

Technological Change and Learning*

Nebojša Nakićenović
IIASA, Laxenburg, Austria

1. Introduction

Energy and carbon intensities of economic activities have been declining since the onset of industrialization two centuries ago. Technologies that are more energy efficient have replaced less efficient ones, and technologies that are less carbon intensive have replaced those that are more carbon intensive. Technological change has made a major contribution to these long-term improvements in the productivity of energy. In particular, the decarbonization of energy – namely, the reduction of the specific carbon content of energy – can be interpreted as a long-term learning process that can be represented by a learning curve. In this paper it is argued that the dynamics of technological change is a cumulative process of learning by doing. Technological change is not an “autonomous” process, although it is often represented as such in energy and economic models.

A number of implications will be considered with reference to the mitigation of carbon dioxide (CO₂) emissions. Various mitigation strategies for countering the possibility of climate change have been proposed. Recently, research has begun to focus on the formulation of global CO₂ emissions profiles that would lead to the stabilization of atmospheric concentrations at some negotiated level in accordance with Article 2 of the Framework Convention on Climate Change (UN/FCCC, 1992). For example, all of the CO₂ emissions profiles that lead to concentrations stabilization that were analyzed by the Intergovernmental Panel on Climate Change (IPCC, 1996) require the eventual reduction of global carbon emissions from well below to less than half the current levels during the next two centuries. In view of the increasing needs for energy services in the world, especially in developing countries, such emission reductions will require a substantial increase in the decarbonization rate. This, in turn, implies a larger future role for new

*This paper reports initial results of introducing technological learning into the model MESSAGE based on the analysis presented in greater detail by Messner (1996). The author is grateful for the permission to use these results. Helpful comments and suggestions were received from Jae Edmonds, Dominique Foray, Bill Nordhaus, and Rich Richels. The views presented are solely those of the author.

technologies with lower CO₂ emissions. Thus, there is an increasing recognition in the literature that abatement of CO₂ emissions requires a sustained commitment to research, development, and demonstration (RD&D) today (see, for example, Wigley *et al.*, 1996).

It will be shown that in conjunction with RD&D timely investment in new technologies with lower CO₂ emissions might be a more cost-effective strategy for reducing global emissions than postponing investment decisions in the hope that mitigation technologies might somehow become more attractive through RD&D, "autonomous" improvements, and cost reductions in step with natural turnover of capital. It has recently been argued that the latter strategy is superior to a more timely introduction of lower-emission technologies, because at present these technologies are generally costlier than the alternatives (see, for example, Wigley *et al.*, 1996, and the paper by Richels *et al.* in this volume). Although this is true, postponement in itself will bring few additional benefits. While the costs and performance of technologies are generally modeled as if they were exogenous, they are not. Costs of new technologies have been shown to decline and performance to increase with accumulated experience and improvements. Unless there is dedicated, timely, and pronounced investment in these technologies, they are unlikely to be developed and thus become commercially viable and competitive in the market place. Learning by doing is a prerequisite for performance improvements, cost reductions, and eventual diffusion. Postponing investment decisions will not bring about the technological change required to reduce CO₂ emissions in a cost-effective way. Even worse, under unfavorable conditions it might bring about further "lock-in" of energy systems and economic activities along fossil-intensive development paths.

The implication is that there may be great leverage in policies and measures that accelerate the accumulation of experience in new technologies with lower environmental impacts, for example, through early adoption and development of special niche markets. This leverage can be important, particularly if these policies can minimize the "deadweight" loss to society associated with the foregone exploitation of cheaper fossil fuels and possible reductions of RD&D in other parts of the economy. That is, an acceleration of energy-related technical progress may be accompanied by a slowdown in labor and capital productivity. These are some of the problems and issues that must be resolved before technological change can become a truly endogenous component in standard modeling approaches. In the meantime, an increasing number of models are being adapted to explore alternative ways of incorporating endogenous technical change. In this paper we will

explore the nature of the relationship between technological learning, costs and performance of new technologies, and resulting emissions profiles from the global electricity generation system with the MESSAGE model.

2. Decarbonization

Through decarbonization, energy services can be provided with lower carbon emissions. The process can be expressed as a product of two factors: decarbonization of energy and reduction of the energy intensity of economic activities, for example, as measured by gross domestic product (GDP). Figure 1 shows the decarbonization of GDP; Figures 2 and 3 show the decarbonization of energy and the reduction of energy intensity of GDP, respectively. The example for the USA is shown in the three figures primarily because the data are of relatively good quality; however, available data allow the assessment of decarbonization trends with reasonable confidence for other major energy-consuming regions and countries, such as France and the UK, and for the world as a whole (see, for example, Nakićenović, 1996; Grübler and Nakićenović, 1996). Over shorter time periods similar decarbonization trends can be obtained for many developed and industrializing countries, such as India and China. In Figure 1, the decarbonization rate is expressed in kilograms of carbon (kgC) per unit of GDP in US dollars measured at 1990 prices. The average annual rate of decline is about 1.3%, meaning that every year about 1.3% less carbon is emitted to generate one dollar of value added.

Today, about a quarter of a kilogram of carbon is emitted per dollar value added in the USA, and about half that amount is emitted per dollar value added in Europe and Japan. However, the amount of carbon emitted per dollar value added is significantly greater in most developing and many re-forming countries. Thus, it is evident there are different paths of economic development that lead to similar levels of affluence at quite different levels of CO₂ emissions. The prime objective of possible mitigation strategies is to reduce these emission levels by increasing the rate of decarbonization throughout the world. At an average decarbonization rate of 1.3% per year, global CO₂ emissions will increase about 1.7% annually, assuming the economic growth rate remains at about 3% per year. This increase will lead to a doubling of emission levels in about 40 years. Thus, to stabilize global emissions at some (higher) level in the future, the decarbonization rate would have to at least double to offset the current rate of economic growth. The second

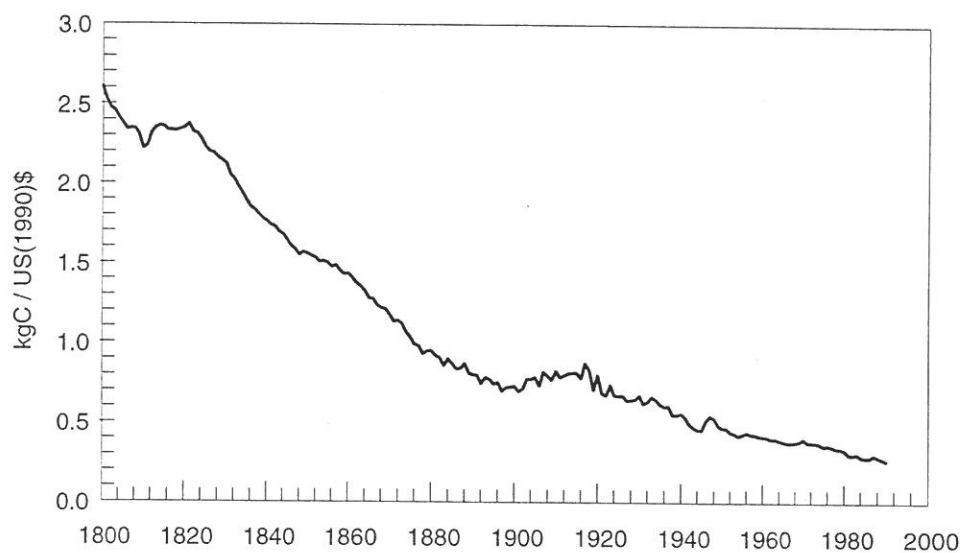


Figure 1. Decarbonization of economic activities in the USA, expressed in kilograms of carbon per unit of GDP at constant 1990 prices [kgC/US(1990)\$].

