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INDUCED TECHNOLOGICAL CHANGE AND SPILLOVERS IN CLIMATE POLICY MODELING

An assessment

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Abstract

Besides primary effects such as reducing greenhouse gas emissions, climate policies may have secondary (side) effects - called 'spillovers' - such as the induced innovation and diffusion of new technologies, both nationally and internationally. These spillovers of climate policies, in turn, may affect the (long-term) performance of these policies, for instance in terms of abatement costs or emission reductions, both at home and abroad.

The aim of this report is to provide a critical assessment of the available literature of both so-called 'top-down' and 'bottom-up' modelling studies on the spillover effects of climate policies on induced technological change - including the innovation and diffusion of new technologies at home and abroad - as well as, in turn, the impact of these technological spillovers on the long-term performance of these policies.

After a review of the central concepts 'induced technological change' and 'technological spillovers', the present assessment report discusses the potential impact of induced technological spillovers on global carbon abatement. Subsequently, it addresses the question whether climate policy will induce technological change by (i) reviewing the (empirical) literature on technological change induced by environmental policies and/or higher energy prices, and (ii) discussing the (theoretical) literature on the relationship between market imperfections and environmental technologies.

Thereafter, the report provides a critical assessment of existing studies on induced technological change and spillovers in 'top-down' and 'bottom-up' approaches of climate policy modelling. Besides major differences between these two approaches, it reveals that the top-down modelling studies are generally characterised by a wide diversity in model outcomes with regard to the impact of induced technological change (ITC) on climate policy performance, whereas the bottom-up studies show some major similarities in their model outcomes.

Finally, the present assessment report considers briefly some implications for the post-Kyoto agenda on climate and technology policies. In general, it concludes that a well-balanced package of internationally coordinated climate and technology policies is necessary to deal with the two sets of international market imperfections in the field of abatement technologies (i.e. environmental externalities and technology market failures).

CONTENTS

SUMMARY FOR POLICYMAKERS

Besides primary effects such as reducing greenhouse gas emissions, climate policies may have secondary (side) effects - called 'spillovers' - such as the induced innovation and diffusion of new technologies, both nationally and internationally. These spillovers of climate policies, in turn, may affect the (long-term) performance of these policies, for instance in terms of abatement costs or emission reductions, both at home and abroad.

The aim of this report is to provide a critical assessment of the available literature of both so-called 'top-down' and 'bottom-up' modelling studies on the spillover effects of climate policies on induced technological change - including the innovation and diffusion of new technologies at home and abroad - as well as, in turn, the impact of these technological spillovers on the long-term performance of these policies.

Potential impact of induced technological spillovers

After a review of its central concepts 'induced technological change' and 'technological spillovers', the present assessment report discusses a paper by Grubb et al. (2002b) on the potential impact of induced technological spillovers on global carbon abatement. By means of some simple (optimistic) assumptions and numerical illustrations, this paper shows that spillover effects from mitigation actions in the industrialised, Annex I countries can exert a huge leverage effect on reducing global emissions, and that over time the diffusion of abatement innovations, induced by mitigation actions in the Annex I countries, outweighs the leakage of emissions due to the relocation of production to other, developing countries (also induced by Annex I actions). On balance, the overall result of mitigation actions in the industrialised countries is to reduce emissions in the developing countries as well.

The outcome of the exercise by Grubb et al. (2002b), however, depends highly on the (implicit) assumption that mitigation actions in the industrialised countries will induce a large variety of (relatively cheap) abatement technologies that are not only widely adopted in industrialised countries but also in developing countries (even if these latter countries do not have a climate policy incentive to adopt these technologies themselves). Moreover, the study of Grubb et al. (2002b) is based on the critical (but unreal) assumption of no emissions trading between Annex I and non-Annex I countries. This implies that the costs (or GDP losses) to meet the Annex I mitigation target for the year 2100 will be rather high, notably because this target is rather stringent, while there is no opportunity to meet this target by means of cheaper emissions reductions in non-Annex I regions through CDM-based trading.

Climate policy encourages innovation and diffusion of technologies

Subsequently, the present report addresses the question whether climate policy will induce technological change by (i) reviewing the (empirical) literature on technological change induced by environmental policies and/or higher energy prices, and (ii) discussing the (theoretical) literature on the relationship between market imperfections and environmental technologies. The most important finding is that the available evidence on induced technological change by environmental policies and/or higher energy prices seems to support the hypothesis that (future, stringent) climate policy will encourage the innovation and diffusion of new technologies that will address the issue of controlling global warming in a more cost-effective way. Some qualifications, however, can be added to this general finding.

Firstly, the impact of climate policies on the promotion of emission abatement technologies will vary depending on the time period and type of technological change considered. Secondly, climate policy may not only induce technological change but, in turn, the innovation and diffusion of more cost-effective abatement technologies may affect the optimal target, timing and/or instrument choice of climate policy. Thirdly, although climate policy may induce abatement technologies that are more cost-effective, that does not necessarily imply that the costs of this policy are lower, depending on the definition of 'costs' and whether the abatement target is fixed or not. Fourthly, the fact that climate policy will induce technological change does not say anything about which (mix of) instruments will be more or less cost-effective to do so.

A final, but perhaps most important qualification is that, while climate policy may induce technological change, the impact of climate policy alone will be far from optimal as the innovation and diffusion of green technologies is generally faced by two related sets of market imperfections. While climate policy may stimulate new technology as a side effect of internalising the costs of the environmental externality (i.e. the greenhouse effect), it does not address explicitly the other set of market imperfections directly related to technological change (such as the incidence of spillover effects). On the other hand, simply relying on the promotion of technological change by technology policy alone is not enough as there must be a long-term, predictable and credible climate policy-induced incentive in place that encourages the process of technological change to occur actually in the direction of innovating and diffusing improved carbon abatement technologies. Therefore, a balanced set of climate and technology policies is necessary to promote the innovation and diffusion of emission abatement technologies and, hence, to address the issue of global warming in an optimal way. It should be acknowledged, however, that the process of technological change is not only characterised by potential market failures but also by potential policy or government failures such as the lack of public information, the incidence of free-riding, and the risk of 'picking the winners/losers' (e.g. in case of subsidising/taxing specific technologies).

Assessment of 'top-down' and 'bottom-up' studies
Thereafter, the report provides a critical assessment of existing studies on induced technological change and spillovers in 'top-down' and 'bottom-up' approaches of climate policy modelling. Top-down models are general macroeconomic models that analyse the economy - including the energy system - in highly aggregated terms, with hardly any detail on energy or mitigation technologies at the sector level. Such models are particularly suitable for analysing macroeconomic effects of climate policies, including the interactions and feedback effects at the intersectoral, (inter)national, regional or global level. Over the past decade, induced technological change has been incorporated in these models, particularly by linking the accumulation of knowledge and experience to changes in climate policy.

Induced technological change in top-down modelling studies
In general, ITC top-down modelling studies show a wide divergence of results with regard to the impact of induced technological change and spillovers on the performance of climate policy. Whereas this impact is generally large and positive in some studies, it is relatively low or even negative in others. This divergence in the major results of top-down modelling studies with regard to the impact of ITC/spillovers on the performance of climate policies can be explained by the methodology and data used. More specifically, besides differences in ITC channel (i.e. R&D versus learning-by-doing) and in policy optimisation criteria (i.e. the cost-effectiveness criterion versus the benefit-cost criterion), these differences in outcomes can be mainly attributed to (i) the specification of some critical model functions, particularly the ITC or knowledge accumulation functions, (ii) model parameterisation and data use, (iii) the role of spillovers, and (iv) the role of other modelling characteristics varying among these studies such as the scope or level of aggregation (sectoral, national, regional, global), the number and type of policy instruments covered, the stringency of the abatement target, or the time horizon considered (i.e. the impact of ITC is often more significant in the long term).

Despite substantial progress made over the past decade, the present ITC top-down studies are still faced by a variety of weaknesses and limitations. Due to these limitations and the diversity of their model outcomes, it is hard to draw firm lessons and implications from these studies. Nevertheless, a major lesson from these studies seems to be that even if climate policy induces technological change at the level of individual sectors or technologies, it does not imply that the social costs of such a policy will decline by necessity. Another lesson is that, when analysing or generating ITC, not only its impact on gross social costs should be considered but also its potential environmental benefits. A final implication of the present state of ITC top-down studies is that further research is necessary in order to draw more firm policy lessons and implications.

Induced technological change in bottom-up modelling studies

On the other hand, bottom-up energy system models are usually characterised by a detailed analysis of energy technologies, including information on the costs and other performance characteristics of these technologies such as the energy efficiency or GHG emissions per unit input or output. Since the mid-1990s, technological change has been endogenised in some of these models by means of so-called learning curves that relate the costs of specific technologies to the accumulation of knowledge and experience during the innovation and diffusion stages of these technologies.

In contrast to the ITC top-down studies, the ITC bottom-up studies reviewed in the present report show some major similarities in performance, in terms of both methodological approach and major findings of the models used. In order to explore the interaction between climate policy and induced technological change, these studies have used a detailed, bottom-up energy technology system model in which learning curves have been added to the cost functions of (some) energy technologies covered by these models. The major outcomes of these studies are that, due to the presence of ITC (i.e. 'learning technologies'), (i) the investment costs of these technologies decline if they built up capacity ('experience'), (ii) the energy technology mix changes in favour of those technologies that built up the relatively highest rate of learning (i.e. cost reduction), and (iii) the total abatement costs of a given abatement target decline significantly.

However, although there is a large degree of agreement among bottom-up studies with regard to these results, the size of the impact of ITC on, for instance, the technology mix or abatement cost may vary substantially between these studies depending on the assumed rate of technological learning, the number of learning technologies included in the analysis, the time frame considered, the stringency of the mitigation target, the setting of market penetration limits, etc.

Moreover, despite significant progress made in endogenising technological change in bottom-up modelling studies over the past decade, the present state of these studies is still characterised by too many weaknesses and limitations to draw a set of firm, specific policy lessons and implications. Nevertheless, a few general lessons and implications can be formulated. Firstly, perhaps the most important policy message from technology learning is that new technologies require markets to become commercial. Hence, as it takes time to build up capacity (i.e. 'learning' or 'experience') and to reduce costs until a market break-even point is reached, there is a need for early policy action to accomplish the required cost and performance improvements in the long term, including the creation of niche markets, the development of small-scale demonstration plants, targeted R&D, and the (temporary and declining) subsidization of promising technologies.

Another lesson is that, owing to the presence of spillovers, the imposition of emission constraints in the Annex I region may induce technological change and, hence, emission reductions in the non-Annex region even when the latter region does not face emission constraints itself. A final lesson or implication is that further research is needed in order to draw more concrete, firm policy conclusions from ITC bottom-up modelling studies.

