_2 = 140$ and without a technological spillover effect. The result of BC4 is shown in Figure 2, from which we can see that agent 2 develops no "revolutionary" technology, and it imports goods from agent 1 as from 2050.

Simulations with different trade costs reveal that when the trade cost is small ($\theta_1 = \theta_2 < 80$), agent 2 develops neither the "incremental" nor the "revolutionary" technology. It exports its resources to agent 1 and imports its goods from agent 1. With increasing trade costs, there is also a general tendency for the trade to appear later and later and for the quantity of trade to become smaller and smaller, which means both agents operate more and more locally, which results in delay of the development of the "revolutionary" technology.



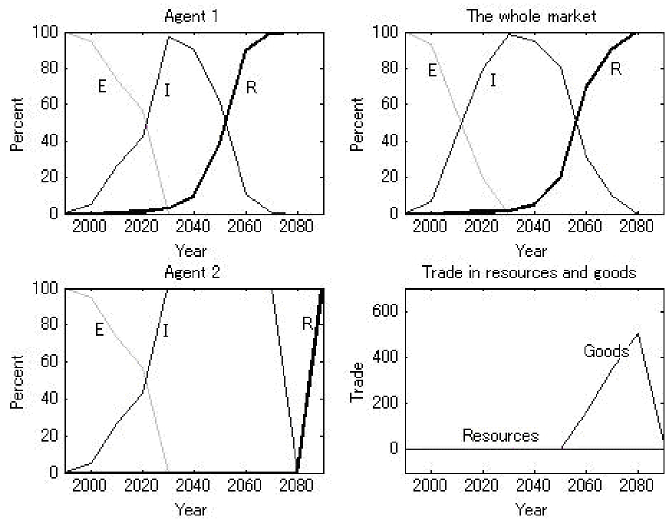
R – Revolutionary, I – Incremental, E – Existing

Figure 2. Simulation result of BC4

From the above simulations, we can learn that the interaction between agents really does influence the technological change process, both at the global and local level. The globalized market may act as a driving force for the development of advanced technologies, as the development of advanced technologies commonly requires huge investment, which is, in turn, likely to require a very large potential market for payback to occur on the investment.

3.2 Optimization with Technological Free Riding

In free-riding terms, although agent 2 may not have made R&D investment in the "revolutionary" technology, it can benefit from agent 1's learning effect. A simulation called BC5 (or BC + free riding) was run with the assumption that agent 2's future investment cost in the "revolutionary" technology relies on agent 1's cumulative installed capacity, but with a one-decade delay. Fig. 3 shows the simulation result of BC5, from which we can see that free riding made agent 2 develop the "revolutionary" technology from 2080 and that its diffusion time was very short. Agent 2 starts to import the goods from agent 1 from 2050, then after successful free riding from 2080, begins to produce the goods for itself and reduces the imports from agent 1. Other simulations based on BC5 revealed that the free riding did not show its effect at all with low trade costs (e.g., $\theta_1 = \theta_2 = 40$). This is because if trade costs are low, it is more economical for the whole system if agent 2 exports resources to agent 1 and imports goods from agent 1.



R – Revolutionary, I – Incremental, E – Existing

Figure 3. Result of BC4 + free riding (or BC5)

Based on BC5, many simulations were run by varying the two agents' weights to see how different weight influences agents' decision behaviors. Figure 4 shows the trade in goods in terms of the different size of the two agents, from which we can see that if agent 1's weight decreases (or agent 2's weight increases), agent 2 imports more goods from agent 1 during the period from 2040 to 2090. With a small w_1, agent 2 exports some goods to agent 1 during the period from 2020 to 2040 because during that period agent 1 is doing R&D on the "revolutionary" technology, while agent 2 builds a bigger capacity for the "incremental" technology. With a big w_1 (i.e., $w_1 > 0.5$), from 2080 to 2090, the imports from agent 1 to agent 2 decrease because agent 2's local market is small and its production can satisfy its own market after free riding.