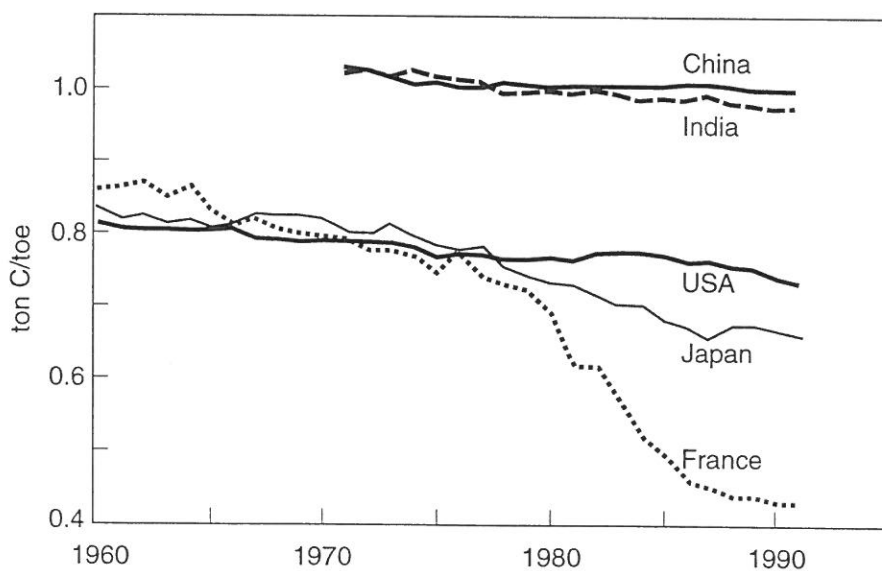


Figure 2. Decarbonization of primary energy in the USA and selected countries, expressed in kilograms of carbon per kilogram oil equivalent (kgC/kgoe).

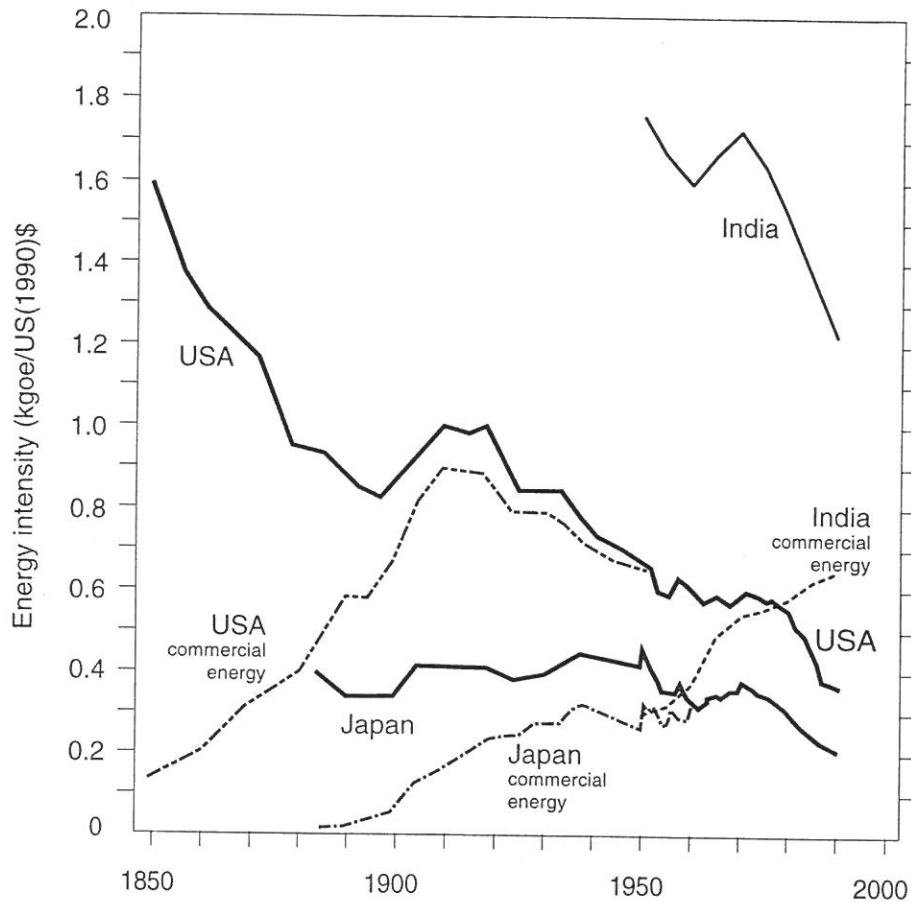


Figure 3. Primary energy intensity of economic activities in the USA and selected countries, expressed in kilograms of oil equivalent per unit GDP at constant 1990 prices [kgoe/US(1990)\$].

alternative, maintaining lower rates of economic growth, is clearly undesirable in light of the existing widespread poverty and deprivation throughout the world.