Implications for post-Kyoto agenda

Finally, this assessment report considers briefly some implications for the post-Kyoto agenda on climate and technology policies. In general, it concludes that a well-balanced package of internationally coordinated climate and technology policies is necessary to deal with the two sets of international market imperfections in the field of abatement technologies (i.e. environmental externalities and technology market failures). More specifically, it suggests that the innovation and diffusion of emission-saving technologies can be stimulated by the following options:

- International co-operation on Research, Development, Demonstration and Deployment activities (R&D3).
- Encouraging technology diffusion through trade, investment and other general, macroeconomic policies.
- Stimulating technology diffusion through emissions trading, notably the Clean Development Mechanism (CDM), and sound technology transfer strategies, including the improvement of the absorptive capacity for technological innovation and diffusion in developing countries.
- Promoting the innovation and diffusion of carbon-saving technologies by means of voluntary agreements ('covenants') between governments of the climate coalition and a few international firms that dominate R&D and technological change in certain areas, for instance the international automobile industry.

These options should be part of the post-Kyoto agenda in order to enhance the potential positive interaction between climate policy, induced technological change and international spillovers, including the potential positive impact of this interaction on mitigating global greenhouse gas emissions and reducing total abatement costs.

1. INTRODUCTION

Besides primary effects such as reducing greenhouse gas emissions, climate policies may have secondary (side) effects - called 'spillovers' - such as the induced innovation and diffusion of new technologies, both nationally and internationally.[1] These spillovers of climate policies, in turn, may affect the (long-term) performance of these policies, for instance in terms of abatement costs or emission reductions, both at home and abroad.

The aim of this report is to provide a critical assessment of the available literature of both so-called 'top-down' and 'bottom-up' modelling studies on the spillover effects of climate policies on induced technological change - including the innovation and diffusion of new technologies at home and abroad - as well as, in turn, the impact of these technological spillovers on the long-term performance of these policies.

The structure of the present report runs as follows. First, Chapter 2 provides a conceptual framework, particularly with regard to the terms 'induced technological change' and 'technological spillovers'. Subsequently, Chapter 3 discusses a study by Grubb et al. (2002b) on the potential impact of induced technological spillovers on global carbon abatement. Next, Chapter 4 tries to answer the question whether climate policy will induce technological change by (i) reviewing the (empirical) literature on technological change induced by environmental policies and/or higher energy prices, and (ii) discussing the (theoretical) literature on the relationship between market imperfections and environmental technologies. Thereafter, Chapters 5 and 6 assess existing studies on induced technological change and spillovers in 'top-down' and 'bottom-up' approaches of climate policy modelling, respectively. Finally, Chapter 7 discusses the implications of the present assessment report for the post-Kyoto agenda on climate and technology policies.

[1] Another example of spillovers due to climate policy concerns 'carbon leakage'. See Kuik (2004) and Chapter 2 of the present study.

2. CONCEPTUAL FRAMEWORK

2.1 Induced technological change

The notion of induced technological change was first introduced by Hicks (1932) who noted that changes in relative prices of production factors such as labour or capital would spur the development and diffusion of new technologies in order to economise on the usage of the more expensive production factor. Starting from the 1960s, this notion of induced (or 'endogenous') technological change has been used by the so-called endogenous or 'new' growth theory in order to account for economic growth and technological changes endogenously within a macro-economic model.[2] Subsequently, the idea of induced technological change has been applied to a variety of other disciplines, such as energy or environmental economics. More recently, i.e. since the mid-1990s, it has also been used in the field of climate policy modelling.[3]

In this paper, the process of technological change covers the widely used Schumpeterian trilogy of *invention* (i.e. the first development and demonstration of a scientifically or technically new product or process), *innovation* (i.e. the first regular commercial production of a new technology) and *diffusion* (i.e. the spread of a new technology across its potential market).[4] For the purpose of this paper, *induced* technological change is defined as the component of technological change that is brought about in response to government climate policy (while the term *endogenous* technological change will be used in the same meaning, although in a modelling context). Climate policy is primarily aimed at controlling greenhouse gas (GHG) emissions (i.e. mitigation) and includes both market-based instruments (such as taxes, subsidies or tradable permits) and command-and-control regulations (such as setting performance- or technology-based standards for firms or households).

Basically, there are two channels through which induced technological change can be implemented, i.e. via 'research and development' (R&D) and 'learning-by-doing' (LBD). Although these two channels are mostly treated quite exclusively in the literature of energy and climate policy modelling, in practice they seem rather complementary in the sense that the invention and innovation stage of technological change are covered largely through the channel of R&D and the diffusion stage via LBD.

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2 In this paper, the terms 'induced technological change' (ITC) and 'endogenous technological change' (ETC) will be largely used interchangeably, although the concept ITC refers primarily to technological changes due to changes in policy or economic conditions (in contrast to 'autonomous' technological changes which are not induced specifically by changes in policy or economic conditions). On the other hand, the term ECT is primarily used as a modelling concept, referring to technological changes that are explained within a scientific model (in contrast to 'exogenous' technological changes which are treated as 'given' and remain unexplained within the model). It should be noted, however, that in a small part of the literature, the terms ETC and ITC refer to different concept in the sense that ETC refers to the broad notion of (neutral) technological progress that responds to economic incentives (in order to account for changes in the general stock of knowledge and R&D that affect overall economic growth), while ITC refers specifically to the bias or direction of technological innovations in response to changes in relative prices or other economic conditions (Jaffe et al., 2003). For instance, Buonanno et al. (2003) distinguish between ETC, referring to changes in the general stock of knowledge that affect the overall productivity of capital and labour, and ITC, referring specifically to changes in the emissions output ratio that are induced by changes in the general stock of knowledge.

3 For a discussion of the evolution of the theory of induced technological change and endogenous economic growth, see Hayami and Ruttan (1985), Grübler et al. (2002), and Mulder 2003.

4 Occasionally, another stage called 'niche market' is distinguished as a separate stage between the innovation and (wide-spread) diffusion stages in the process of technological change. The term 'niche market' refers to the first phase of diffusion of a new technology in a special, separate market (i.e. with high positive demand) in which a new technology can relatively easily spread, even though the production costs are still high (Grübler and Messner 1998; Grübler and Gritsevskyi, 2002; and Gerlagh et al., 2004).

In the first case, i.e. through R&D, the introduction of climate policies such as a carbon tax or standard increases the market for carbon-mitigation technologies and, hence, creates an incentive for increased R&D investments in these technologies. In modelling terms, these increased investments lead to an increase of the knowledge capital stock, which is part of the production or innovation function of a firm, sector, country or region.

In the second case, i.e. via LBD, climate policies encourage primarily the adoption of GHG-mitigation technologies, resulting in declining costs of these technologies due to the accumulation of knowledge and experience among producers and users as the installed capacity of these technologies expands (where the declining costs further encourage their adoption, etc.). In modelling terms, this process of technological change is expressed by a learning or experience curve that relates the costs of a technology to its cumulative installed capacity. This capacity is used as a measure of the accumulation of knowledge and experience during the manufacturing stage of the technology ('learning-by-doing').[5]

The speed of learning is usually expressed by the progress rate (PR) or its complementary learning rate (LR=1-PR), defined as the rate at which the costs of a newly installed technology declines each time its cumulative installed capacity doubles. For instance, a progress ratio of 0.8 (or a learning rate of 0.2) means that the costs per unit of a newly installed capacity (e.g. a wind turbine) decrease by 20 percent each time its cumulative installed capacity is doubled (Seebregts et al., 2000).

The impact of technological change induced by climate policy is usually analysed by two broad approaches for modelling the interaction between the economy, energy and environment: bottom-up (BU) versus top-down (TD).[6] These approaches differ mainly with regard to the emphasis placed on a detailed, technologically based treatment of the energy system, and a theoretically based treatment of the general economy. Bottom-up models are partial models of the energy sector, lacking adequate interactions with the rest of the economy. In general, these models are characterised by a detailed analysis of the energy system, covering a wide variety of energy technologies, including data on the costs and other performance characteristics of these technologies (such as the energy efficiency or GHG emissions per unit output). Bottom-up models are mostly used to compute the least-cost option of meeting an exogenous demand for final energy services subject to various system constraints such as a GHG mitigation target. In addition, they often analyse the deployment or market penetration of specific energy technologies based on (policy-induced changes in) their costs and other performance characteristics. Technological change occurs as one technology is substituted by another (Löschel, 2002).

Top-down models, on the other hand, are general macroeconomic models that analyse the economy - including the energy system - in highly aggregated terms, with hardly any detail on energy or mitigation technologies at the sector level. Such models are particularly suitable for analysing macroeconomic effects of climate policies, including the interactions and feedback effects at the intersectoral, (inter)national, regional or global level (Sijm et al., 2002). Top-down models, however, do not provide much insight in the process of innovation and diffusion of concrete, individual technologies. In such models, technological change is usually expressed at an abstract, aggregated level through a change in the production or innovation function, either

[5] In some parts of the literature, a distinction is made between three basic types of learning: learning in the R&D stage of a technology ('learning-by-searching'), learning at the production or manufacturing stage ('learning-by-doing') and learning as a result of using the technology ('learning-by-using'). See Mulder (2003), and Jaffe et al., (2003 and 2004).

[6] This section is based on Löschel (2002). For a further discussion of the characteristics and performance of these two modelling approaches, see Hourcade et al. (1996); Weyant and Hill (1999); IPPC ((2001)) and Sijm et al. (2002). These references discuss also some 'mixed' approaches which link a top-down representation of the economy with a bottom-up description of technologies in the energy sector, See, for instance, Criqui et al. (1999) or Manne and Richels (2004).

exogenously - i.e. by means of autonomous efficiency parameters - or endogenously, i.e. by means of an induced change in the knowledge stock or learning capacity of an economy.

In bottom-up models, induced technological change is generally effectuated via the channel of learning-by-doing (LBD). In top-down models, on the other hand, it is usually implemented via the channel of R&D, although a few top-down approaches have relied on the LBD channel, either exclusively or including alternately (but not simultaneously) the LBD and R&D channel (see Chapters 5 and 6 for a further assessment of the performance of different modelling approaches in analysing induced technical change).