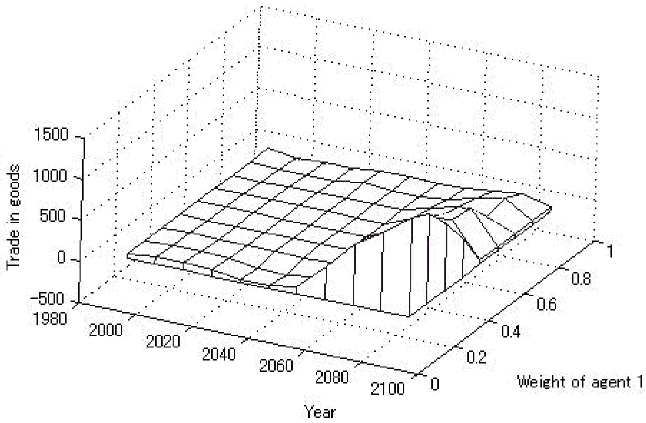
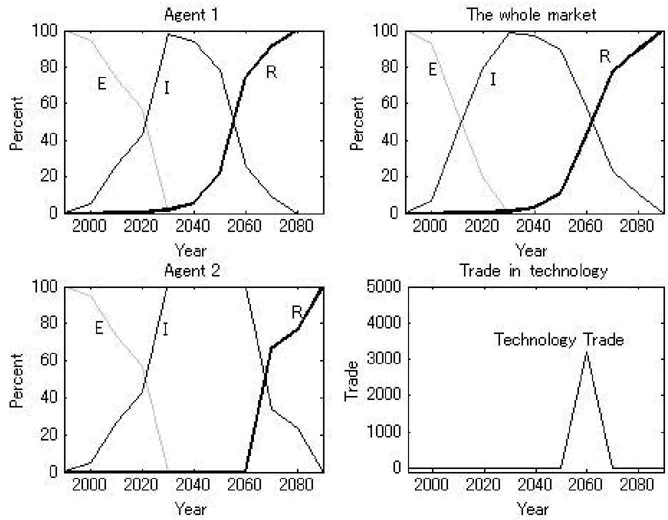


Figure 4. Trade in goods with different agent weights

3.3 Optimization with Technology Trade instead of Free Riding

In terms of technology trade, an agent is allowed to decide whether it needs to buy technology or, more precisely, experience in a new technology from the other and when to buy. Based on BC4, a simulation called BC6 (or BC4 + technology trade) was run assuming that agent 2 will buy the "revolutionary" technology from agent 1, with trade costs being $\theta_3 = 10$ for each unit experience (quantified by cumulative installed capacity). Figure 5 shows the result of BC6, from which we can see that agent 2 buys the "revolutionary" technology in 2060, and the diffusion of the "revolutionary" technology in agent 2 is of shorter duration than that in agent 1. Simulations with different technology trade costs show that with a small trade cost (e.g., $\theta_3 < 6$), the quantity of trade is higher but the trading time remains the same—in 2060—which makes the breakeven time of the "revolutionary" technology in agent 2 slightly earlier; and with a high technology trade cost (e.g., $\theta_3 > 12$), it becomes uneconomical for agent 2 to import technology from agent 1, and agent 2 keeps using the "incremental" technology without developing the "revolutionary" technology during the 100-year period.

With different attitudes to risk regarding the future cost of advanced technology and with a technological spillover effect between them, agent 1 and agent 2 act as pioneer and follower, respectively; and the diffusion time of the "revolutionary" technology is shorter for the follower than for the pioneer, which accords with the historical observation that the later developer of a new technology can obtain a shorter diffusion period (see Grübler et al., 1999). The global optimal solutions of the two-agent model are of Pareto optimality, in the sense that none of the two agents could be made better-off without the other being made worse-off.



R – Revolutionary, I – Incremental, E – Existing

Figure 5. Result of BC6

4. Carbon Emission Paths as Results of Different Technological Change Processes

There are two important factors contributing to emission paths: the demand (or consumption) and the technologies used to satisfy the demand. Figure 6 shows the different emission paths of different simulations. BC3 shows the strongest carbon abatement, while BC2 shows the weakest. The main discoveries related to carbon emission paths in our simulations follow.