Figure 4 portrays another image of the dynamics of decarbonization. The data from Figure 1 are now shown as a learning or experience curve. The ratio of carbon emissions to GDP is shown versus the cumulative emissions in a double logarithmic diagram. There is an exponential decline (linear on double logarithmic scales) in specific carbon emissions per doubling of cumulative emissions. Apparently, the more we emit, the more we learn

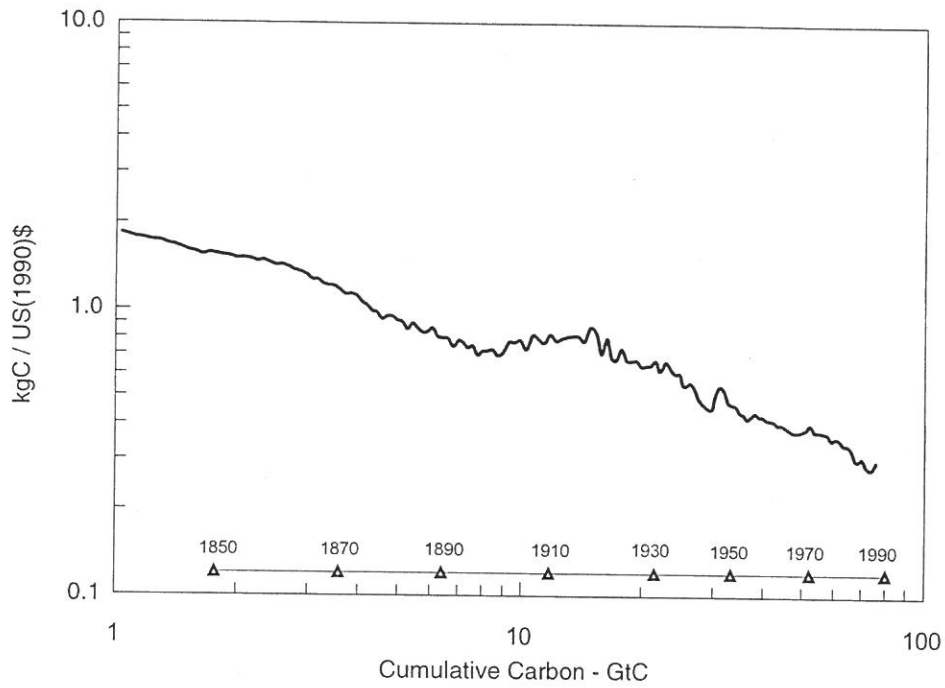


Figure 4. Decarbonization of economic activities in the USA as a learning process where accumulated experience is represented by cumulative CO₂ emissions, expressed in kilograms of carbon per unit of GDP at constant 1990 prices [kgC/US(1990)\$] versus cumulative CO₂ emissions in gigatons of carbon (GtC) on double logarithmic axes.

about how to emit less per unit value. This is a typical process of learning with cumulative experience. The progress ratio is actually quite high at about 76% (representing a 24% cost reduction in specific emissions) per doubling of cumulative emissions. This figure compares with progress ratios in the range of 70–90% across a number of energy technology learning curves reported in the literature (e.g., see Christiansson, 1995).

As a kind of thought experiment, assume a hypothetical case where this rate of learning continues for another century. In this case, one could expect the specific carbon emissions to continue to decline. To date, the USA has emitted about 100 gigatons of carbon (GtC, or billion tons of carbon), slightly less than half the cumulative global emissions, estimated at about 250 GtC. If the rate of learning were to remain the same, another 100 GtC would be emitted before the specific emissions could be reduced

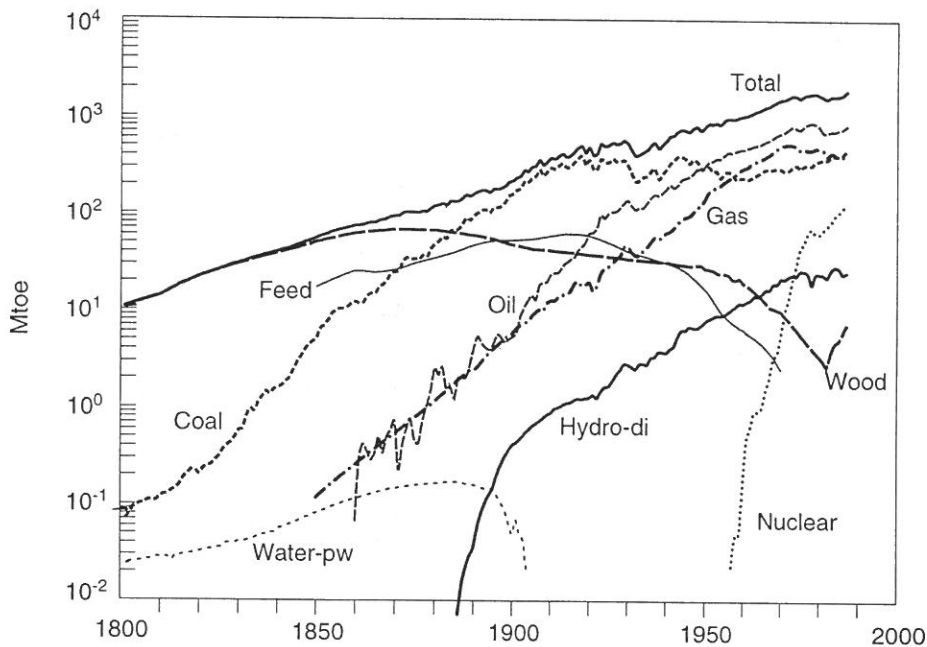


Figure 5. Primary energy consumption by major energy sources in the USA, expressed in million tons of oil equivalent (Mtoe).

another 24%. This rate is clearly too slow for a transition to the post-fossil era within a century or two. Thus, for a more drastic increase of decarbonization, substantially higher rates of technological learning would be required.

Before discussing the process of endogenizing technological learning, let us first consider the technology dynamics behind the historical rates of decarbonization and the implications decarbonization carries for the possible diffusion of less-carbon-intensive energy technologies in the future. Figure 5 shows the hierarchy of replacements of old energy sources with new ones in the USA. This dynamic process of technological substitution is the driving force behind the historical rates of decarbonization.

Traditional energy forms such as animal feed and wood have a high carbon content, both per unit of energy and per unit of economic activity, because of the relatively low efficiency with which they deliver demanded energy services. Draft animals and open fire have very low energy conversion efficiencies compared with contemporary prime movers and furnaces. It is true that some of the released carbon can be reabsorbed by new plant growth

and new trees, and by the replanting of animal feed, but quite often the land is not used in a sustainable fashion. For example, because many of these activities are associated with deforestation and land degradation, they often lead to net carbon flux to the atmosphere. The carbon intensity of fuelwood and animal feed is substantially higher than that of coal. Moreover, coal can be used with generally higher efficiencies. For these reasons, coal eventually supplanted traditional energy forms. This progress toward energy sources with lower carbon contents and higher conversion efficiencies has continued, with shifts from coal to oil to natural gas, and more recently to nuclear energy and new renewable sources of energy, both of which have minimal carbon emissions. Natural gas in itself brings enormous reductions in carbon emissions (with half the carbon emissions of coal) as well as higher efficiencies.

Using the available data, the historical replacement of coal with oil and later with natural gas can be illustrated for most countries and major energy-consuming regions, as well as for the world as a whole (Marchetti and Nakićenović, 1979; Nakićenović, 1979). If all energy sources are considered the replacement process is very intricate and complex, as can be seen from Figure 5. Similar dynamics of technological substitution have been studied for other systems, such as transport and steel making (Grübler and Nakićenović, 1988; Nakićenović, 1990). It is a process with long transition periods from older to newer technologies, especially in the areas of energy systems and infrastructure. The competitive struggle between the five main sources of primary energy – wood, feed, coal, oil, gas, and nuclear materials – has proved to be a process with regular dynamics that can be described by relatively simple rules. This process is shown in Figure 6 for the USA, based on the data from Figure 5.