2.2 Technological spillovers

The concept of spillovers originates in the literature of R&D and technological change - including the innovation and endogenous growth theories - where it has been applied under a variety of largely synonymous labels such as 'R&D spillovers', 'knowledge spillovers', 'technological spillovers', 'innovation spillovers' or equivalent terms such as 'R&D or knowledge externalities'. These concepts all refer to the fact that knowledge has a high non-rival, public-good character and that, as a result, a private innovator may be unable to fully appropriate the social returns of investments in R&D and technological change. A major part of these social returns will accrue as 'spillovers' or 'positive externalities' to competitors - who will be able to use the knowledge as well - or to downstream firms and customers who purchase the innovator's product at a price that captures only a portion of its full value (including the enhanced quality of the innovated product). This 'appropriability problem' or 'spillover gap' between the private and social returns of innovations is likely to lead to significant underinvestment by private firms in R&D, relative to the social optimum (Jaffe et al., 2003).[7]

This paper will use the concept 'technological spillovers' defined as 'any positive externality that results from purposeful investment in technological innovation or development' (Weyant and Olavson, 1999). They can be distinguished with regard to the level at which they occur: technological spillovers may be intra- or intersectoral, varying from the local to the international level. Moreover, they can be either embodied in tradable goods or disembodied, i.e. not directly related to the flows of intermediate and end-use products.[8] More specifically, in the field of global GHG mitigation, technological spillovers can take place through a wide variety of channels, including local or international trade of goods and services, foreign direct investments, R&D collaboration at the sectoral and international level, personal communications, technological and scientific upgrading through relevant literature and business networks, JI/CDM transactions, and the migration of scientists and skilled labour forces.

Recently, the concept of spillovers has been used in a wider meaning in the literature on climate policy. For instance, according to the Third Assessment Report of the IPCC, 'spillovers from domestic mitigation strategies are the effects that these strategies have on other countries. Spillover effects can be positive or negative and include effects on trade, carbon leakage, transfer and diffusion of environmentally sound technology, and other issues' (IPCC, 2001). A similar definition of spillovers has been used by Grubb et al. (2002a and 2002b; see also Grubb, 2000).

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7 Besides spillovers, there are a variety of other externalities and imperfections in the markets for investments in R&D and technical change such as uncertainties, imperfect information, capital constraints, 'rent-stealing' or 'common-pool' effects, and network (or 'positive adoption) externalities. For a discussion of these market imperfections and their implications for private investments and public interventions in the field of environmental R&D and technological change, see Section 4.4. below as well as Parry (2001), Grubb and Ulph (2002), and Jaffe et al. (2002, 2003 and 2004).

8 Similar distinctions of 'embodied' versus 'disembodied' spillovers concern 'market' or 'rent' spillovers versus 'pure knowledge' spillovers. For these and other distinctions of spillovers, see Griliches (1992), Jaffe (1998), Weyant and Olavson (1999), Keller (2001), Grünfeld (2002), and Cincera and Van Pottelsberghe de Potterie (2002).

In their definition, spillovers refer to the impact of mitigation actions by the industrialised countries on the level of GHG emissions in the developing countries. They distinguish three components of international spillovers:

- Spillovers due to economic *substitution* effects, such as price or terms-of-trade effects, resulting in a *leakage* (or negative spillover) of emissions.[9]
- Spillovers due to the diffusion of *technological* innovations induced by abatement action in the industrialised countries and transferred to the developing countries. This component corresponds to the (narrow) definition of spillovers originating in the R&D literature mentioned above.
- Spillovers due to *policy and political* influence of industrialised countries mitigation efforts on developing countries abatement actions, such as the spread around the world of abolishing fossil fuel subsidies, accepting mitigation commitments, liberalising electricity markets or implementing other energy efficiency-enhancing measures.

Whereas the first component implies a negative spillover, the other two components are in most cases sources of positive spillovers. According to the quantitative analysis of Grubb et al. (2002b), the positive spillovers of climate policies may over time far outweigh the negative spillovers (see Chapter 3 for a discussion of this quantitative analysis).

[9] In their definition of (the first component of) international spillovers, Grubb et al. (2002) are merely focused on the physical implications of international spillovers, i.e. on the impact of abatement efforts by the industrialised countries ('carbon leakage'), including the impact on global average temperature and long-term sea level rise. In contrast, Böhringer and Rutherford (2002 and 2004) focus their analysis on the welfare implications of international spillovers, i.e. the impact of carbon abatement policies of industrialised countries on international market prices, the allocation of economic resources and, hence, on the costs and benefits of these policies accruing to other countries.

3. THE POTENTIAL IMPACT OF INDUCED TECHNOLOGICAL SPILLOVERS ON GLOBAL CARBON ABATEMENT

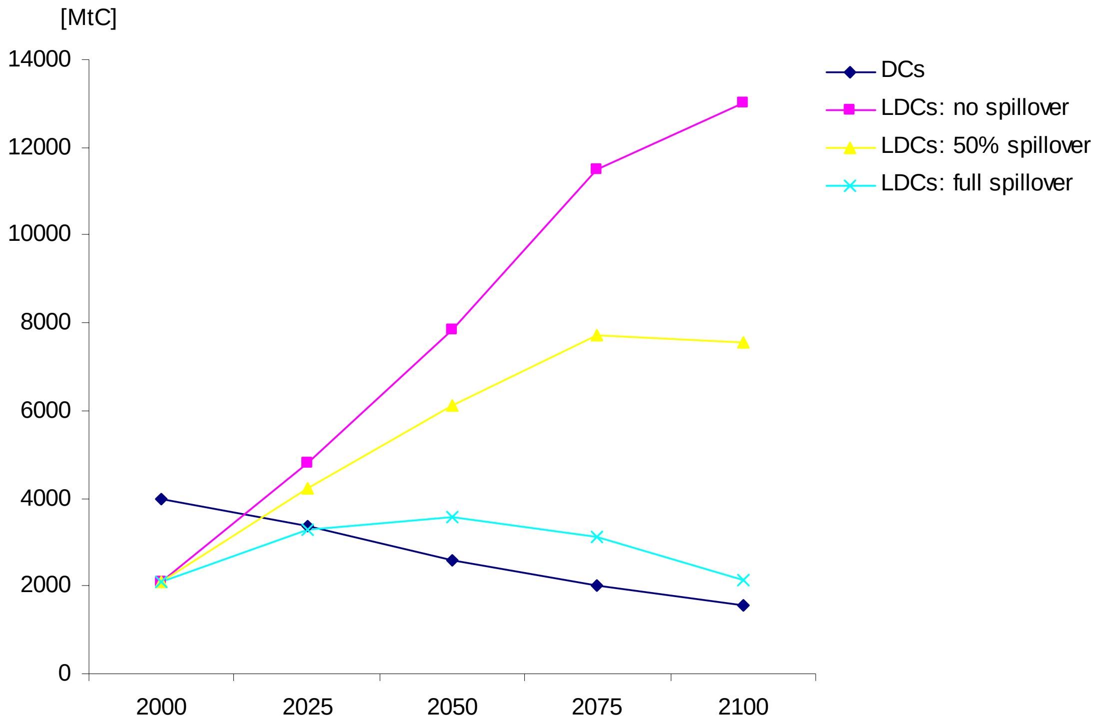
Recently, Grubb et al. (2002b) have estimated the potential impact of international spillovers due to mitigation actions by the industrialised countries on the level of GHG emissions in the developing countries. As noted in Section 2.2, they employ a broad definition of international spillovers, including three components. Spillovers due to *economic substitution* (‘emission leakage’), spillovers due to the diffusion of *technological innovation*, and spillovers due to *policy and political influence* of industrialised countries' mitigation efforts on developing countries' abatement actions. In their quantitative analysis, they represent international spillover in terms of its impact on the relative *emissions intensity*, defined as the ratio of CO_2 emissions to GDP, in different parts of the world (based on Grubb, 2000).

More specifically, by means of a simple equation that links emission intensities in the industrialised, Annex I region to those in the developing, non-Annex I region, Grubb et al. (2002b) represent international spillover in terms of the relative convergence of these regional emissions intensities over the 21st century by an aggregate spillover parameter σ (which includes the three components of international spillovers mentioned above). If σ = 0 there is no spillover effect, representing the case in which the emission intensities of the developing countries is completely independent of those in the industrialised counties. On the other hand, if σ = 1, there is full or perfect spillover, representing the case in which average emission intensities in the non-Annex I region converges to the same level of the (declining) emissions intensity in the Annex I region by the end of the 21st century.

In order to illustrate the potential impact of spillover effects on the emission level of developing countries, Grubb et al. (2002b) take as their reference case the SRES A2 scenario of the IPCC (2000a), modified by the assumed mitigation commitments of the industrialised countries, i.e. the Kyoto commitments until 2012 followed by a decline in Annex I emissions by 1% per year thereafter. In this ‘stringent’ mitigation scenario, carbon emissions of the industrialised countries decrease from about 4000 MtC in 2000 to less than 1600 MtC by the end of the 21st century (see Figure 3.1). In the absence of international spillovers (σ = 0), emission intensities in the developing countries are projected roughly to halve in the business-as-usual case by 2050 (when they will reach roughly the levels of the industrialised world in 1990). By 2100, in this case, emission intensities in the developing, non-Annex I region will be about five times those in the industrialised, Annex I region. In the case of full international spillovers (σ = 1), on the contrary, non-Annex I intensities will decline roughly twice as fast until 2050 and, as indicated, they will converge to the levels of the industrialised region by 2100, while the abatement technologies and practices induced by the mitigation actions in this region diffuse through the developing world (Grubb, 2000; Grubb et al. 2002a).

Figure 3.1 illustrates the potential spillover effects of stringent mitigation actions in the industrialised countries in total developing country emissions over the 21st century. It shows that these effects can be very large. For instance, in case of no spillover (σ = 0), total non-Annex I emissions increase steadily from 2,100 MtC in 2000 to 13,000 MtC in 2100, while in case of full spillover (σ = 1), they are stabilised around mid century and start to decline slowly thereafter, amounting to some 2,100 MtC again in 2100 (i.e. about one-sixth of their level in case of no spillover).

By means of the PAGE95 integrated assessment model, Grubb et al. (2002b) are able to estimate the potential implications of international spillovers in terms of cumulative emissions, atmospheric CO_2 concentrations, and changes in mean global temperature or long-term sea level rise. In the stringent mitigation scenario (Kyoto + 1%/yr decline of Annex I emissions), unitary spillover reduces total cumulative emissions in 2100 by almost 700 GtC, from 1480 GtC (zero spillover) to 800 GtC. The corresponding changes in atmospheric CO_2 concentrations by 2100 amount to a decline of 170 parts per million by volume (ppmv), from 740 ppmv ($\sigma = 0$) to 570 ppmv ($\sigma = 1$). This would imply a change in mean global temperature from pre-industrial levels by 2100 of 2.7°C in case of full spillovers (compared to 4.2°C if $\sigma = 0$), resulting in a reduction of the mean sea level rise in 2100 by about 40 cm. As sea level continues to rise for many decades after concentrations have stabilised, the impact of full spillovers upon sea level rise in the 22nd century would be even greater (Grubb et al. 2002b).



