Importance of Technological Change and Spillovers in Long-Term Climate Policy

Shilpa Rao, Ilkka Keppo* and Keywan Riahi**

This paper examines the role of technological change and spillovers within the context of a climate policy in a long-term scenario of the global energy system. We use the energy-systems optimization model MESSAGE considering endogenous learning for various technologies, such that they experience cost reductions as a function of accumulated capacity installations. We find that the existence of technological learning while reducing overall energy system costs becomes particularly important in the context of a long-term climate policy. Diversity in technological portfolios is emphasized and results indicate deployment of a range of energy technologies in reducing emissions. An important finding is that technological learning by itself is not sufficient for climate stabilization and that climate policies are an absolute necessary complimentary element. Under a climate constraint, spillovers across technologies and regions due to learning results in increased upfront investments and hence lower costs of carbon free technologies, thus resulting in technology deployment and emissions reductions, especially in developing countries. We conclude that learning and spillover effects can lead to technologically advanced cost-effective global energy transition pathways. We suggest that coordinated climate stabilization policies can serve as important institutional mechanisms that facilitate the required technological investments, especially in developing countries and thus ensure long-term cost reductions.

1. INTRODUCTION

Technological change forms one of the cornerstones of any analysis involving long-term scenario development, particularly for climate change. It is an

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* International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361 Laxenburg, Austria. Corresponding author: rao@iiasa.ac.at.

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important factor in understanding the dynamics of the system and in formulating subsequent policy conclusions with respect to emission reduction strategies. The assessment of opportunities for new technologies in shaping future energy systems is a complex task involving the interaction of a number of technical, economic, environmental and social driving forces, but the understanding of such complex dynamics of technology is a central issue in policy decisions, concerning the definition of future sustainable trajectories for the energy systems (Kemp, 1997).

The rate of technological change in an economy and its energy system depends on the diffusion of innovations and the dynamics of their adoption (Nakicenovic, 1996). In this regard, capital turnover rates are one of the critical drivers of the process as by definition they embody technological change i.e., investments are required into physical plant and equipment capital. This link between technological change and investment (rates) is captured by the well known “experience” or “learning” curve that is well documented in manufacturing industries (Argote and Epple, 1990). R&D mechanisms are another important driver of technological change and can influence cost reductions and performance improvements particularly in the early stages of development of a technology (Barreto and Kypreos, 2004).

Incorporation of technological change (or learning) is central for understanding the potential interplay between continuous experiences in order to stimulate the development of new technologies. It thus helps to identify promising technologies and related investment needs to make environmentally more benign technologies competitive, essential information for policy makers and private investors alike. On the other hand, policy mechanisms themselves often have an important role to play in accelerating technological progress. In order to achieve the necessary cost improvements, technologies require policy measures to support their learning processes, i.e. to cover the “learning investments” and thus sustained efforts in research, development, demonstration and deployment activities are required (Riahi et al., 2004).

It is clear that complying with any long-term global climate policy will involve a large-scale transformation of the energy system. While there is debate on the exact costs and benefits of climate stabilization, the inclusion of technological learning can be expected to have a significant impact on such costs. In addition, technological and regional spillovers play a central role in systems with learning and can have significant impacts on broadening the range of technological options and their improvement rates. For instance, within the framework of a long-term climate policy, learning and spillover rates will be critical in determining availability and economics of low-emission technologies that will be affordable to developing countries to reduce greenhouse gas (GHG) emissions. Thus spillovers emphasize the potential benefits of international cooperation between industrialized and developing regions on research, development, demonstration and deployment of clean energy technologies (Barreto and Klaassen, 2004). This can serve as an incentive to cooperation of these countries in international climate negotiations and provide incentives to adopt technologies that could lead to climate-friendly and sustainable futures.

In this study, we mainly focus on the dynamics of 'learning by doing' in the energy system, treating the complex processes governing technological innovation and diffusion as a simplified 'black box' with a focus on the link between technological change and investments as well as the impact of learning and spillover effects on the adoption of technologies and the implications this in turn has for the costs and development of a climate policy. In the following sections we first examine the overall treatment of technological change in the energy systems models and then present our methodology and results using the MESSAGE model.

2. TECHNOLOGICAL CHANGE IN ENERGY SYSTEMS MODELS

As stated in Nakicenovic and Riahi (2001), technological change in energy scenarios is of two kinds, one in which technologies change incrementally over the time horizon (cost reductions, efficiency improvements, etc.) and the other is the more radical introduction of completely new technologies at some points in the future. Both kinds of change usually co-exist in energy systems as well as in energy models. However the models differ with respect to the type of representation of technological change.