A glance reveals the dominance of coal as the principal energy source between the 1880s and the 1950s, after a long period during which fuelwood, animal feed, and other traditional energy sources were predominant. The mature coal economy meshed with the massive expansion of railroads and steamship lines, the growth of steel making, and the electrification of factories. During the 1960s, oil assumed a dominant role in conjunction with the development of automotive transport, the petrochemical industry, and markets for home heating oil. If this substitution continues to progress at similar rates in the future, natural gas (methane) will be the dominant source of energy during the first decades of the next century, although oil is likely to maintain the second largest share until the 2020s. Such an exploratory look into the future requires additional assumptions to describe the subsequent competition of potential new energy sources such as nuclear, solar, and other

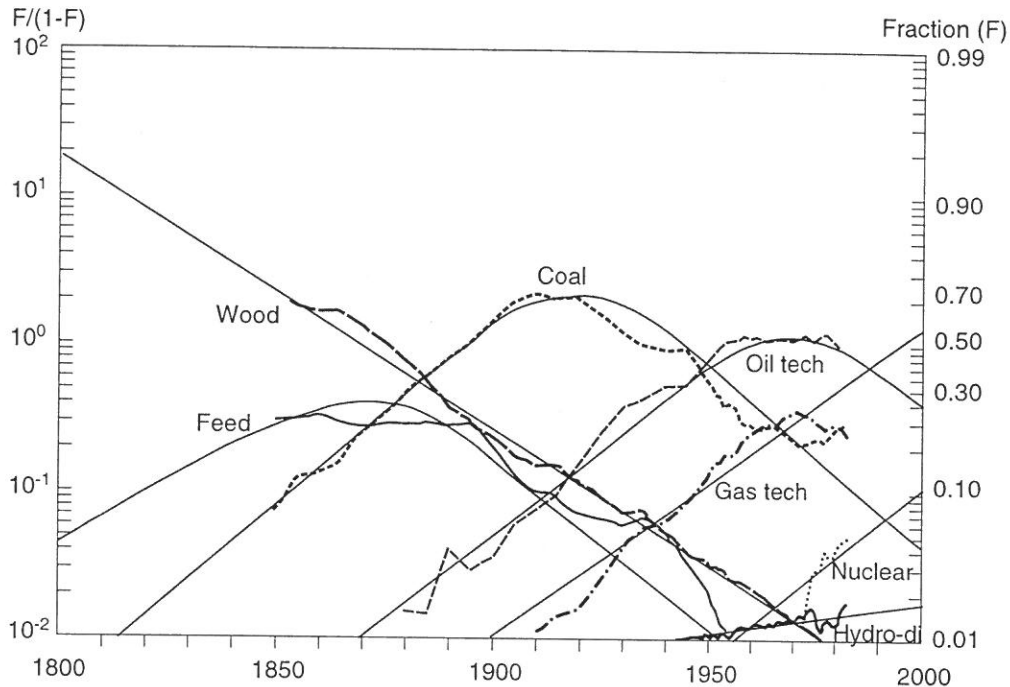


Figure 6. Primary energy substitution in the USA, historical data and model projections for the future, expressed in fractional market shares (F) and transformed as $F/(1-F)$ on logarithmic axes.

renewables, which have not yet captured sufficient market shares to allow an estimation of their penetration rates and market potentials. Because all of these alternative energy sources have only minimal CO_2 emissions and natural gas has the lowest emissions of all fossil fuels, the unfolding of primary energy substitution implies a gradual continuation of energy decarbonization throughout the world.

3. Technological Learning

The replacement of old technologies with new ones occurs gradually. The performance of new technologies improves and their costs decrease with increases in production and use. Accumulated experience and learning can be assumed to increase with increases in the market shares of a new technology. As technologies mature, their improvement potentials decrease. A somewhat stylized difference between new and old technologies is that the

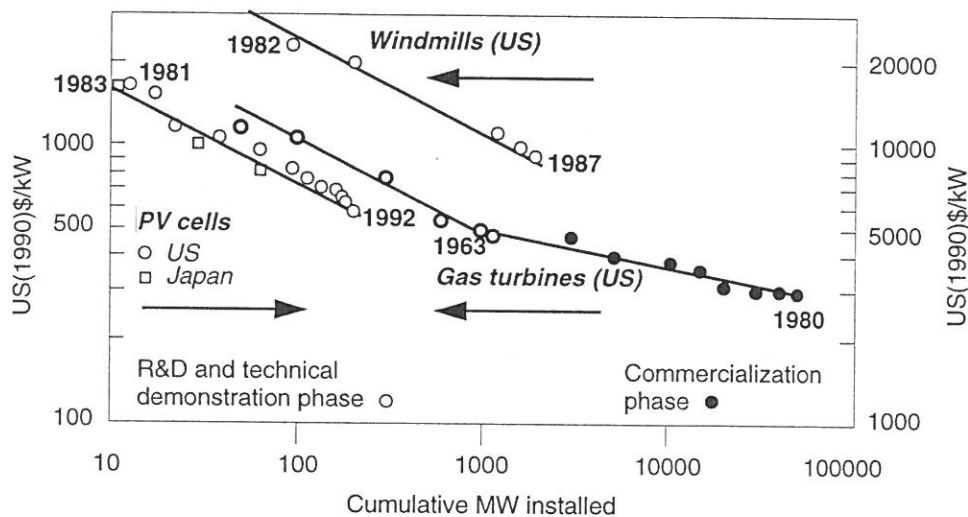


Figure 7. Reductions of investment costs for three representative new and advanced technologies as a learning process, expressed in US dollars at constant 1990 prices per unit installed capacity [US(1990)\$ / kW] versus cumulative installed capacity (MW) on double logarithmic axes.

former are costlier at the time of their introduction, but their costs can be assumed to decrease with increases in their market share so that at some point the cost curves might cross, making them a more attractive choice than the old technology. Learning curves capture this process. Figure 7 presents a number of illustrative examples (IIASA-WEC, 1995; Gröbler *et al.*, 1996; Nakićenović and Rogner, 1996). It shows rapid declines in investment costs with every doubling of cumulative installed capacity of gas combustion turbines and wind and photovoltaic (PV) systems. This pattern of performance improvement and cost reductions with accumulated experience and learning is common to most technologies, although its specific shape depends on the technology. Typical progress ratios listed in the literature range between 65% and 95% for all technologies and between 70% and 90% for energy technologies (Christiansson, 1995). There are significant cost improvements during the RD&D. For example, in Figure 7 (with a progress ratio of 88%) an 18% reduction in investment costs per doubling of cumulative production is shown for the case of gas combustion turbines. These improvements during the RD&D phase are followed by more modest improvements after commercialization, 7% per production doubling for combustion turbines, for example. If such cost reductions were to continue in the future for the PV