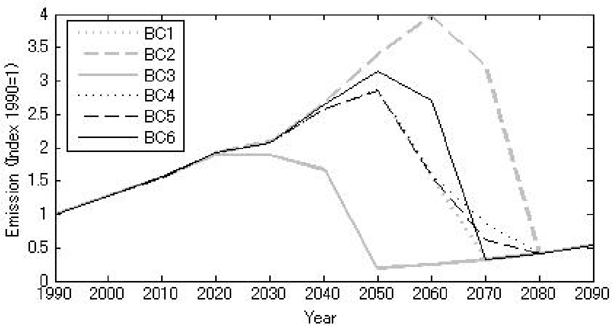


Figure 6. Different carbon emission paths

- The model demonstrates an endogenous learning mechanism for the advanced technology to replace the existing one. Even without carbon tax, the carbon emissions could be reduced by the wide application of advanced technology.
- The uncertainty in the learning rate will delay the development of the "revolutionary" technology and thus result in delayed and weaker carbon abatement.
- Carbon tax, especially the uncertainty in carbon tax, is a driving force for the earlier development of the "revolutionary" technology, which is why BC3 shows the strongest carbon abatement. BC4, BC5, and BC6 include a deterministic carbon tax, rather than an uncertain one, making the carbon abatement weaker than that in BC3.
- Although technological learning can lead to the reduction of carbon emissions, a carbon tax is still important in the following two senses:
    i. It can control the maximum annual emissions. As show in Figure 6, without carbon tax, the maximum annual emissions are relatively high in BC2, while in BC3, with the uncertain carbon tax, the maximum annual emissions are low.
    ii. It can bring forward the time of low emissions. In Figure 6, with the uncertain carbon tax in BC3, the carbon emissions start to decrease from 2030; while without carbon tax (i.e., in BC2) the carbon emissions start to decrease from 2060. In some special situations,

carbon tax will become extremely important. For example, the emission reduction caused only by technology improvement may, without carbon tax, come too late to maintain the ecosystems of some cities that have a high population density and a rapid increase in energy consumption demand.

- Some people believe that technological spillover should assist carbon abatement, but this is not always true. Sometimes, the anticipation of technological spillover can weaken carbon abatement in a given period. As shown in Figure 6, with technology trade, the carbon emissions in BC6 are higher than in BC4 during the period from 2040 to 2065. This is because, with the anticipation of the technological spillover effect, agent 2 imports fewer goods from agent 1 during that period, which has two consequences. The first consequence is that agent 1 develops the "revolutionary" technology slightly late as its market is smaller. The second is that the two agents, especially agent 2, consume more goods produced by the "incremental" technology rather than by the "revolutionary" one during that period, which results in weaker carbon abatement. We also learned from the simulations why technological spillover could weaken carbon abatement during a certain period, namely, that when the trade in goods is light because of high trade costs, agent 2 may rely more in the short or medium term—and in anticipation of technological spillover effort—on the "existing" technology and develop "incremental" technology less, waiting for the "revolutionary" technology to be developed by the pioneer agent.

5. Concluding Remarks

Based on earlier pioneering work done at IIASA, this paper presented a model of endogenous technological change with increasing returns, uncertainty, and heterogeneous agents. Although the model and simulations are highly stylized, they can provide a better idea as to how the three stylized facts impact technological change processes. Here I summarize what we can learn from the modeling and simulations:

- The model and simulations demonstrate an endogenous learning mechanism whereby the advanced technology will replace the existing one. The S-shape diffusion pattern of new technologies in our simulations accords with historical observations.
- Facing uncertainty in technological learning, decision makers would prefer late R&D on advanced technologies. Of course, decision makers' different attitudes to risk will play an important role in their decisions. A risk-taking decision maker would prefer earlier R&D on advanced technologies than a risk-averse decision maker.
- The globalized market may act as a driving force for the development of advanced technologies, which usually require a huge investment and a very large potential market to achieve payback.
- Anticipation of technological spillover could slow or delay the wide application of advanced technologies and thus weaken carbon abatement, mainly in a short or medium-term period.

In terms of minimizing their aggregated costs, the two heterogeneous agents are assumed to be cooperative. In the real world, some decision makers may not accept the optimization result because they wish to maximize their profit. For example, if a technology pioneer develops an advanced technology earlier than others, it could apply a very high pricing strategy for its products and technology; this would delay the wide adoption of the new technology longer than is suggested by Pareto optimization. Other factors preventing decision makers from following Pareto optimization include security issues. For example, in some situations, Pareto optimization suggests that an agent with a small local market should import goods such as gasoline from others instead of building its own capacities; however, as the agent believes that the goods are very important for it, it refuses to completely depend on imports as it does not wish its fate to be controlled by others.

Matlab Optimization Toolbox was used to solve the optimization problems, and the global optimality of solutions was checked by employing different starting points. In future work, global optimization software or solvers (e.g., BARON [see Sahinidis, 2000]) will be applied for global optimization. Moreover, the stability of Pareto optimal solutions should be explored when the model is used for real applications.

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