There are basically three major ways in which technological change is treated in energy systems models:

1. The first is a so-called 'static' approach that treats the costs and technological parameters of a given technology (or technologies) as constant, i.e., it does not include any improvements in cost or performance. Such an approach is inflexible with regard to switching between technologies and is at odds with both historical and current experience in the energy sector.
2. The second is representing technological change 'exogenously' whereby costs decline and technical performance improvements in the analysis are exogenously predefined over time. This is the most common treatment of technical change in bottom-up energy systems models. The rates of improvement of the technology are usually determined depending on the basis of the scenario being analyzed and the state of the future world in such a scenario. The main critique of such an approach (see for example Grübler and Messner, 1998) in intertemporal optimization models is that it ignores the fact that early investments in expensive technologies are necessary in the first place in order to enable the system to adopt these technologies. Technology cost declines do not happen automatically but depend on the accumulated investments made in them in the previous time periods.
3. The third approach is the most sophisticated and involves explicit treatment of elements of 'endogenous' technological change models. For instance the link between technological change and investments is explored via a learning curve approach in which technological improvement rates are modeled as a function of accumulated experience. This is the commonly referred to 'learning by doing' approach. This method has successfully been applied and tested in many types

of models. In energy systems models, the cumulative capacity of a technology is usually taken as explanatory variable of experience and cost reductions (see for example Messner 1997). The inclusion of endogenous technological progress typically leads to earlier investments in energy technologies, a different mix of technologies and a lower level of overall discounted investments, as compared to the case of exogenous technological progress (Messner, 1997; van der Zwaan et al., 2002).

3. SCENARIO DEVELOPMENT

For our illustrative analysis, we choose the B2 scenario from the IPCC SRES family (IPCC, 2000). The B2 scenario is characterized by a world that places emphasis on community-based solutions and places a high priority on environmental issues at the regional level. Economic growth and population changes in this scenario are also relatively ‘middle of the road’ compared to the other SRES scenarios. World GDP increases with a long-term average growth rate of 2.2% to around US$235 trillion by 2100, while population increases over the course of the century to around 10.4 billion. The advances in energy technologies in the B2 scenario are ‘dynamics as usual’ i.e., long-term rates of technological change[1] do not deviate substantially from historical experience (Riahi and Roehrl 2000). Technological innovation and diffusion at the regional level in the future can be quite rapid even though they usually translate into more modest aggregate global rates.

We develop two variants of the B2 scenario:

a. B2-Fixed (B2-F): This scenario assumes that costs and technical parameters like efficiency stay constant for the energy system. It is hence a static scenario with no technological change.
b. B2-Learning (B2-L): The B2-L scenario maintains basically the same assumptions of the original B2 world but assumes ***endogenous*** technological learning for a range of technologies.

Since our goal here is to highlight the importance of technological change per se, we compare and contrast two such extreme scenarios and do not include here a comparison to the original SRES B2 scenario with exogenous learning rates. We further impose a long-term (2000-2100) CO_2 concentration constraint of 500 parts per million by volume (ppmv) on both the B2-F and B2-L scenarios and label these B2-F-500 and B2-L-500 respectively.

The learning rates as stated earlier are based on past experience and do not assume any further acceleration in the future. The learning rates for existing technologies are based on various studies that have examined historical learning for energy technologies (for example IEA, 2000; Nakicenovic et al., 1998; Rabitsch, 2001; McDonald and Schrattenholzer, 2002). For new technologies like carbon scrubbers, we use Riahi et al., (2004) to indicate possible rates of technological progress. We acknowledge that the choice of the learning rate can greatly influence

1. The original SRES B2 scenario included exogenous technological change

the performance of a technology. Overestimation of the learning rate represents a risk as investments in a given technology may turn out to be more costly than expected, affecting the competitiveness of the actors involved. Underestimation, on the other hand, will alter their profitability margins (Grübler and Gritsevskyi, 1997). For sensitivity analysis and cost assessment of alternative assumptions concerning technological change using MESSAGE see Roehrl and Riahi (2000).