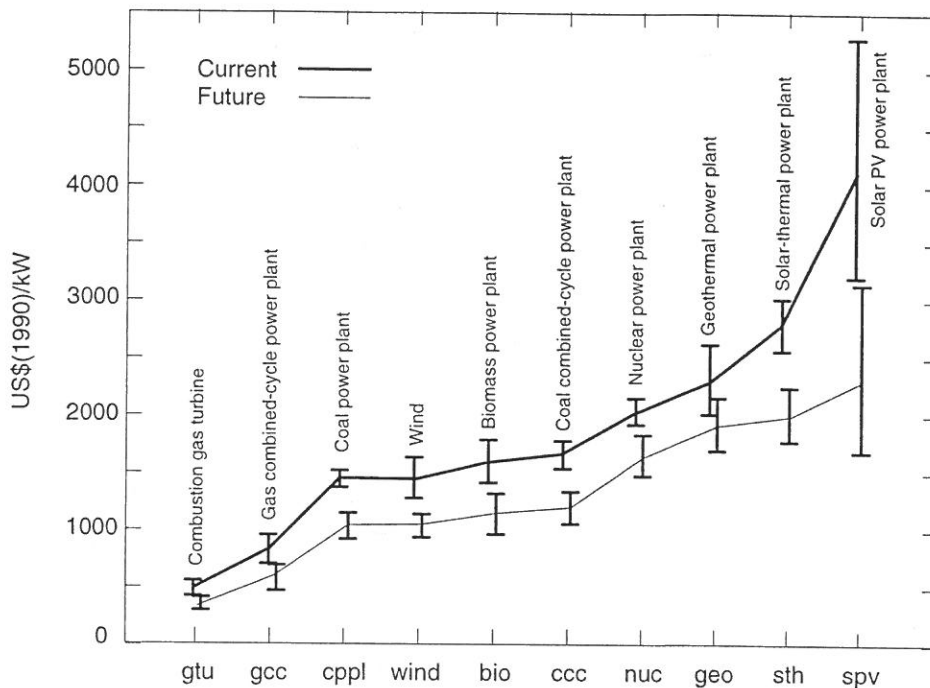


Figure 8. Mean and standard deviation of investment costs for 10 representative conversion technologies, current and future (about 2020), based on data in the IIASA technology inventory CO2DB. Source: Strubegger and Reitgruber, 1995.

systems, these systems could become commercially viable in a few decades, with cost reductions of about a factor of five to one order of magnitude compared with today's costs (from between US\$10,000/kW and US\$5,000/kW to as little as US\$1000/kW; see IIASA-WEC, 1995; Ishitani *et al.*, 1996; Nakićenović *et al.*, 1996).

Technological learning is reflected in most energy and emission scenarios and their underlying assumptions. New and emerging technologies are assumed to have better performance and lower costs in the future compared with current levels. Figure 8 reflects a range of such assumptions for some new and emerging energy conversion technologies. It is based on the International Institute for Applied Systems Analysis (IIASA) inventory of mitigation technologies, CO2DB (Messner and Strubegger, 1991; Messner and Nakićenović, 1992; Schäfer *et al.*, 1992). This database currently includes characterization of about 1600 energy technologies, from energy extraction

and conversion to energy end use. The database includes current and future technologies based on information from the literature for a number of countries and representative world regions. A large share of technology descriptions come from various energy modeling efforts. Most of the information is available for energy conversion technologies. In many cases, there are a sufficient number of data points for a given type of technology, such as for gas combustion turbines or PV systems, so that sample mean and standard deviation can be meaningfully derived. Figure 8 shows such statistics for 10 representative conversion technologies and gives the mean and standard deviation for current and future (about 2020) investment costs (Strubegger and Reitgruber, 1995). A glance reveals a clear pattern: current costs are higher than the assumed future costs. The less mature a technology is today (such as the PV systems), the higher the future cost reductions and the higher the uncertainty, as evidenced by wider distribution of cost estimates. This is indeed consistent with the phenomenon of cost reductions associated with learning, assuming that the installed capacities of these technologies will increase in the future, making them more competitive compared with current alternatives.

Equivalent assumptions are made in most modeling efforts and scenarios about future energy and emissions. Over time, new technologies become more attractive as their costs decrease and their performance improves. Sometimes such new technologies are called "backstops." Originally, Nordhaus (1973) formulated the concept of a backstop to mean a technology that has a virtually infinite resource base (for example, photovoltaic systems). Generally it is assumed that backstop technologies require RD&D and that they are too costly to be competitive at the present time. Alternatively, if the costs of other technologies increase, the backstops may become competitive at some point in the future. There is, of course, a fundamental difference between the two approaches. In the first approach, it is assumed that new technologies will become cheaper and have better performance through RD&D and "autonomous" technological change, without however explicitly accounting for RD&D and appropriability issues. In the second approach, backstops become more attractive as supply limitations of currently competitive technologies lead to increases in their costs compared with those of the alternatives. In either case, technological change is either assumed to occur implicitly through specified market increases or takes the form of an exogenous parameter. This is a standard view of technological change in most economic modeling approaches. In some manner technologies are "ready" before entering the economic world and the entrepreneurs

can choose among them according to their costs and relative performance so that they do have incentives to postpone investment in new technologies. For example, Richels *et al.* argue in this volume that “exogenous specification of technology change tends to *overstate* the costs of carbon” emissions reductions.

In general, the problem is that new technologies appear as “*mana from heaven*” in the standard approaches of modeling technological change: as time passes, new technologies become the best choices without any explicit RD&D effort or investment and without any of the risks that entrepreneurs usually face. This is why these models are said to have an “autonomous” rate of technological change.

Models that employ autonomous technological change portray exogenous improvement of technologies over time. Because these models employ market allocation algorithms, the technologies gradually penetrate the market. This kind of simulation can emulate the introduction of new technologies and their diffusion. The employment of autonomous technological change assumptions can lead to either too much or too little technological change relative to an endogenous model, unless the nature of the autonomous path of technological change is known *a priori* as a scenario assumption.

The exogenous specification of costs of new technologies and their decrease over time implies that later adoption would be cheaper than early adoption. Thus, it is evident that in a model where a given autonomous rate of technological change is assumed, is a cost-effective strategy to postpone investment in low-carbon technologies until they become cheaper and until the current vintages become obsolete. In reality, such results are misleading. If such mitigation strategies were to be adopted, there would be no investment in new technologies: all agents would wait for them to become more attractive, and no one would risk an early investment. Consequently, the technologies would not enter the market place and there would be no backstops in the future to reduce emissions. Instead, an emissions-intensive development path would be adopted that might prove difficult if not impossible to change midcourse. Even worse, there is some evidence that technological “forgetting by not doing” can occur (Rosegger, 1991). Figure 6 illustrates how important inertia is in the energy systems: it takes decades to achieve a transition from old to new technologies through active innovation and diffusion of new technologies, and for each of the successes there are many failures. It is in this light that the policy-relevant assessments of cost-optimal time paths of emissions reductions should be considered.