Source: Grubb et al. (2002b).

Figure 3.1 *Spillover effects of stringent mitigation actions of industrialised countries (DCs) on total emissions of developing countries (LDCs) over the period 2000-2100 (in MtC)*

Overall, the analysis of Grubb et al. shows that spillover effects from mitigation actions in the industrialised countries can exert a huge leverage effect on reducing global emissions, and that even relatively low levels of technological and institutional spillovers are sufficient to offset the (negative) spillover of carbon leakage. Over time, the diffusion of abatement innovations, induced by mitigation actions in the Annex I countries, outweighs the leakage of emissions due to the relocation of production to other, developing countries (also induced by Annex I actions). On balance, the overall result of mitigation actions in the industrialised countries is to reduce emissions in the developing countries as well (Grubb et al., 2002a and 2002b).

The results of Grubb et al., however, depend critically on the value of the aggregated spillover variable (σ). Based on some historical reflections and some assumptions with regard to the long-term future, they argue that zero or negative international spillovers, as assumed in many other studies, is 'not credible' and that the most likely range for the spillover variable in their model is 0.5-1.0. However, the empirical database or parameterisation of this aggregate variable, including its constituent components, is weak and highly uncertain.

More specifically, the (optimistic) outcome of the analysis by Grubb et al. depends highly on the (implicit) assumption that mitigation actions in the industrialised countries will induce a large variety of relatively cheap abatement innovations that are not only widely adopted in industrialised countries but also in developing countries (even if these latter countries do not accept mitigation commitment themselves). Only if these innovations are relatively cheap, carbon leakage from the industrialised countries will be low while their diffusion among developing countries will be high, resulting in a relatively high value of the aggregate spillover variable (in the range of 0.5-1.0). If not, carbon leakage will be high while developing countries (with no mitigation commitments) will lack the incentive to adopt cleaner, but more expensive technologies, leading to relatively low values of the spillover parameter (0.1-0.2 or even negative). Although there is some evidence that stringent climate policies in industrialised countries may induce cost-reducing abatement innovations in these countries (and, hence, reduce carbon leakage from these countries), little is known about the relative cost aspects and adoption rates of these innovations in developing countries. Therefore, although the analysis of Grubb et al. is quite illustrative with regard to the potential implications of spillover effects on global emissions, at present it lacks empirical validation and, hence, it may turn out to be too optimistic.

Another limitation of the paper of Grubb et al. is that it is based on the critical (but unreal) assumption of no emissions trading between Annex I and non-Annex I countries, and that it does not consider the implications of this assumption. The major implication of this assumption, however, is that the costs (or GDP losses) to meet the Annex I mitigation target for the year 2100 will be rather high, notably because this target is rather stringent, while there is no opportunity to meet this target by means of cheaper emissions reductions in non-Annex I regions through CDM-based trading. Allowing such trading (as agreed by the Kyoto protocol) would reduce these costs substantially. In addition, however, it would also imply that the impact of international technology spillovers on total, global emissions would be nullified as it would allow non-Annex I countries to sell their emission reductions - resulting from these spillovers - to Annex I regions, which could subsequently raise their emissions accordingly. Hence, there seems to be a trade-off between the impact of emissions trading on total abatement costs and total emissions reductions (see also the discussion in Chapter 6 on emissions trading and global technological spillovers).

4. DOES CLIMATE POLICY INDUCE TECHNOLOGICAL CHANGE?

4.1 Introduction

This chapter reviews some of the existing literature on energy and environmental policies in order to deal with the basic question whether climate policy induces technological change. More specifically, it addresses the following issues:

- What is the empirical evidence with regard to the induced innovation and diffusion of 'green' technologies, i.e. technologies that are favourable to protecting the environment in general and to controlling global warming in particular (Section 4.2)?
- What are the major market imperfections and other factors affecting the inducement of technological change (Section 4.3)?
- What are the major policy implications of the two issues mentioned above (Section 4.4)?

Beforehand, it should be emphasized that the empirical literature on the evidence of induced technological change by climate policies as such is still extremely limited as these policies have only been introduced in Annex I countries over the past few years. Hence, this period has generally been too short to observe and explore major examples of technological innovation and diffusion induced by climate policies. Therefore, in order to assess the potential role of climate policies versus other factors affecting technological innovation and diffusion, the scope of the literature review in this chapter will be focused on studies dealing with changes in similar ('green') technologies induced by similar policies or events over the past three decades such as environmental regulation, pollution abatement subsidies, energy saving measures or higher fuel prices due to either the oil shocks of the 1970s or higher energy taxes thereafter.[10]

4.2 Empirical analyses of induced changes in green technologies

Induced innovation

Empirical studies on the progress of green technologies have used a variety of proxy variables to explore the relationship between environmental policies and induced changes of these technologies. For instance, in Lanjouw and Mody (1996), pollution abatement expenditures serve as a proxy for the stringency of environmental regulation while the rate of patenting in related technology fields is used as an indicator for induced innovation. By means of country-level data on these variables, they found a significant correlation across nations between environmental regulation and induced innovation of pollution abatement technologies. Similarly, Jaffe and Palmer (1997) explored the relationship between pollution abatement expenditures and indicators of innovation across industries, using US data. They found a significant correlation between these expenditures and the level of R&D spending, as indicated by the estimated elasticity of pollution control R&D with respect to pollution control expenditures of 0.15. However, when estimating the same relationship using patents as the indicator of innovation, they did not find an impact of pollution control expenditures on overall patenting.

Other studies have used energy prices or related regulations as the mechanism of induced innovation, notably in the field of energy saving. Although the observed price changes might not be policy related, the results can also be applied to situations where policy affects prices, such as energy or carbon taxation. For instance, Newell et al. (1999) analysed the impact of both energy prices and energy saving regulations on technological innovations in energy efficiency of home

[10] The sections below are based on review studies of the relevant literature by Jaffe et al. (2002, 2003 and 2004), and Grubb et al. (1995 and 2002a), supplemented by other studies mentioned in the main text.

appliances - such as air conditioners and gas water heaters - in the US over the period 1958-1993. They found that a substantial portion (estimated at 62 per cent) of the overall change in energy efficiency of these products could be associated with ‘autonomous’ factors rather than with ‘induced’ or ‘endogenous’ variables such as energy prices or regulations. Nevertheless, a significant amount of innovation was still due to these endogenous variables, with energy prices accounting for the largest inducement effect (mainly because changes in energy prices induced both commercialisation of new models and elimination of old models, whereas regulations worked largely only through energy-inefficient models being dropped). Moreover, this effect of energy price increases on model substitution was particularly strong after product-labeling requirements became operative in the US. Indeed, simulations by Newell et al. (1999) suggest that the post-1973 energy price increases account for one-quarter to one-half of the observed improvements in the mean energy efficiency of models offered for sale over the period 1973-93. Hence, besides autonomous factors, a significant amount of innovation in terms of enhancing energy efficiency of home appliances can be ascribed to endogenous variables, notably energy price increases combined with regulations to inform customers on the energy efficiency of different models of these appliances.

The relationship between energy prices and energy-selected innovation has been explored more broadly by Popp (2001, 2002, 2003a and 2004c; see also Chapter 5). He uses the number of successful US patents sorted by application date as an indicator of innovative activity. Perhaps the most striking result of this empirical work is the speed at which innovative activity responds to incentives. By correlating US data on energy prices and patenting activity for various energy technologies over the years 1970-93, he shows that innovation responds strongly and quickly to price incentives. For instance, following the first energy crisis of the early 1970s, the number of successful patents for solar energy (sorted by their application data) jumped from 10 in 1972 to 36 in 1973, 104 in 1974, 218 in 1975, and a peak of 367 patents in 1977 (Popp, 2002 and 2003a). This result suggests that part of the first wave of innovation after the energy crisis of the early 1970s was not due to new ideas being discovered, but rather the introduction of existing, technologically feasible ideas that may simply have been taken ‘off the shelf' and brought to market when the conditions were right.

In addition, some other relevant findings of the empirical work of Popp on the relationship between energy price and induced innovation include:

- Estimates of the long-run elasticity of energy R&D with respect to changes in energy prices suggests that the response is inelastic (i.e. 0.35)[11]. Hence higher energy prices (or similar policies that increase the cost of using fossil fuels) can be expected to stimulate new research on energy saving, although less than proportionally.
- There are diminishing returns to energy R&D within a given field of technological innovations. Although energy prices peaked in the early 1980s, patenting activity in energy-related technologies began to drop already during the late 1970s. Popp (2002 and 2003a) provides evidence that this decline can be explained by diminishing returns to R&D over time. Hence, the inducement effect of energy prices on technological innovation in a given field will fall over time (Popp, 2004c).
- In order to estimate the impact of technological innovations on energy use, Popp (2001) uses patent data to create stocks of knowledge of 13 energy intensive industries. He found that approximately one-third of the overall response of energy use to changes in energy prices is associated with induced innovation, with the remaining two-thirds associated with factor substitution, i.e. a movement along a given production function by substituting energy for other production factors such as capital or labour (see also Popp, 2003a as well as Jaffe et al. 2002).

[11] As mentioned above, in a similar study, Jaffe and Palmer (1997) estimated a comparable elasticity of pollution control R&D with respect to pollution control expenditures of 0.15.

Some qualifications, however, have to be added to the work of Popp (and other authors) with regard to the use of patent data as a proxy for innovative activity. In order to explore the inducement effect of (energy) prices or policies on innovative activity, ideally one would need detailed, reliable data on public and private R&D activities and the performance of these activities in generating specific (successful) innovations, including data on the importance of these innovations in terms of potential or actual adoption rates and impact on, for instance, the average cost, energy or emission savings of a sector. As the present database is generally far away from this ideal situation, proxy variables have to be used as an indicator of innovative activity.

Using patent data as an indicator of innovative activity offers some advantages (Popp, 2003a). Firstly, unlike more aggregate data on R&D expenditures, patents provide a detailed record of each invention. Moreover, economists have found that, to some degree, patent counts not only serve as a measure of innovative output, but are also indicative of the level of R&D activity itself. In addition, patent data are available from many different countries and can be used to examine levels of innovative activity across countries or to track patterns of diffusion. Finally, when a patent is granted, it contains citations to earlier patents that are related to the current invention. As a result, the previous patents cited by a new patent should be a good indicator of previous knowledge that was utilized by the inventor.[12]

On the other hand, using patent data has some limitations (Popp, 2002 and 2003a; Schmitz, 2001). Firstly, the quality or importance of individual patents varies widely. Some inventions are extremely valuable, whereas others are of hardly any value in terms of commercial success or output performance, including energy or emission savings. Hence, a peak of patenting activity in a certain year following a price hike may represent a large number of minor, hardly valuable innovations ('taken from the shelf'), while a trough of such activities five years later may contain a major, time-consuming breakthrough.