In total, a range of 18 technologies are assumed to undergo learning, i.e., have the potential for cost reductions as a function of accumulated capacity. Table 1 presents the scenario's investment costs of fossil power generation technologies for the years 2000 and 2100. In the scenarios that consider endogenous learning, the costs of fossil power plants decrease in line with the deployment of the respective technology and the increase in cumulative installed capacity. The assumed learning portfolio is diverse and is not biased towards any one individual technology or particular groups of technologies. This is important to recall especially to avoid policy misinterpretation that may occur if any type of technology is assumed to learn while another set assumed to remain static. Also, we include learning for both existing high GHG emitting technologies like coal-fired power plants as well as cleaner renewable technologies.

Table 1. Learning Rates and Investments of Main Groups of Technologies

	Learning rate	Initial investment cost in 2000, $/kW	Investment cost in 2100, $/kW	
			B2-L	**B2-L-500**
Subcritical coal power plants	0%	1000-1300	1000-1300	1000-1300
Supercritical coal power plants	5%	1650	1650	1650
IGCC	10%	1400	332-366	414
Single cycle gas PPL	0%	710	710	710
NGCC	8%	730	411	411-453
Solar photovoltaics	15%	5100	540	540
Solar thermal PPL	7%	2900	1174-2900	1100-2900
Wind power	7%	1400	1400	1400
Conventional biomass PPL	4%	1600	1370	1370
Advanced biomass PPL	5%	1800	1033	985-1033
Renewable H2	10%	985-3200	985-3200	985-3200
Fossil H2	Ex.*	462-1206	320-850	320-850
Ethanol	10%	1580	534	534
Methanol	Ex*.	676-1328	480-1150	480-1150
Carbon capture and storage	13%	509-940	509-940	281-940

Exogenous learning rates assumed in the range of 3-5%, according to the B2 scenario

In our analysis, the learning rates are assumed to be constant throughout the century. It is of course debatable whether the rates of improvement assumed are sustainable in the long-term till the end of the century and it can well be expected that there will be some deviation from past or current trends. Hence the learning rates assumed here constitute yet another important scenario uncertainty which explains the interest to explore also model formulations in which learning rates are treated as uncertain (stochastic) variables (e.g., Gritsevskii and Nakicenovic, 2000). Schrattenholzer (1998) illustrates the variability of the progress ratio using the example of several energy technologies and finds that some technologies experience declining learning rates over time. The uncertainty inherent to the progress ratio highlights the need to provide, if possible, a stochastic treatment for this parameter.

We also use the idea of 'technology clusters' which has been applied in several modeling approaches (Seebregts et al., 2000; Riahi et al., 2005). Technology clusters are shaped when related technologies interact and enhance each other, contributing to their mutual development (Nakicenovic, 1997). Technological spillovers can occur within a cluster (for example: carbon capture technologies, centralized and decentralized solar PV) but not from outside the cluster (for example: improvements in the semi-conductor industry). Thus, in the language of our model, technologies within a cluster form a common 'technology' in terms of a common learning curve.

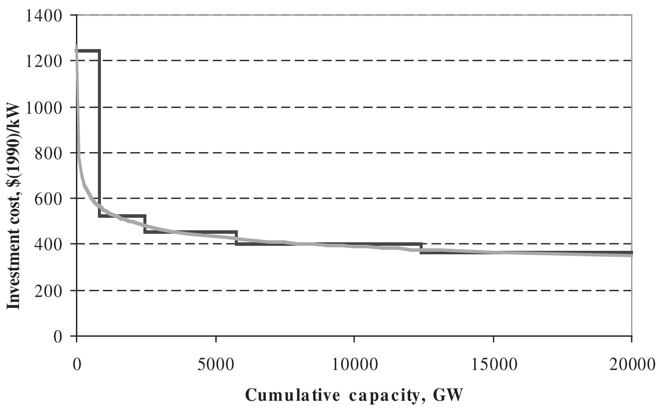
The learning process for technology improvements in our analysis is assumed to take place on a global scale. Although this might not necessarily be consistent with the existence of trade barriers, regional economic blocks or the importance of localized learning, we have retained this simplifying assumption here, mainly to reduce computational complexity.

4. METHODOLOGY

We use the MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) for our analysis. MESSAGE is a systems-engineering optimization model used for medium-to long-term energy system planning, energy policy analysis and scenario development (Messner and Strubegger, 1995). The model maps the entire energy system with all its interdependencies from resource extraction, imports and exports, conversion, transport and distribution to end-use services. The model's current version, MESSAGE IV, provides global and sub-regional information on the utilization of domestic resources, energy imports and exports and trade-related monetary flows, investment requirements, the types of production or conversion technologies selected (technology substitution), pollutant emissions, inter-fuel substitution processes, as well as temporal trajectories for primary, secondary, final, and useful energy. It is a long-term global model with a time horizon of a century (1990-2100).