4. Endogenizing Technological Change

The lack of technological realism and dynamics in most energy modeling work obviously must be rectified. This has been recognized for a long time. For example, Nordhaus and van der Heyden (1977) attempted to endogenize technological change in an energy model of the USA two decades ago. They included RD&D and learning by doing in the form of cost reductions as a function of cumulative output of a technology. In the meantime, mathematical programming and computing techniques have improved so that it is now possible to capture RD&D and learning processes in greater detail, although computations requirements are still quite challenging.

A new research effort currently under way at IIASA aims at endogenizing technological change into the energy systems mathematical programming model MESSAGE (Messner, 1995) and introducing uncertainty into the characteristics of new and emerging technologies (Messner *et al.*, 1996). The article by Grübler and Messner in this volume summarizes some of this work in the area of technological uncertainty analysis. This paper reports on some of the research findings based on introducing technological learning into the model MESSAGE, including some results that are relevant for future rates of decarbonization of electricity generation. This analysis is presented in greater detail by Messner (1996).

Messner (1996) introduced technological learning into MESSAGE in terms of investment-cost reductions as a function of cumulative installations for six new and emerging electricity generation technologies: advanced coal, natural gas combined-cycle, advanced nuclear, wind, solar thermal, and PV systems. The learning process starts at present costs and can reach much lower and more competitive costs by accumulating experience. For example, for PV systems the assumed learning curve can lead to cost reductions of a factor of five between the base year (1990) and 2050 (from US\$5,100 to US\$1,000 per kW installed); the reduction potential for gas combined-cycle systems is approximately 45% (from US\$730 to US\$400 per kW installed). The technological learning assumptions for all six conversion technologies are shown in Table 1, reproduced from Messner (1996). In the model, RD&D activities and investments must be made in expensive new technologies if the technologies are to become cheaper through accumulated experience, represented by cumulative increase in installed capacity.

The representation of endogenous RD&D and technological learning in the energy systems model MESSAGE requires so-called mixed integer programming techniques, because the constraint set is nonconvex. Computationally, this approach is very demanding so that only six new technologies

Table 1. Reductions of investment costs as a learning process for electricity generation by six new and advanced technologies, expressed in US dollars at constant 1990 prices per unit installed capacity [US(1990)\$ /kW].

Technology	1990	2050	Progress ratio
Advanced coal	1,650	1,350	0.93
Gas combined cycle	730	400	0.85
New nuclear	2,600	1,800	0.93
Wind	1,400	600	0.85
Solar thermal	2,900	1,200	0.85
Solar PV	5,100	1,000	0.72

are explicitly modeled as a single-region world model of the electricity sector. The next research tasks will include the extension of the approach to the whole energy system and inclusion of other down-stream technologies in addition to electricity generation. Among the shortcomings of the approach are that the shape of the learning curves is specified exogenously (including RD&D) and that the uncertainty of technological change is not yet captured in this particular model. The article by Grübler and Messner in this volume presents a version of the MESSAGE model that captures technological uncertainty analysis.

In order to compare the technological learning case with alternative ways of modeling technological change, Messner (1996) developed two additional cases. The first variant, the “static” case, is the least realistic of the three cases. In this variant, it is assumed that the investment costs of the new technologies remain at their 1990 levels over the entire time horizon. The “dynamic” variant assumes the same degree of cost reductions given in Table 1, but they are exogenous (“autonomous”), occurring at continuous rates between the base year (1990) and 2050. The dynamic case emulates the most common approach to modeling technological change in energy systems. In fact, it corresponds to Case A presented in the joint IIASA and WEC study, *Global Energy Perspectives to 2050 and Beyond* (IIASA-WEC, 1995).

Figure 9 shows the mix of global electricity generation in 2050 from eight different conversion technologies, including the six selected new and emerging technologies. The static variant relies primarily on established technologies such as standard coal and nuclear power plants, and to a more limited degree on less costlier advanced coal and natural gas combined-cycle technologies. With the exception of some coal, the new and advanced technologies are hardly used, because of the relatively high investment costs. In comparison, the dynamic cost profile does indeed lead to greater investment

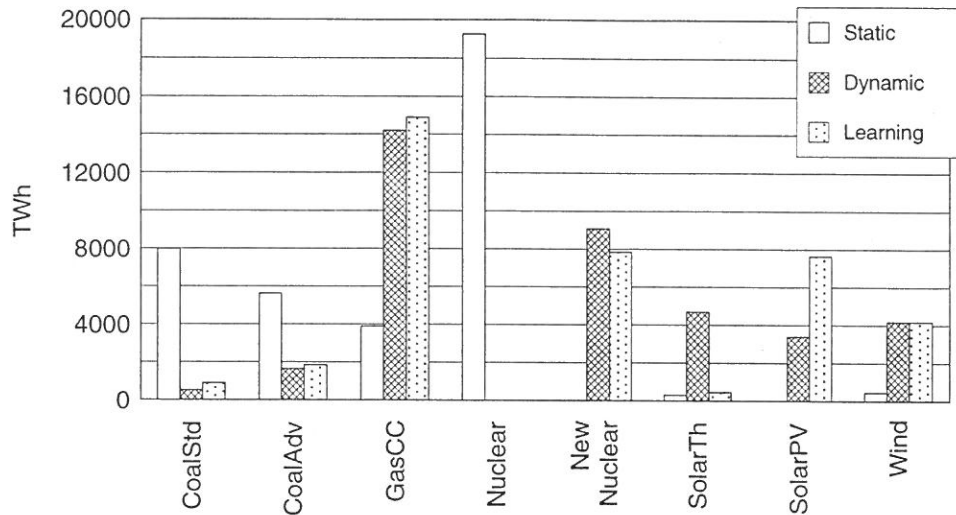


Figure 9. World electricity generation (TWh) in 2050 by eight generation technologies for three alternative cases: the “static” case, with constant investment costs, the “dynamic” case, with exogenously declining costs; and the “technology-learning” case, with endogenously declining costs.

in new and advanced technologies. The roles of coal and standard nuclear technologies diminish compared with the static case; they are replaced by natural gas combined-cycle, new nuclear, solar, and wind technologies. Because in the dynamic case these technology improvements are exogenous, the shift in investments from traditional to new and advanced technologies changes in step with the cost reductions. In contrast to the dynamic case, with technological learning investments in new technologies must be made up front, when these technologies are much costlier than the conventional alternatives, if they are to become cheaper with cumulative experience as installed capacity increases. With technological learning, the structure of electricity production in 2050 is not all that different from the dynamic alternative, with the exception of a slight shift from advanced nuclear to PV systems.