Secondly, another limitation is that not all successful R&D results are patented. In return for receiving a patent, the inventor is required to publicly disclose the invention. Rather than make this disclosure, firms may prefer to keep an invention secret in order to avoid other firms 'inventing around' the new technology or, secondly, to prevent the product from being copied once the exclusive property rights expire (Popp 2003a and Schmitz, 2001).

Finally, a related limitation or difficulty of using patent data is that the 'propensity to patent' - and, hence, the correlation between R&D and patenting activity - varies significantly amongst technological fields and industries as well as over time. These variations can be due to different and changing patenting laws, patenting costs (compared to potential patent revenues) and the degree of 'R&D opportunities' in the surrounding scientific network (Schmitz, 2001, Popp, 2002). Therefore, because of these limitations, patent (or similar) data as an indicator of innovative activity have to be used with due care.

Another qualification to the work of Popp is offered by Schmitz (2001) who also uses patent data to estimate the effect of energy prices on energy-efficient innovations. In contrast to Popp, however, Schmitz found that energy prices had no significant positive impact on innovative activity as measured by patents. To some degree, this difference in outcome can be attributed to differences in data and methodologies used. More interestingly, however, is that Schmitz did find a significant positive relation between innovative activity and energy taxes (expressed as the ratio of taxes in energy prices). According to Schmitz, this result points to the importance of taxes in price signals as one might regard the tax ratio as an indicator of public concern about ecological problems related to energy consumption. Hence, following this interpretation, the tax ratio is a better indicator of real expectations than mere prices since price movements may be regarded as temporary, whereas energy taxes can normally be expected to be of a more perma-

[12] Interestingly, Popp (2003a) mentions a study on citations made to NASA patents, which concludes that aggregate citation patters represent knowledge spillovers.

nent nature. Therefore, perhaps, the most important result of Schmitz (2001) - and qualification of Popp (2002) - is that, if energy shows any price increases, then only long-term predictable ones have a significant impact on major innovations, which support a credible tax policy such as the 'eco-taxation' of energy use in several European countries.

Up to now, the studies considered above have all explored the link between innovative activity and variables such as energy prices or environmental policies, which are either directly or indirectly related to and comparable with climate policies. As mentioned in Section 1, the empirical literature on the evidence of induced technological change by climate policies as such is still extremely limited as these policies have only been introduced in Annex I countries over the past few years. A noticeable exception is the study of Christiansen (2001), who assesses the impact of Norwegian carbon taxes - the key instrument in Norway's climate policy - on technological innovation in the petroleum sector. The balance of evidence suggests that the imposition of carbon taxes has provided some incentive for innovation that has shifted upstream petroleum operations in a less emission-intensive direction. The pattern of technological change pertains mostly to small, incremental process innovations, cumulative improvements, and adaptations of technologies already available, such as technologies to reduce and eliminate flaring. In addition a few examples of more radical innovations encouraged by carbon taxation are mentioned by Christiansen (2001), notably the application of carbon capture and storage technologies in oil and gas production.

Induced diffusion

In the field of pollution abatement and energy efficiency, there are several empirical studies on the inducement effect of environmental policies or energy prices on the diffusion of 'green' technologies.[13] For instance, US studies on the reduction of SO_2 emissions or the elimination of lead in gasoline show that the introduction of a tradable permit system has provided a strong incentive for the diffusion and adoption of cost-effective technologies to deal with these environmental issues.

Other studies have found a positive effect of fuel price increases on the adoption of new fuel-saving technologies in the transport sector, the power-generating sector and the energy-intensive industrial sectors. A similar, although often less strong effect has been found in the residential sector with regard to the diffusion of energy-saving appliances and thermal insulation technologies. In general, the adoption of these residential technologies turns out to be more sensitive to the level or changes of the up-front installation costs than the level or changes of energy prices and other longer-term operational expenditures. This indicates that subsidies on installation costs may be more effective than 'equivalent' energy taxes in encouraging technology diffusion in the residential sector (Jaffe et al., 2002; see also Section 4.4 below).

In addition, there is a lot of empirical evidence on the positive inducement effect of market or price policies on the diffusion of green technologies, notably renewable energy technologies. For instance, turbines for generating wind power have been adopted widely over the past 15 years in countries such as Denmark, Germany and Spain owing to a favourable policy package, including 'eco-taxation' of fossil fuel-generated electricity and/or supportive measures for wind-generated electricity such as granting subsidies or relatively high feed-in tariffs (Sijm, 2002; Lako 2004).

On the other hand, studies that have explored the inducement effect of command-and-control instruments on technology diffusion have shown ambiguous results depending on the stringency of these instruments, including the differentiation of this stringency among old versus new sources of environmental pollution. In the US, some standards - for instance, on automobile fuel use - have been very effective, whereas others - for instance, on state building codes - have

[13] For a review of these studies see Grubb et al. (2002a) and, particularly, the publications of Jaffe et al. (2002, 2003 and 2004).

shown no discernable effect as they were hardly binding relative to existing standards of typical practice. In some cases, notably when pollution abatement regulations have been set more stringent for new sources than for existing ones, these regulations have even exerted a negative impact on the diffusion of new, green technologies by encouraging firms to postpone the retirement of older, dirtier installations (see Jaffe et al., 2002, 2003 and 2004 for a review of these studies).

At the international level, there are hardly any studies on diffusion of green technologies (let alone on the international diffusion of technologies induced by climate policies). A major exception is offered by Lanjouw and Mody (1996), who show that green technologies have indeed diffused from developed to developing countries in three ways, i.e. through (i) imports of technologies embodied in pollution abatement or energy saving equipments, (ii) imports of disembodied environmental technology, i.e. foreign patents registered and used in developing countries, and (iii) development of domestic patents geared towards adapting imported technology to local conditions.

In addition, a few other available studies have provided some examples of the international diffusion of green technologies, including (a) the development of more fuel efficient cars in Japan in response to the oil price shocks and, subsequently, the diffusion of these cars to foreign markets, (b) the diffusion of more fuel-efficient, steel-making technologies among developed and developing countries, and (c) the international diffusion of bio-energy and other renewable energy technologies, for instance wind turbines from Denmark to other countries, encouraged by the learning effects and resulting decreases in specific investment costs of these technologies owing to the expansion of the (domestic) installed capacity of these technologies (see Grubb et al., 1995 and 2002b, as well as the companion papers of the spillover project, notably Oikonomou et al., 2004; Annevelink et al., 2004, and Lako, 2004).

To conclude, there is ample empirical evidence on the inducement effect of policies and prices on the innovation and diffusion of 'green' technologies to support the hypothesis that (future, stringent) climate policy will indeed induce technological change. The available evidence, however, seems to be less ambiguous with regard to the induced diffusion of green technologies than to their induced innovation, notably of major, fundamental breakthroughs (compared to the evidence on a variety of minor, commercial applications of induced innovations). Moreover, the performance of induced technological change seems to depend not only on the choice (and stringency) of alternative policy instruments but also on a variety of other factors, such as the prevalence of market imperfections, which will be discussed further in the sections below.

4.3 Market imperfections and green technologies

Introduction

A fundamental aspect of environmental issues such as climate change is that when it comes to developing and diffusing technologies to address these issues, there are basically two mutually reinforcing sets of market imperfections at work, which make it very likely that the rate of investment in the development and diffusion of such technologies is less than would be socially optimal (Jaffe et al., 2004). The first set of market imperfections concerns the existence of so-called 'environmental externalities', while the second set refers to the prevalence of market failures and other, related factors that inhibit the socially optimal development and diffusion of technologies to address environmental issues such as climate change. While the present section will briefly outline these two sets of market imperfections, the subsequent section will discuss the policy implications of the prevalence of these imperfections for the optimal inducement of these green technologies.

Environmental externalities

An economic or social activity may have a harmful consequence on the environment, which is borne (at least in part) by a party or parties other than the party who controls this activity. In the field of environmental economics, such a consequence is usually denoted as a negative 'external effect' or 'externality'.[14]

For instance, a firm or car that pollutes the air without bearing the full consequences or costs of this negative impact on the environment causes an externality. As the firm or car owner does not have an economic incentive to minimize the 'external' costs of this pollution (by restricting or changing its underlying activity), the market - i.e. Adam Smith's 'invisible hand' - allows too much of it and, hence, does not operate to produce an outcome that is socially desirable. Therefore, such an environmental externality is an example of a so-called 'market failure' or 'market imperfection'.

At their core, all environmental policy interventions are designed to deal with the above-mentioned externality problem, either by internalising environmental costs so that polluters will make socially efficient decisions regarding their consumption of environmental inputs (for instance, by eco-taxing these inputs), or by imposing a level of environmental pollution that policy makers believe to be more socially efficient than that otherwise chosen by firms or car owners (for instance, by imposing an emission cap or pollution standard). A socially efficient environmental policy requires, firstly, the comparison of the marginal cost of reducing pollution with the marginal benefit of a cleaner environment and, subsequently, the abatement of this pollution as far as at its marginal cost is lower or equal to its marginal benefit (Jaffe et al., 2004).

Market imperfections regarding technological change

New, green technologies improve the terms of the trade-off between the marginal costs of pollution abatement and its social benefits. This means that not only a specific level of pollution abatement can be achieved at lower costs to society but also that it will be more efficient to enhance this level than would be efficient if pollution abatement were more expensive (Jaffe et al., 2004). On the other hand, it also implies that environmental policy interventions will have two effects: they reduce pollution by addressing the environmental externality problem explained above, while they also change the incentives to develop and adopt new technologies to reduce pollution by changing the environmental cost/benefit ratio. Hence a socially efficient environmental policy requires not only the weighing of the static costs and benefits of reducing pollution but also the consideration of the dynamic interaction between environmental policy and induced technological change.

Technological change, however, is not itself free, but costly as both innovation and diffusion/adoption of new technologies demand the investment of resources, for instance to conduct R&D and to purchase, adapt and learn about new technologies (compared to using available, cheaper but dirtier technologies). Therefore, a socially efficient technology policy requires, first of all, the comparison of the marginal cost of technological change with its marginal benefits and, subsequently, the promotion of technological change as far as its marginal cost is lower or equal to its marginal benefits.