Implementation of endogenous learning as learning rates in linear programming models leads to a non-linear and non-convex optimization problems, thus posing significant difficulties in implementation. Such problems possess several local optima and a global optimum solution is not guaranteed even with standard non-linear solvers. Following Messner (1997), a piece-wise linear approximation of the learning curve is implemented in the MESSAGE model as shown in Figure 1 and mixed integer programming (MIP) techniques are applied to obtain an optimum solution . For more details on the approach see also Riahi et al., (2004).

Figure 1. Example of Linear-Approximation of Learning Curve



For this study, we also use MACRO, a top-down macroeconomic equilibrium model (Manne and Richels, 1992). The capital stock, available labor, and energy inputs determine the total output of an economy according to a nested constant elasticity of substitution (CES) production function. MESSAGE and MACRO are linked iteratively to include the impact of policies on energy costs, GDP and on energy demand. The linking of a bottom-up technology-rich model and a top-down macroeconomic model results in a fully consistent evolution of energy demand quantities, prices, and macroeconomic indicators (such as GDP, investments and savings). MACRO's outputs include internally consistent projections of world and regional realized GDP (i.e., taking into account the feedback that changing energy and other costs have on economic growth) including the disaggregation of total production into macroeconomic investment, overall consumption, and energy costs. A detailed description of the link between the two models can be found in Messner and Schrattenholzer (2000).[2]

2. By linking bottom-up and top-down models, our approach permits to give a detailed account of imputed systems engineering costs as well as macroeconomic welfare losses (including producer and consumer surplus). Our macroeconomic model though adopts a coarse view of the economy outside the energy system. I.e., heterogeneous categories outside the energy sector (e.g., agricultural goods, medical services, IT, etc.) are all aggregated into a single representative category. Clearly, this would be inappropriate if we were dealing with short-term balance-of-payments issues for individual countries. Our approach is also less adept to account for costs due to market inefficiencies and shares with the vast majority of the integrated assessment models a more generic representation of other intangible costs due to e.g., institutional barriers, inefficient legal frameworks, transaction costs, or potential free-rider behavior of geopolitical agents.

We further use the MAGICC climate model version 4.0 (Wigley et al., 2000). A MESSAGE-MAGICC iterative linkage is established whereby the GHG emissions and initial concentrations (to achieve stabilization) from MESSAGE are fed to MAGICC. The new concentrations from MAGICC are now iterated back to MESSAGE and the process repeated until the concentration target is achieved.

5. RESULTS

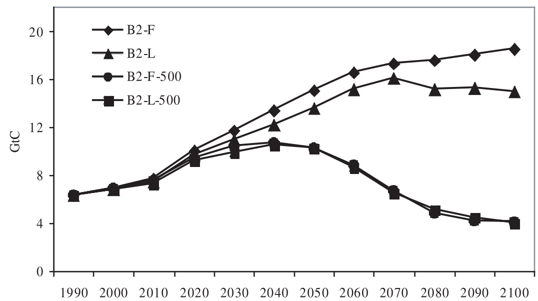
Assumptions on technological change lead to differences in baseline emissions. As Figure 2 shows, the B2-L scenario with endogenous learning leads to a somewhat lower carbon future as compared to the static costs B2-F case. However, the carbon reductions achieved due to technological learning are seen to be insufficient to achieve climate stabilization. This highlights the important finding that while endogenous technological change is an important part of analyzing carbon mitigation options, it has to be coupled with a stringent environmental constraint to achieve the necessary long-term climate goals.

This conclusion can be considered robust in all cases without asymmetrical technological change. As there is little theoretical or empirical reason to assume[3] for instance that biomass-gas fired gas turbines are subject to technological learning, whereas fossil fuel based gas turbines are not, we consider the present illustrative scenario as, if not more, plausible than alternative scenarios assuming ex ante asymmetrical technological learning rates among different (clusters of) technologies. Note however, that this conclusion only holds in cases assuming comparatively modest learning rates (as done in the simulations reported here). Earlier studies using the MESSAGE model (Roehrl and Riahi, 2000; Nakicenovic and Riahi, 2001) have investigated the sensitivit y of scenario results to alternative assumptions for technological change. Their analysis has shown that alternative parameterizations of technological change have significant implications for the technology portfolio as well as associated costs. The difference in the results is seen to be more pronounced for baselines as compared to climate stabilization scenarios. For example, Roehrl and Riahi (2000) note an increase in emissions intensity of the baseline by a factor of two in case of asymmetric technological change and less favorable assumptions for learning of renewable technologies. By the same token, more optimistic assumptions for the learning rates of renewable technologies are seen to lead to considerable reductions in emissions in the long term even in absence of climate policies. The corresponding uncertainty range (assuming everything else being equal) would translate into 7 to 30 GtC of CO_2 emissions by 2100, compared to about 15 GtC in the baseline scenario with balanced learning rates analyzed here. The difference in parameterization of technological change is also seen to have significant implications for the long-term energy systems costs. Most interestingly, emissions intensive baselines are seen