Messner (1996) has analyzed the different dynamics of investment paths in new and advanced technologies in the two alternative cases – the dynamic case with exogenous cost reductions and the technology learning case with endogenous cost reductions. Figure 10 presents her findings for global annual investments in electricity generation in the technological learning and dynamic cases compared with the static case. The most striking difference

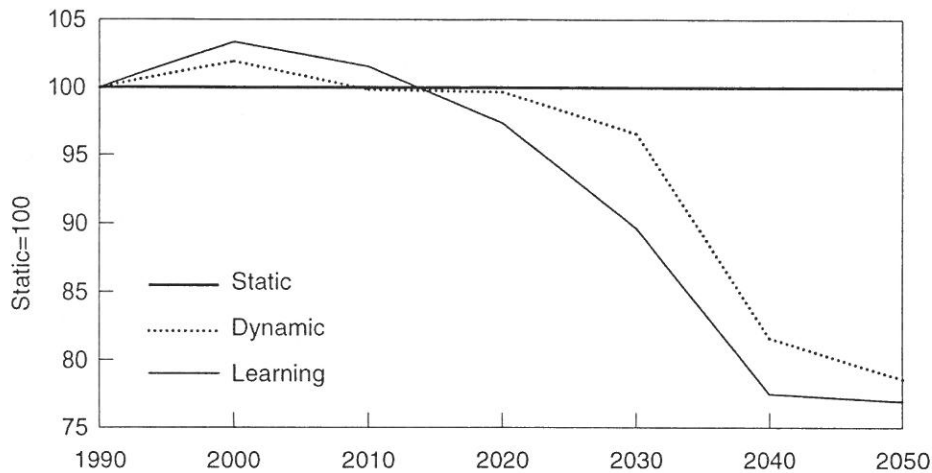


Figure 10. Annual investment requirements for electricity generation in the world for three alternative cases: the “dynamic” case, with exogenously declining costs, and the “technology-learning” case, with endogenously declining costs, compared with the “static” case, with constant costs (index=100), expressed as an index.

is that the case with endogenous learning shows higher up-front investment costs but has lower discounted systems costs than the dynamic case with exogenous cost reductions. Both cases lead to roughly the same investment costs in 2050, because there is sufficient cumulative investment in new and advanced technologies to reduce the costs along the learning curve to the level of exogenous reductions in the dynamic case. Over the entire time period (1990–2050), cumulative discounted investments are 6.6% lower in the dynamic case with exogenous learning and 9.7% lower in the case with endogenous learning than in the static case (Messner, 1996). The difference in the investments is particularly large between 2020 and 2050. The discounted investment costs in the case with technological learning are 50% below the discounted investment costs of the dynamic case.

This single example illustrates some of the generic differences between the two approaches in modeling future technology costs and performance. In the dynamic case it pays to postpone some investment in new technologies until the costs are reduced (exogenously). In the case of technological learning there is no time to waste. Higher levels of costly investments are made immediately in order to accrue sufficient experience to be able to reap the benefits of cost reductions at some point further along the learning curve.

If these costly investments are not made, the technology stays expensive. Nonetheless, despite high initial investments, the overall discounted costs are lower in this example than in the other cases. This result means that early RD&D expenditures and development of niche markets for new technologies may be able to reduce the overall discounted costs of long-term mitigation strategies, even if similar rates of “autonomous” technology improvement are assumed in the case without learning. In reality, however, the exogenous cost reductions are unlikely to occur unless someone else invests instead. At the global level this is of course a contradiction, because even in the dynamic case such investments must be included in the calculations if cost reductions are to occur.

5. Conclusion

Incorporating the concept of technological learning into the energy model MESSAGE led to lower CO₂ mitigation costs compared with an alternative model employing a fixed rate of autonomous technological change, as is usually done in studies of future energy and emissions perspectives. The costs were also lower although exactly the same rates of performance improvements and cost reductions were assumed to occur over the study time horizon in both approaches. Compared with the case of endogenized learning, the “autonomous” case leads to the postponement of investment decisions until lower-emission technologies “become” cheaper. This means that initially the investments are somewhat lower. In the case with endogenous technological learning initial investments are higher, but this higher investment is offset later through the possibilities of reducing emissions at substantially lower costs when installed capacities and emission levels are higher. Even with discounting at 5% per year, the endogenous learning case leads to lower total costs in the global electricity sector. Of course, these results are sector specific, and do not reflect any of the deadweight loss or intersectoral trade-offs stipulated by Goulder (1996). That is, the analysis does not consider the potential loss of welfare associated with the costly initial market penetration of the new technologies or the transfer of resources away from other technology development toward the development of new technologies. The results, however, do shed light on the process by which new technologies enter and penetrate the market, which has important implications for both the cost and timing of policy interventions designed to achieve emission mitigation.

Endogenization of technological change through technology learning captures some of the positive externalities generated by RD&D and early

investment in new technologies. This means that not only will a given technology be improved through RD&D and learning, but other technologies of the same "family" will improve, as well. Knowledge spillover is often assumed to be determined by the combination of processes by which knowledge diffuses and by which it becomes obsolete. It has a positive impact on the social return of the technology learning development strategies.

The introduction of technological learning into the model does not solve all the problems associated with understanding technological change or the future costs of alternative energy technology strategies. Some basic problems also encountered in the autonomous technological change approach are still unsolved. Technical performance and cost profiles of learning-by-doing must be specified *a priori*. In the real world the performance improvement rates of new technologies are not known *a priori*, which is reflected in the risks that entrepreneurs usually face when they make new technology adoption decisions. It should be acknowledged that technical change is only one of several factors that determine technology costs and performance and thus ultimately also emissions paths.

Including this "stylized" treatment of technological change in the model captures some of the dynamic patterns common to the cost reductions and improvement in performance of almost all technologies that are successful at the market place. Initially, costs are high due to batch-production methods that require highly skilled labor. Performance optimization and cost minimization are rarely important; the overriding objective is the demonstration of technical feasibility. When the technology seeks entry into a market niche, costs begin to matter, although usually what is of central importance is the technology's ability to perform a task that cannot be accomplished by any other technology. Examples are fuel cells in space applications, PV systems for remote and unattended electricity generation, gas turbines for military aircraft propulsion, and drill-bit steering technology in oil and gas exploration. Including in the model the more costly new and advanced technologies with the promise of lower costs and better performance through accumulated learning captures these effects of early and pre-commercial technology development and entry into specialized market niches.