This raises the question whether the market or 'invisible hand' will choose the optimal level of investment in the process of technological change (or whether technology policy interventions can, in principle, be justified on social efficiency grounds). It turns out that, independent of the prevalence of environmental externalities, both the innovation and diffusion of technology are characterised by a variety of market imperfections. More specifically, the most important mar-

[14] More generally, Jaffe et al. (2004) define an externality as 'an economically significant effect of an activity, the consequences of which are borne (at least in part) by a party or parties other than the party who controls the externality-producing activity'.

ket failures with regard to technological innovation include (Parry, 2001; Grubb and Ulph, 2002; and Jaffe et al., 2002, 2003 and 2004):

- *Knowledge externalities or spillover effects*. As explained in Section 2.2, this category of market imperfections refers to the fact that, due to the high public-good character of knowledge, a private firm may be unable to fully appropriate the social benefits of investments in R&D, leading to underinvestment in technological innovation by the private sector, relative to the social optimum. Hence, whereas a social or economic activity creates usually a negative environmental externality - of which the market allows too much - investments in R&D and technological innovation generally creates a positive externality, of which the invisible hand produces too little.
- *Capital market failure*. Investments in R&D are characterised by large risks and uncertainties due to the wide and specific variation of their expected returns (i.e. often low-profitability but high-value outcomes). In addition, the asset produced by the R&D investment process is specialised, sunk and intangible, so that it cannot be mortgaged or used as collateral. This combination of great uncertainty and intangible outcomes makes financing of R&D through capital market mechanisms more difficult than for traditional investment. The difficulty of securing financing for research from outside sources may lead to underinvestment in R&D, particularly for small firms that have less internally generated cash and/or less access to financial markets (Jaffe et al., 2003).
- *Rent-stealing or 'common-pool' effects.* This category refers to the problem that a firm may not take into account that its investments in R&D may reduce the potential rents of a patentable innovation of other firms investing in similar R&D. This problem is analogous to the over-exploitation of a fishery: individual fishermen do not take into account their effect on depleting the stock of fish and hence reducing the expected catch of other fishermen (Parry, 2001). The prevalence of this 'rent-stealing' or 'common-pool' effect may result in an over-investment in R&D. Overall, the empirical evidence suggests that the rent-stealing effect is dominated by the two other categories of market imperfections, notably by the positive spillover effect, leading to social rates of return to R&D that are substantially higher than the private rates of return (Griliches, 1992; Parry, 2001). Hence, in order to optimise social efficiency, there seems to be scope for policy interventions to encourage technological innovations (see Section 4.4 below).

In addition, there are some market imperfections with regard to the diffusion and adoption of new technologies. These imperfections are due to the following causes (Jaffe et al., 2002, 2003 and 2004):

- *Inadequate information.* Information plays a particularly important role in the diffusion and adoption of technologies. Firstly, information is a public good that may be expected in general to be underprovided by markets. Secondly, to the extent that the adoption of technology by some users is itself an important mode of information transfer to other parties, adoption creates a positive externality and is therefore likely to proceed at a socially sub optimal rate.
- *Agency problems.* Related to inadequate information are so-called agency problems that can inhibit the adoption of superior technology. An example of an external agency problem would be a landlord/tenant relationship, in which a tenant pays for utilities, but the landlord makes decisions regarding which applications to purchase.[15] Internal agency problems can arise in organisations where the individual or department responsible for equipment purchase or maintenance differs from the individual or department whose budget covers utility costs. Agency problems are probably also part of the basis for the hypothesis that energy-saving investments are ignored simply because energy is too small a fraction of overall costs to justify management attention and decision-making (Jaffe et al., 2003).

[15] For instance, a builder or landlord chooses the level of investment in energy efficiency in a building, but the energy bills are paid by a later purchaser or tenant. If the purchaser has incomplete information about the magnitude of the resulting energy savings, the builder or landlord may not be able to recover the cost of such investments, and hence might not undertake them (Jaffe et al., 2004).

- *Risk and uncertainty*. The expected returns of adopting new technologies are risky and uncertain. This uncertainty about future returns means that there is an 'option value' associated with postponing the adoption of new technology (Jaffe et al., 2002; Mulder, 2003). The prevalence of risks and uncertainties may also explain why purchasers of energy efficiency technologies appear to use relatively high discount rates in evaluating these technologies (which may further slow down their diffusion and adoption).
- *Capital market imperfections*. Adoption of new technologies with significant capital costs may be constrained by inadequate access to financing, notably for households and small firms. And in some countries, lack of foreign exchange or other important barriers may inhibit the adoption of embodied/disembodied technology from other countries.
- *Adoption externalities*. For a number of reasons, the cost or value of a new technology to one user may depend on how many other users have adopted the technology. In general, users will be better off the more people use the same technology. This benefit associated with the overall scale of technology adoption is sometimes referred to as 'dynamic increasing returns' (Jaffe et al., 2004). These returns can be generated by learning-by-using, learning-by-doing or network externalities. 'Learning-by-using' refers to the phenomena that an adopter of a new technology creates a positive externality for others, in the form of the generation of information about the existence, characteristics and the successfulness of the new technology. The supply-side counterpart, 'learning-by-doing', describes how production costs tend to fall as manufacturers gain production experience (see Chapter 6). If this learning spills over to benefit other manufacturers it can represent an additional adoption externality. Finally, 'network externalities' exist if a product is technologically more valuable to an individual user as other users adopt a compatible product (for example, telephone and computer networks). Altogether, the prevalence of adoption externalities and dynamic increasing returns with regard to the adoption of a particular technology or system may result in a 'lock-in' or 'path dependency' of such technology or system, meaning that once a particular standard has been chosen, the barriers of switching to another one may be prohibitively high (Jaffe et al., 2003). It should be noted, however, that increasing returns and technology lock-in do not necessarily imply market imperfections, leading to social inefficiencies. In cases where they may, the question becomes which policy interventions, if any, can reduce such inefficiencies (see Section 4.4 below).

The prevalence of market imperfections may explain certain characteristics of the diffusion of new technologies, which may be insightful for policy makers and analysts interested in understanding and optimising (induced) technological change. For instance, a major characteristic of the adoption process of new energy-saving technologies is that these technologies often diffuse slowly although they are efficient at current prices (the so-called 'energy efficiency paradox'). This paradox can be explained by the prevalence of market imperfections - inadequate information, uncertainties, agency problems, etc. - together with the incidence of adjustment costs or other factors. For instance, a major additional factor to explain the energy efficiency paradox is the so-called 'complementary effect' (Mulder, 2003; Mulder et al., 2003). This effect refers to the fact that different technologies to produce a similar product (e.g. electricity or steel) may not only differ with regard to their energy efficiency but also to other qualities such as differences in variable versus fixed cost structures, flexibility with respect to inputs (different technologies use different types of fuels or raw materials), or required managerial and organisational skills. Because of this variety in different qualities, it may be beneficial to use several (both old and new) technologies next to each other to produce a similar product. Hence, beside the incidence of market imperfections, this complementarity effect may offer an additional explanation for the energy efficiency paradox as many new technologies pass through a life cycle, in which they initially complement older technologies, and only subsequently (and often slowly) substitute for older technologies (Mulder et al., 2003).

This specific explanation of the slow diffusion of energy saving technologies leads to a more general qualification to the factors affecting the process of (induced) technological change in the field of energy/environmental policies. Besides the interaction between market imperfections and inducement factors - including (environmental) policies, (energy) prices, relative factor scarcities and market expectations - the process of technological change may be influenced by a variety of other factors such as the size of the market for new technologies, the available set of technological opportunities to be exploited, the role of technological networks and vested interests, or the achievement of other objectives besides profit or welfare maximisation (Criqui et al., 2000; Luiten, 2001). These factors have to be accounted for when considering the policy implications of the interaction between market imperfections and inducement factors for the process of technological change in addressing environmental issues such as controlling global warming (see Section 4.4 below as well as similar sections on policy implications in Chapters 5 and 6).

4.4 Policy issues

Based on the findings of the previous sections, some policy issues will be indicated briefly below, while some of these issues will be discussed further in Chapters 5 and 6.

A major finding of the sections above is that the available evidence on induced technological change by environmental policies and/or higher energy prices seems to support the hypothesis that (future, stringent) climate policy will encourage the innovation and diffusion of new technologies that will address the issue of controlling global warming in a more cost-effective way. Some qualifications, however, can be added to this general finding.

Firstly, the impact of climate policies on the promotion of emission abatement technologies will vary depending on the time period and type of technological change considered. For instance, in the short term this impact will most likely be higher on R&D investments in commercial applications and diffusion of minor, specific innovations that are already largely available ('lying on the shelf') than on general, major innovative breakthroughs (which may take a long-term set of incentives, including a supportive package of technological and climate policies).

Secondly, climate policy may not only induce technological change but, in turn, the innovation and diffusion of more cost-effective abatement technologies may affect the optimal target, timing and/or instrument choice of climate policy. For instance, while some instruments - compared to others - may be more efficient in controlling global warming in a dynamic than static sense, owing to this dynamic efficiency it may be beneficial to postpone abatement actions or to set a higher abatement target for a certain period.

Thirdly, although climate policy may induce abatement technologies that are more cost-effective, that does not necessarily imply that the costs of this policy are lower, depending on the definition of 'costs' and whether the abatement target is fixed or not. For instance, if the abatement target is based optimally on cost-benefit considerations, technological change may lead to a more stringent climate policy and, hence, to higher marginal and/or gross total abatement costs, whereas net costs - i.e. after subtracting social environmental benefits of abatement - will generally, be lower, depending on the slope of the marginal cost-benefit curves of emission abatement. But even if the abatement target is fixed, induced technological change is not necessarily welfare improving due to the potential adverse effects of climate policies on (i) the allocation of R&D resources to other types of technological change ('crowding-out effect') and (ii) the turnover of emission-intensive industries, which may reduce their R&D budgets and, hence, their future productivity (notably when R&D budgets are determined as a fixed percentage of output and hardly responsive to changes in climate policies). Therefore, although the available evidence points to substantial scope for induced technological change at the level of individual sectors or technologies, the implications of this finding for the macroeconomic cost of climate policy remains unclear (see Sue Wing, 2003, and other studies discussed in Chapter 5).