3. Evidently this statement only holds in the absence of a convincing theory that can explain the wide variations in extent and rates of learning phenomena observed in the empirical literature.

to be more costly due to the 'lock-in' in mature energy infrastructures and lack of increasing returns to scale of advanced technologies. Adopting the results from Roehrl and Riahi (2000) for our analysis suggests that the variation of learning assumptions would lead to a range of energy expenditures over the course of the century of about 35.9 to 41.3 trillion US$.[4 5] This compares to 39.7 trillion US$ for the central case with endogenous learning presented here.[6] It is, thus, important to keep in mind that our scenario results presented here are mainly representative for intermediate or 'middle of the road' learning assumptions.

Figure 2. CO_2 Emissions in B2-F and B2-L Scenarios



We now examine the contribution of main mitigation measures for achieving the stabilization of CO_2 under both dynamic and static technology assumptions. While the total carbon emissions profiles of the 500-ppmv stabilization cases did not deviate significantly in the learning and static cases, the profile of technologies used for carbon mitigation is very different in these two scenarios as seen in Figure 3. The B2-F-500 mitigation profile exhibits a dominant share of deployment of carbon capture and sequestration technologies. This is caused by the relative inflexibility in a static system where moving to low carbon alternatives is not cost effective due to the relatively high investment costs of such technologies. This leads to a further 'lock-in' to fossil fuel technologies and the system is meets the climate constraint by mainly scrubbing carbon from fossil fuels. In contrast, the B2-L-500 is a more balanced mix of mitigation technologies. The energy system with a balanced learning technology portfolio

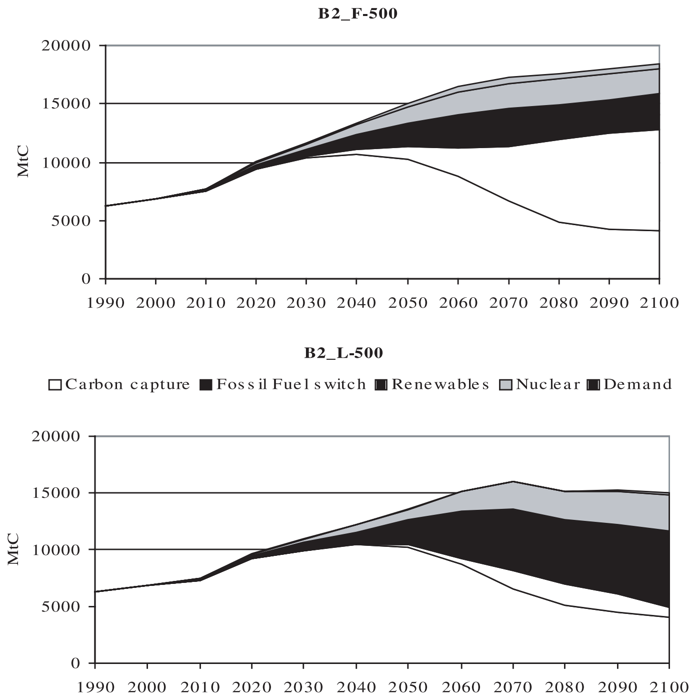
4. Note that in order to enhance comparability between the scenarios, results from Roehrl and Riahi (2000) were normalized using the same energy demand assumptions as for the scenarios presented in this paper.

5. A discount rate of 5 percent was used to calculate the net present value of energy expenditures.

6. Similarly, alternative parameterizations of learning have also implications for the costs of mitigation. Roehrl and Riahi (2000) report an uncertainty range for the net present value of mitigation – measured as the increase in energy expenditures over the course of the century compared to the baseline – between 0.01 and 4.9 percent. This compares to 0.2 and 1 percent for our stabilization scenarios with and without endogenous learning.

adopts a diverse mix of technological options to achieve the same climate constraint. Also important to consider is that price-induced demand changes due to the MESSAGE-MACRO iteration have a role in mitigation, especially in the B2-F_500.