A technology's success in a niche market, however, does not ensure its successful commercialization. Improvements must be made in reliability, durability, and efficiency, and, even more important, costs must be reduced. Any RD&D devoted to these objectives creates a supply push. This supply push must be complemented by a demand pull, by which initial markets are expanded sufficiently to further reduce costs through economies of scale. The demand pull may be policy driven. Technically feasible technologies that are

not yet economically competitive might benefit from environmental or energy security policies that increase their competitors' costs. For example, other electricity generation options benefit from requirements for flue gas desulfurization in coal-fired plants, or from bans on electricity generation from natural gas that restrict combined-cycle gas technology. New technologies may also benefit from economies of scale and market dominance already achieved by older technologies. The existing transmission infrastructure, for example, can be readily used by new electricity generating technologies (IIASA-WEC, 1995). Including such effects in the model by initially introducing new and advanced technologies only in some "niche" markets and later in more widespread applications as their costs decrease, captures some of these complex phenomena associated with innovation diffusion and technological change.

Thus, the rate of technological change depends on the diffusion of innovations and the dynamics of their adoption. The replacement of carbon-intensive technologies with zero- or low-carbon alternatives can be expressed as the process of energy decarbonization. Scenarios with high shares of coal actually lead to a reversal of the historical trends toward decarbonization. Other scenarios that envisage that the transition to the post-fossil era will occur during the next century portray decarbonization rates similar to, or sometimes even higher than, historical rates. Decarbonization must continue if CO₂ emissions are to stabilize in the future. Quite high rates would be required to actually reduce global CO₂ emissions, as would be required to achieve stabilization of atmospheric concentrations at some negotiated level in accordance with Article 2 of the Framework Convention on Climate Change (UN/FCCC, 1992). Figure 11 captures the differences in the decarbonization of global electricity generation with and without technological learning presented in this paper.

Without improvements in technological performance or cost reductions compared with the present situation, the static case actually leads to a reversal of historical trends toward decarbonization after the 2020s as the global electricity generation is "locked-in" on the carbon-intensive generation technologies. Decarbonization occurs in the dynamic case, indicating a high degree of structural change in electricity generating capacity. However, the rate slows down after the 2030s compared with the technological learning case. The more dynamic interplay among different technologies in electricity generation leads to the highest degree of decarbonization, and yet here the total discounted costs are the lowest of all three alternatives. That the costs are lower than in the static case is not at all surprising as the static case does not include any reduction in costs, and thus older and cheaper technologies

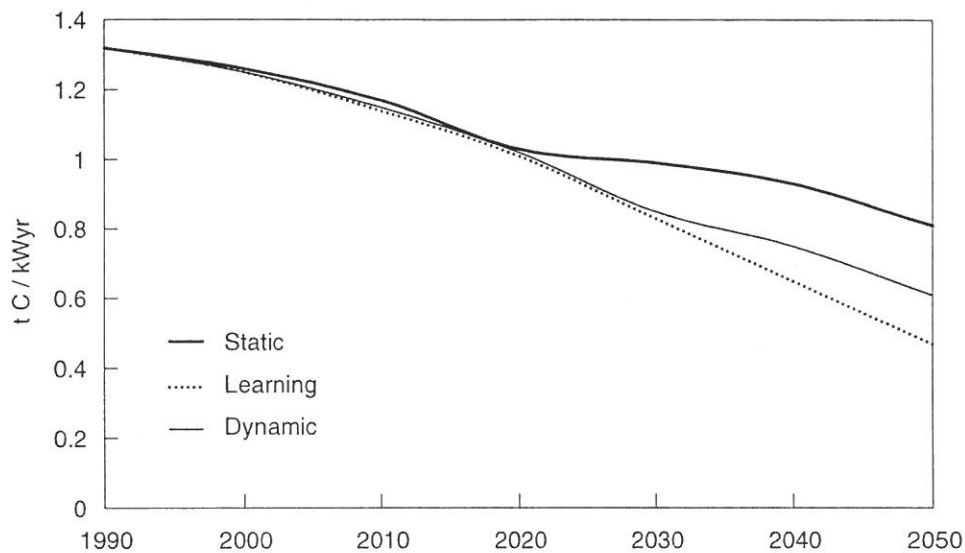


Figure 11. Decarbonization of electricity in the world for three alternative cases: the “static” case, with constant investment costs; the “dynamic” case, with exogenously declining costs; and the “technology learning” case, with endogenously declining costs [expressed in kilograms of carbon per watt-year of electricity (kgC/Wyr)].

are generally chosen, leading to relatively high emissions and high costs. An interesting result of this analysis is that technological learning leads to lower emissions and costs compared with the dynamic case, even though costs and emission-reduction potentials are the same as the exogenously assumed improvement rates in the dynamic case by the end of the time horizon. The additional degree of freedom of initially introducing promising technologies in the niche markets although they are still too costly leads to overall cost reductions, because cumulative learning allows for significant cost reductions later on, when installed capacities and emissions levels are high. In contrast, the dynamic case does not lead to early market entry of new and advanced technologies. These technologies diffuse as they become more attractive, but by that time the system’s inertia and the still-high shares of older technologies in the vintage structure do not allow a more dynamic transition toward lower emissions.

The “stylized” treatment of RD&D and technological learning in the model requires further improvement. Endogenous technological change is captured only for six new technologies in the presented example. This is

seriously deficient and clearly needs to be extended to other technologies in the energy system and other sectors of the economy. High computational requirements are a serious barrier to such extensions, so that new research is required. There are serious methodological shortcomings to the approach, as it captures RD&D and learning only for low carbon-emitting technologies. According to Goulder (1996), knowledge-generating resources are generally scarce, so that expansion of technological progress in one industry often implies a reduction in the rate of technological progress in others, even if the policy in question does not intend to discourage any industry's rate of technological progress. Another critical issue is that endogenization of technological change through learning by doing means that the energy system will be "locked in" a few technologies that have high progress ratios. But variety has a value in itself. This means that a number of speculative projects should be funded in any case, with the idea that this will enlarge the stock of future possibilities.

This first result of endogenizing technological change indicates that the postponement of investments in new and advanced technologies in itself will bring few additional benefits to future CO₂ mitigation strategies. In other cases there might be benefits from delay. Costs of some technologies might decrease due to "exogenous" improvement of other technologies. For example, improvements in information technologies might benefit energy technologies so that postponement might be attractive. The main result of the analysis, however, is robust: unless there is dedicated, timely, and pronounced investment in CO₂ mitigation technologies, they are less likely to be developed and thus become commercially viable and competitive in the market place. Learning by doing is a prerequisite for performance improvements, cost reductions, and eventual diffusion. Postponement of investment decisions will not bring about the technological change required to reduce CO₂ emissions in a cost-effective way. Even worse, it might bring about further "lock-in" of energy systems and economic activities along fossil-intensive development paths.

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