Fourthly, the fact that climate policy will induce technological change does not say anything about which (mix of) instruments will be more or less cost-effective to do so. Actually, climate policy may consist of a variety of instruments, usually distinguished between (i) 'market-based instruments' such as taxes, subsidies, tradable permits, and some types of information programmes, and (ii) 'command-and-control' regulations notably technology- or performance standard for production or end-use purposes. Although there seems to some (theoretical) evidence and consensus among several scientists - particularly economists - that, in general, market-based policy instruments are more efficient than command-and-control regulations (not only from a static but also a dynamic point of view), this consensus has been contended by other scientist. Moreover, there seems to be even less empirical evidence and consensus with regard to the dynamic efficiency of market-based instruments, including the 'ranking' of these instruments (i.e. which instrument is most efficient, second best, third best, etc.), or the optimal mix of climate policy instruments to achieve an abatement target most efficiently from both a static and dynamic point of view.[16]

A final, but perhaps most important qualification is that, while climate policy may induce technological change, the impact of climate policy alone will be far from optimal as the innovation and diffusion of green technologies is generally faced by two related sets of market imperfections (Grubb and Ulph, 2002; Golombek and Hoel (2003); Jaffe et al., 2004). While climate policy may stimulate new technology as a side effect of internalising the costs of the environmental externality (i.e. the greenhouse effect), it does not address explicitly the other set of market imperfections directly related to technological change (such as the incidence of spillover effects and adoption externalities). On the other hand, simply relying on the promotion of technological change by technology policy alone is not enough as there must be a long-term, predictable and credible incentive in place that encourages the process of technological change to occur actually (Popp, 2002 and 2004c; Schmitz, 2001). Moreover, as shown recently by Buchner and Carraro (2004), international technological cooperation – without any commitment to emissions control - may not lead to a sufficient abatement of greenhouse gas concentrations. Therefore, a balanced set of climate and technology policies is necessary to promote the innovation and diffusion of emission abatement technologies and, hence, to address the issue of global warming in an optimal way.

More specifically, in order to stimulate the innovation of new technologies, a government can use several R&D policy instruments of which the performance can vary widely, depending on the specific incidence and relative importance of market imperfections or other constraints to promote innovation. These instruments and their performance include:

- *Granting patents.* In theory, this instrument can deal effectively with the problem of imperfect appropriability of R&D by offering exclusive property rights to private innovators. In practice, however, the effectiveness of the patent system is often limited either because other firms can invent around the patent by developing their own imitations or because innovators prefer not to patent in order to avoid the disclosure of patent information to rival firms. On average, innovators appear to appropriate very roughly 50 percent of the full social benefit from new technologies (Griliches, 1992; Parry, 2001).[17]
- *Subsidising R&D ex ante,* through research tax credits or research contracts to private or (semi-) public institutions, or *awarding prizes ex post* for new technologies. If there were no uncertainties over the costs and benefits of R&D, the optimal amount of R&D could be induced by one of these instruments. In practice, however, there is usually a situation of asymmetric information as firms know more about the costs and benefits of their own R&D than the government. As a result, by using one of these instruments, the government may pay too much or too little and, hence, encourage R&D too much or too little.

  If asymmetric information is the most important market imperfection, a patent system can be preferable on efficiency grounds, while research contracts and prizes may be more efficient

[16] For a review of studies on the dynamic efficiency of instrument choice in the field of environmental policies, see Jaffe et al. (2002, 2003 and 2004), as well as Parry (2001), Popp (2003a and 2003b), Stavins (2002), Driessen (2003), and Philibert (2003).

[17] Another disadvantage of patents is that they may discourage the diffusion of new technologies, including the spillover effects to other countries.

if imperfect appropriability is a more important problem (Parry, 2001). Moreover, besides the problem of asymmetric information, other potential disadvantages of subsidizing R&D are (i) the danger of 'picking a winner' and becoming 'locked-in' an inefficient technology system, (ii) the use of scarce public resources, and (iii) the opportunity of technological spillovers to other countries (which requires international cooperation of national R&D support in other to reduce this effect).

- *Encouraging joint research ventures among firms*, for instance, by removing the threat of anti-trust prosecutions if firms openly collude over research strategies (rather than pricing strategies). To some extent, this would allow firms to internalise technology spillovers. However, joint research ventures may not be feasible when a large number of firms can benefit from new technologies (Parry, 2001; Grubb and Ulph, 2002).
- *Subsidizing education and training* of scientists and engineers in appropriate areas. This instrument can be particularly effective if the supply of appropriately trained scientists and engineers is relatively inelastic in the short run, thereby avoiding the danger that any increased expenditure on R&D in a given area will be at least partly consumed by an increase in wages rather than going to more research effort (Jaffe et al., 2003). Besides demanding scarce public resources, however, this instrument does not address the problem of imperfect appropriability or other imperfections in the R&D market.

To conclude, a variety of R&D policy instruments may be used to promote technological innovations cost-effectively. However, although the optimal mix of these instruments may depend on country- and technology-specific situations, unfortunately limited evidence is available to determine this policy mix in practice.

In addition, a government can use a variety of policy instruments to promote the diffusion and adoption of new technologies, including:

- *Providing information*, including technology demonstration and deployment. This instrument will be most appropriate to promote technologies that appear cost-effective, but are not yet widely used due to imperfect information. On the other hand, it will be hardly appropriate to deal with other market imperfections.
- *Setting command-and-control regulations.* If implemented at an appropriate level, setting technology- or performance standards for production or end-use purposes may be very effective to force the diffusion of particular technologies, if only by removing 'inferior' technologies from the market (Jaffe et al., 2004). However, if set too low, they may be hardly binding, whereas if set too stringent, they may become very expensive and inefficient (including the danger of 'carbon leakage' or other forms of plant closure and relocation).
- *Subsidizing the adoption of green technologies* (or taxing competing 'dirty' technologies). This instrument may be very appropriate to encourage the adoption of green technologies that at present are more expensive then competing 'dirty' technologies (or face up-front capital constraints), especially if these green technologies show major learning effects and resulting cost reductions to 'break-even' points within an acceptable time period. However, similar to subsidizing R&D (as discussed above), it raises some problems, notably (i) the danger of 'picking a winner' and becoming 'locked-in' a certain technology system, (ii) the scarcity of public resources, including the problem of a low efficiency of public expenditures to subsidize the purchase of a new technology since customers who would have purchased the technology even in the absence of the subsidy still receive it, and (iii) the problem that learning effects and the resulting cost reductions of deploying new technologies may spill over to other countries even if they have not contributed to finance the support of adopting and deploying new technologies. The first problem of 'picking a winner' can be reduced by means of a 'technology neutral' policy of portfolio diversification that supports a wide cluster of related technologies, but such a policy may be either very expensive or hardly effective, while sacrificing the increasing returns by focusing on a small number of technologies.

  The second 'fiscal' problem can be resolved by taxing dirty technologies (rather than subsiding green technologies), but such a policy may harm industrial competitiveness or social equity and, hence, it may be politically hard to accept. Finally, the 'spillover problem' equity and, hence, it may be politically hard to accept. Finally, the 'spillover problem' may be reduced by international coordination of supporting the diffusion of green technologies, but such a policy may be time-consuming and hard to realize in practice.

- *Purchasing new technologies by the government itself.* As the government (and, more generally, the public sector as a whole) is a very large landlord, vehicle operator and user of many other kinds of equipment, its decision to purchase certain technologies for its own use could have a significant effect on the rate of diffusion of that technology through the creation of niche markets and the achievement of any associated benefits of dynamic increasing returns (Jaffe et al., 2004). However, as purchasing new technologies at high market prices - compared to those of existing technologies - is similar to subsidizing the adoption of these technologies, it raises similar problems as discussed above.

The discussion above on the technology policy instruments to encourage the innovation and diffusion of technologies to control global warming raises the question whether a specific technology policy in the field of climate change can be justified once the external costs of the greenhouse effect have been fully internalised by climate policy alone, e.g. by means of emissions trading or taxing, thereby meeting the overall abatement target. In theory, such a specific technology policy is hard to justify as the greenhouse externality will be fully addressed by climate policy alone (with a 'spillover' or 'side-effect' on technological change) and, hence, only general technology policies and instruments can be justified to deal with the other, remaining set of potential market imperfections in the field of technological change. In practice, however, some specific technology policies or instruments in the field of climate change may still be justified if this field is characterized by the incidence of specific market imperfections (compared to other fields of technology interests, for instance the prevalence of specific forms of imperfect information or specific uncertainties due to the long-term, international character of controlling global warming). In addition, specific technology policies in the field of climate change may be justified - or even necessary - due to a lack of public resources, which raises the need to set priorities with regard to the ex ante subsidization of technological innovation and diffusion. Moreover, some specific technologies - for instance solar PV or wind power - may be encouraged for a variety of other reasons besides controlling global warming. Hence, even if the abatement target is fully met by climate policy alone, the innovation and diffusion of these technologies may still be continued, justified by other policy considerations.

Some of the policy issues outlined above, including their policy implications, will be discussed further in Chapter 5 and 6 below, dealing with an assessment of induced technological change in top-down and bottom-up approaches of climate policy modelling, respectively.

5. INDUCED TECHNOLOGICAL CHANGE AND SPILLOVERS IN TOP-DOWN APPROACHES OF CLIMATE POLICY MODELING

5.1 Introduction

As outlined in Chapter 2, top-down models are general macroeconomic models that analyse the economy - including the energy system - in highly aggregated terms, with hardly any detail on energy or mitigation technologies at the sector level. Such models are particularly suitable for analysing macroeconomic effects of climate policies, including the interactions and feedback effects at the intersectoral, (inter)national, regional or global level. Over the past decade, induced technological change has been incorporated in these models, particularly by linking the accumulation of knowledge and experience to changes in climate policy.

This chapter will assess the performance of some major top-down models with regard to endogenising technological change and the implications for CO_2 abatement policies. Section 5.2 will first of all review the performance of individual studies using such models. Subsequently, Section 5.3 will compare and evaluate the performance of these studies. Finally, Section 5.4 will discuss some lessons and implications following from the assessment in this chapter.

5.2 A review of top-down studies

Goulder and Mathai (2000)

A comprehensive and pioneering study in the field of analysing the impact of induced technological change (ITC) on climate policy is the work of Goulder and Mathai (2000). Their study employs analytical and numerical simulation models to explore the implications of ITC for the optimal design of CO_2 abatement policies, notably for the design of optimal abatement and carbon tax profiles (i.e. the timing and level of carbon taxes and abatement). Goulder and Mathai derive these profiles under different model specifications for the channels through which knowledge is accumulated (both R&D and LBD) and under two different policy optimisation criteria: the *cost-effectiveness* criterion of obtaining by a specified date and thereafter maintaining, at minimum cost, a given target for the atmospheric CO_2 concentration; and the *benefit-cost* criterion, under which they also choose the optimal concentration target, thus obtaining the benefits from avoided climate damages net of abatement costs.[18]

In order to design the optimal CO_2 abatement policies, Goulder and Mathai develop a simple (partial) 'cost-function' model in which a central planner decides on the optimal carbon tax and abatement patterns to minimise the discounted costs of abatement and knowledge investment subject to a carbon concentration constraint (Weyant and Olavson, 1999). ITC is incorporated in the abatement cost function (C) that depends on the level of abatement (A) and the stock of knowledge (H). As noted, the accumulation of knowledge may be either R&D of LBD based. In the first case, the evolution of the knowledge stock is a function of R&D investments, whereas in the second case it is a function of the level of abatement. While knowledge accumulation is costly in the R&D-based case, it is free in the LBD-based representation (Goulder and Mathai, 2000; Löschel, 2002).