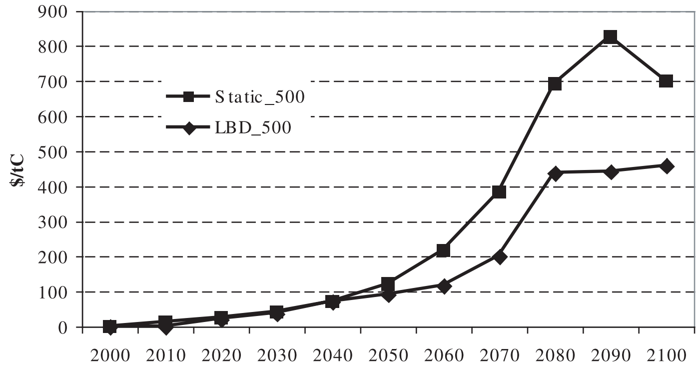
Figure 3. Sources of CO_2 Mitigation in B2-F-500 and B2-L-500 Scenarios



The shadow prices in the static B2-F_500 and the learning B2-L_500 scenarios are shown in Figure 4. As seen, incorporation of learning leads to significantly cheaper mitigation profiles as compared to the static case in the long run. This again illustrates the result that the static costs scenario has to invest heavily into expensive technologies in order to achieve climate stabilization. In contrast, the learning case benefits from the fact that many low-carbon technologies have already experienced significant learning in the baseline and hence the options for mitigation in the constrained case are not as expensive.

As mentioned earlier, an iterative approach was used between the MESSAGE and MACRO models to calculate the price-induced reductions in GDP and energy that result from the imposition of a climate constraint on the system. MACRO balances changes in prices with resulting changes in energy demand as well as the impacts of rising energy and carbon prices on GDP. The macroeconomic implications (costs) of climate stabilization include the costs

Figure 4. Shadow Prices ($/tC) in B2-F_500 and B2-L_500 Scenarios



of carbon emission reduction in a direct, narrow sense (e.g., through carbon sequestration and disposal), the costs of switching to more expensive alternative energy sources, the costs of energy conservation, as well as the macroeconomic costs (or benefits) of the resource transfers that go along with emission trading[7] (Nakicenovic and Riahi 2003). Thus, the coupling of a technology-rich engineering model with a macroeconomic model results in a more balanced view of the macroeconomic costs of climate stabilization at challenging low levels. Table 2 shows the percentage GDP and demand reductions that result in the B2-L_500 and B2_F_500 as compared to the B2-L and B2-F baselines respectively. GDP losses and demand reductions are substantially higher in the static technology case.

Table 2. Percentage Reductions in GDP and Energy Demand

	B2-F-500		B2-L-500	
	% GDP loss	% demand reduction	% GDP loss	% demand reduction
2000	0.0	0.0	0.0	0.0
2050	0.8	1.7	0.01	0.1
2100	1.5	9.5	0.1	0.7

An important aspect of the learning process is the investment patterns. Figure 5a shows that in the cumulative long run investments in the different scenarios. The B2-L scenario displays a reduction in long-term costs due to cost-effective low-carbon technologies becoming available.[8] The existence of technological learning while reducing overall costs becomes particularly important under the existence of environmental constraints. The B2-F-500 is the most expensive case due to inflexibility in the system and the high cost of

7. We do not consider emission trading costs here

8. Demand changes due to such reduced costs are accounted for by the MACRO iterations.

mitigation. In contrast, the B2-L-500 is cheaper due to learning of mitigation technologies and corresponding reductions in costs. Technological change can thus significantly soften the economic burdens of meeting environmental targets. This is particularly important because given the substantial uncertainties on the stringency of ultimate climate constraints, investments into low carbon intensive technologies due to technological learning, can constitute an important risk minimizing element in climate mitigation policies.

Figure 5a. Cumulative Investments in the Different Scenarios (2000-2100)

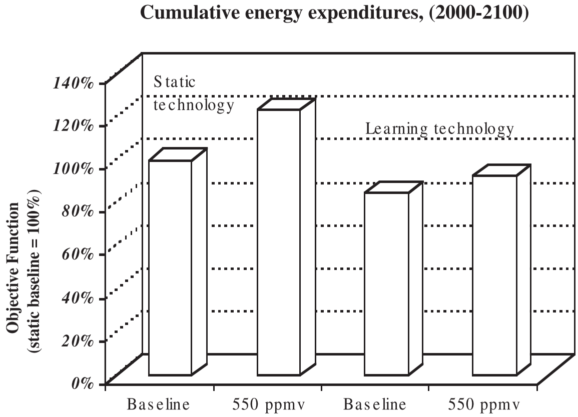


Figure 5b. Cumulative Investments in the Different Scenarios (2000-2030)

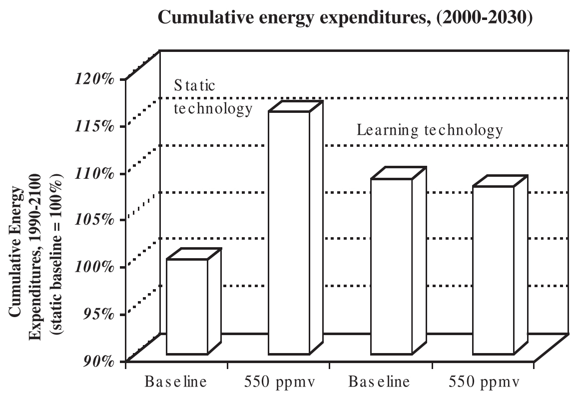


Figure 5b illustrates the changes in investment patterns in the learning cases compared to the static one. Both the B2-L and B2-L_500 indicate higher short term investments compared to the B2-F case. In the longer term, this trend is reversed with lower investments in both learning cases, a typical picture portrayed by all scenarios exploring technological learning phenomena. The exact nature of this 'investment shift' is a function of both the learning rates assumed in the model simulations (see Table 1) as well as of the discount rate assumed in the model calculations (5% in our case). This highlights the fact that, from a long-term perspective, it could be sensible to invest today on the 'buy-down' process of promising technologies that could become competitive in the long run (Riahi et al., 2004). This emphasizes the need for early R&D efforts and creation of niche markets for advanced (carbon free) technologies in order to bring down their costs in the long-run. We further observe that the presence of a clearly defined and structured climate policy serves as a significant incentive for inducing innovation and diffusion of such technologies.

The illustrative model simulations reported here assume perfect temporal and spatial flexibility typical for social planner models with perfect foresight. It is therefore important to discuss the implications of 'who learns when' in scenarios in which technology dynamics result from perfect regional spillovers[9] in the cost lowering investment effects of technological learning. Figures 6a and 6b present cumulative regional investments in developing countries to 2030 as regional totals and shares in global investments as well as a break-out of investments into renewable technologies by macro-region.

Figure 6a. Cumulative Investments (shares) in 2030 in Developing Countries (bln)$

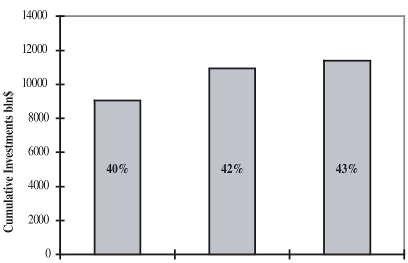


Figure 6b. Shares of Investments in Renewable Technologies in B2-L_500

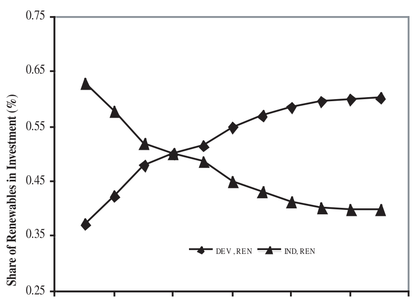


Figure 6a shows that in the B2-L learning scenario total cumulative investments by 2030 in developing countries[10] increase compared to the B2-F

9. Under global learning, the deployment of a technology in a given region affects its investment costs in all of them and, as a consequence, may render it more attractive also in other regions (Riahi et al., 2004).

10. Investment size in developing countries and their share in global investments are first of all determined by the underlying demand scenario (B2), which in accordance to the vast majority of recent energy demand scenarios (cf. the review in IPCC 2000) projects much more vigorous demand growth in developing countries.

and the imposition of the climate constraint in the B2-L_500 leads to further increase in such investments. The possibility of learning effect, especially when combined with climate constraints increases the early deployment of new energy technologies in developing countries thus increasing investments. This shift in early investments towards the rapidly growing energy markets of the 'South', results from the global cost minimum criterion underlying the objective function of the model that assumes a strict separation of economic efficiency and equity.

As Figure 6b indicates, under the climate constraint, investments into renewable technologies are initially higher in industrialized countries but already by 2030, more than half of the global investment into such technologies move to developing regions and by the end of the century, these regions dominate the share of such investments. This indicates the existence of large potentials and markets for such carbon-free technologies in these regions. In developing countries, where much less infrastructure is available and energy demands are likely to grow, the system could move more readily into a renewable path, using leapfrogging techniques, where efficient technologies and infrastructures are preferred to large-scale fossil based systems (Barreto et al., 2003). However the results presuppose the existence of perfectly functioning capital markets in which in addition the issues of who performs early investments for 'cost buy down' of new technologies is separated from the issue of who actually *pays* for such investments. In the terminology of climate policy the modeling results illustrate the importance of instruments such as CDM and associated emission reduction credits that would need to be developed vigorously in order to enable global cost minimal solutions such as those reported here. In case of capital constraints in developing countries or lack of such institutional arrangements the costs of technological learning and of meeting climate constraints would be substantially higher. A quantification of this important effect however awaits further model improvements such as the representation of capital markets and the representation of alternative burden sharing mechanisms underlying a particular global climate constraint. A global perspective of technological learning without considerations of the critical issue of 'who learns when and how' risks of projecting an overoptimistic picture that might not necessarily stand the test of reality of capital constraints in developing countries and of insufficient global coordination mechanisms necessary in a scenario of technological learning.

Importantly, early investments into new energy technologies in developing countries under the assumptions of technological change and climate constraints indicate the potential of substantial synergies between meeting short-term development needs in these countries and the need for accelerated deployment of climate friendly technologies. For example, connecting the poor to the electricity grid and providing every individual in the world with electricity would require cumulative investments of 600 billion US$ in 2020 (WEC 2000). The spillover effects due to a climate policy could play an important role in making available such investments in these countries and ensure that they embark on technological pathways that fulfill their growing development needs and simultaneously ensure a long-term climate friendly future.

6. CONCLUSION

In this paper we explore the implications of a representation of a stylized mechanism of endogenous technological change in the energy system under the learning by doing hypothesis. We confirm earlier findings about the general importance of this effect in lowering long-term energy systems costs. We find that technological diversity in the learning portfolio is important to avoid technological 'lock-in' effects. This in turn implies that it is necessary to invest in a wide range of technologies and create niche markets to ensure that learning effects can lead to long-term cost reductions.

An important finding is that technological learning by itself is not sufficient for climate stabilization and that climate policies are an absolute necessary complimentary element. Without inducement mechanisms in place, any model of endogenous technological change is unlikely to yield the substantial emissions reductions required in the long-term for climate stabilization. Under a climate constraint, the costs of the energy system are substantially reduced over the very long-term through upfront investments into carbon free technologies in the short and medium term. However it is important to acknowledge that the large magnitude of the 'upfront shift' in investments, especially in developing countries (which have the largest long-term market potential for new technologies) may be difficult due to constraints of capital unavailability, imperfect markets and insufficiently developed institutions.

Under a climate constraint, spillovers across technologies and regions due to learning results in increased upfront investments and hence lower costs of carbon free technologies, thus resulting in technology deployment and emissions reductions, especially in developing countries. Thus learning and spillover effects can lead to cost-effective, climate-friendly and technologically advanced global energy transition pathways. An added bonus might be that these accelerated early investments could also provide the much needed access to modern energy services of the poor in developing countries. In fact our results suggest that such mechanisms are an integral part of global cost-effective solutions to climate change. But the realization of such cost lowering effects presupposes the existence of appropriate institutional mechanisms that bridge the gap between where early, upfront investments yield the largest return in terms of technological learning (incl. developing countries) and where the capital for funding such upfront investments (predominantly in the industrialized countries) is available. This highlights the importance of mechanisms like CDM and of globally coordinated climate stabilization policies. Under existing fragmented institutional and policy frameworks the substantial economic benefits of perspectives such as outlined here are unlikely to be realized.

We conclude with some methodological observations. First, in order to better understand the inherent linkages between climate regimes and their inducement mechanisms on technological change such as represented under a learning-by-doing hypothesis and perfect international technology spillover effects, it is necessary to represent capital markets and resulting capital flows between regions explicitly in energy and climate policy models. Secondly, a better representation of (imperfect) spillover effects across technologies and regions is needed to remediate the rather optimistic assumption of perfect global spillovers underlying the model calculations reported here. Finally, the inherent uncertainty in technological learning rates imputes both risks and additional opportunities. The use of stochastic approaches and limited foresight in modeling technological learning can help explore this critical issue more deeply.

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