The analytical model results of Goulder and Mathai reveal that the presence of ITC generally implies a lower time profile of optimal carbon taxes, i.e. compared to a situation with no ITC, the level of carbon taxation over a certain time path to meet the abatement target is generally

[18] This is equivalent to minimizing the sum of abatement costs and CO_2-related damages to the environment (Goulder and Mathai, 2000).

lower.[19] The impact of ITC on the optimal abatement path varies, depending on the channel of knowledge accumulation. When knowledge is gained through R&D investments, ITC makes it preferable to shift some abatement from the present to the future. The reason is that ITC lowers the costs of future abatement relative to current abatement, making it more cost-effective to place more emphasis on future abatement. However, when the channel for knowledge accumulation is LBD, the timing of abatement is analytically ambiguous. On the one hand, ITC makes future abatement less costly but, on the other hand, there is an added value effect to current abatement because such abatement contributes to LBD and helps reduce the costs of future abatement. Which of these two opposing effects dominates, depends on the specification (and underlying assumption) of the knowledge accumulation function (Goulder and Mathai, 2000; IPCC, 2001). If the LBD effect is strong enough, initial abatement rises (which in fact happens in most of the numerical simulations presented by Goulder and Mathai).

When the government (the central planner) employs the benefit-cost policy criterion, the presence of ITC justifies greater overall (cumulative) abatement than would be warranted in its absence. This does not imply, however, that ITC encourages more abatement in every period. When knowledge accumulation results from R&D expenditures, the presence of ITC implies a reduction of near-term abatement, despite the overall increase in the scale of abatement over time.

The illustrative numerical simulations of Goulder and Mathai reinforce the qualitative predictions of their analytical model. The quantitative impact of ITC depends critically on whether the government is adopting the cost-effectiveness criterion or the benefit-cost criterion. This impact on overall abatement costs and optimal carbon taxes can be quite large in a cost-effectiveness setting but typically is much smaller under a benefit-cost criterion. This weak effect on the tax rate in the benefit-cost setting reflects the relatively trivial impact of ITC on optimal CO_2 concentrations, associated marginal damages, and (hence) the optimal tax rate (Goulder and Mathai, 2000). As for the optimal abatement path, the impact of ITC on the timing of abatement is very weak, but the effect on cumulative abatement over time (applicable in the benefit-cost case) can be very large, particularly when knowledge is accumulated via LBD. Although the work of Goulder and Mathai offers some valuable contributions and useful insights with regard to the analysis of the ITC impact on climate policy, it suffers from some limitations. As indicated by sensitivity analyses, the outcomes of their analytical and numerical simulation models depend highly on the specification, the parameterisation and the underlying assumptions of some critical functions such as the abatement cost function, the CO_2 concentration damage function and the knowledge accumulation function. Goulder and Mathai assume that these model functions are perfectly known and that knowledge accumulation and technological change are deterministic processes. Actually, however, these functions and processes are highly uncertain (which affects the policy outcomes of ITC). Moreover, the empirical database for the parameterisation and calibration of these model functions is still very weak.

Another major limitation of the model study of Goulder and Mathai concerns the assumed presence of a central planner, i.e. a single agent who actually represents a single source (a firm, a sector or a region) of CO_2 emissions, abatement, knowledge accumulation and technological change. As a result, this type of model studies sidesteps the possibility of technological spillovers and related issues such as the problem of R&D appropriability and lack of R&D investment incentives.[20] Similarly, as the model of Goulder and Mathai examines only a sole policy

[19] However, under the benefit-cost criterion, this result depends on the assumption of a convex damage function in the atmospheric CO_2 concentration (which Goulder and Mathai think most reasonable). If this function is assumed to be concave, the opposite result could be true in a benefit-cost setting.

[20] Goulder and Mathai acknowledge that they disregard the market failure associated with knowledge spillovers, i.e. the inability of firms to appropriate the full social returns on their investments in knowledge (Goulder and Mathai, 2000, page 4, note 6). Nevertheless, on page 29 of their paper they discuss the sensitivity of a variable that governs the intertemporal knowledge spillovers. This latter term refers to the question whether knowledge accumulation today makes future accumulation easier ('standing-on-shoulders') or more difficult ('fished-out' pool). However, these are not real knowledge spillovers in the sense of an externality, i.e. the appropriability problem, as discussed in Section 2.2.

instrument available to the central planner (i.e. a tax on CO_2 emissions), it does not explore the potential of other, additional instruments such as a R&D subsidy, a technological 'command-and-control' standard or an optimal policy mix of these instruments.

Finally, in the model of Goulder and Mathai, ITC comes in addition to (not instead of) autonomous technological change. This means that the ITC scenario is a more technology optimistic scenario than the scenario without ITC. It would have been interesting to also explore the impact of *replacing* autonomous technological change with ITC (see Rosendahl, 2002, as discussed below).

Goulder and Schneider (1999)

In this study, Goulder and Schneider (1999) investigate the significance of ITC for the attractiveness of CO_2 abatement policies. More specifically, they explore the impact of carbon abatement policies on R&D expenditures and resulting ITC across different industries as well as the implications of this ITC for the total GDP costs of these policies. When analysing these implications, Goulder and Schneider made a distinction between *the costs of a given abatement target* (with a flexible carbon tax rate) and *the costs of a given carbon tax rate* (with a flexible abatement level). In addition, they made a distinction between *gross social costs* (i.e. the social costs of carbon abatement without considering the environmental gains) and *net social benefits* (i.e. the environmental benefits of carbon abatement minus gross social costs). Moreover, they analyse these costs in both the presence and absence of knowledge spillovers and other inefficiencies in the R&D market.

In order to analyse these cost implications, Goulder and Schneider construct a dynamic general equilibrium model in which abatement policies affect R&D investment of private firms and consequent changes in knowledge accumulation, technological innovations and input requirements across different industries. Notably, the model distinguishes between fossil-based and alternative fuel-based industries, and energy-intensive materials and 'other' materials industries. For each representative firm in these industries, R&D investments result in knowledge accumulation, which generates productivity-enhancing technologies and, hence, reduces the requirements for intermediate inputs, including conventional and alternative energy fuels, energy-intensive and other materials, as well as other inputs such as capital or labour. Knowledge accumulation is costly and only partly appropriable. Intersectoral spillovers are represented in the model through the accumulation of knowledge capital enjoyed by all firms in a specific industry. Although the model has been primarily developed to gain qualitative, analytical insights in the cost implications of ITC for abatement policies, it has been extended by some numerical simulations - based on data from US economic activities in 1995 - in order to explore these implications more closely.

The overall finding of Goulder and Schneider (1999) is that *'ITC generally makes climate policies more attractive'*. In their study, however, the cost implications of ITC diverge significantly, depending on the different cases distinguished, namely the distinction between (i) the costs of a given carbon tax versus the costs of a given abatement target, (ii) the gross costs versus the net benefits of carbon abatement, and (iii) the abatement costs in the absence versus the presence of inefficiencies in the R&D market. More specifically, assuming no distortions in the R&D market, the main findings of Goulder and Schneider are:

- For a given carbon tax, the gross abatement costs in terms of GDP losses are higher in the presence of ITC. This is the consequence of the twin assumption that knowledge accumulation through R&D investments is costly (i.e. such investments have an opportunity cost) and that the R&D market is in equilibrium (i.e. no distortions): the rate of return on R&D is equal across sectors and equals the rate of return in other sectors (Azar and Dowlatabadi, 1999; Löschel, 2002). Although a carbon tax stimulates R&D in the low- or free-carbon energy industry - leading to cheaper abatement technologies and higher sectoral output - it tends to discourage R&D in other industries. Overall, the carbon tax results in a fall in the aggregate levels of R&D and GDP (relative to the baseline of no ITC). Hence, ITC studies that ignore these substitution or 'crowding-out' effects in the R&D market are likely to understate the gross GDP costs from a carbon tax.

- For a given carbon tax, the net benefits of abatement are larger in the presence of ITC, even though - as noted above - the gross costs are raised as well. Since a carbon tax induces cheaper abatement technologies, a higher optimal level of abatement can be achieved, resulting in an increase of environmental benefits. Goulder and Schneider show that the additional benefits of the additional abatement outweigh the higher social costs. Overall, for a given carbon tax, net benefits of abatement are higher with ITC (compared to no ITC). Hence, ITC studies that ignore these environmental benefits are likely to overstate the net GDP costs from a carbon tax.
- For a given abatement target, the required carbon tax and, hence, the gross cost are lower in the presence of ITC. Unfortunately, however, for this case Goulder and Schneider do not indicate the cost implications of potential 'crowding-out' effects in the R&D market (or of potential inefficiencies in this market, as discussed below).

Finally, Goulder and Schneider show that the costs implications of ITC depend on the prevalence of inefficiencies in R&D markets prior to the introduction of CO_2 policies. These inefficiencies result from a mismatch between the external benefits of knowledge spillovers from R&D and the value of subsidies to R&D, reflected in differences between the private and social (opportunity) costs of R&D. For instance, in case of relatively high spillovers but no subsidies to R&D in the conventional energy industry, prior to imposing a carbon tax, the marginal social value of R&D is relatively higher in that industry than in others. Hence, in this case, the opportunity cost of reallocating R&D towards other industries by imposing a carbon tax is especially high.[21]

The results of Goulder and Schneider turn out to be quite sensitive to the parameterisation of their model, notably the substitution elasticities of their knowledge accumulation and production functions. In sum, whenever parameters are changed to make stock of knowledge more important as a productive input, cheaper to acquire, or more easily substitutable which other factors, GDP costs of a given carbon tax rise and the costs of reaching given abatement targets fall (Goulder and Schneider, 1999).

A major strength of the model of Goulder and Schneider is the distinction between different industries, which allows the model to begin to address the importance of heterogeneity of firms and investment incentives (Weyant and Olavson, 1999). Another strength is that the model covers explicitly intrasectoral (but no international) knowledge spillovers, and that the study offers some major qualitative insights in the cost implications of ITC for CO_2 abatement policies. The study, however, does not explore the implications of the existence of knowledge spillovers for CO_2 abatement and emission levels, while adequate quantitative estimates of the impact of ITC on the performance of climate policies are largely missing due to a lack of empirical data. Moreover, despite the long-term character of the analyses (covering 60-80 years), the model is deterministic - firms are assumed to have perfect foresight - and does not allow for uncertainty in the markets for ITC and carbon abatement.[22]

Another limitation of the study of Goulder and Schneider is that it is only focused on R&D-based ITC and ignores learning-by-doing (LBD). However, as acknowledged by Goulder and Schneider, a carbon tax may encourage LBD-based ITC related to the production of alternative (low or free carbon) fuels. On the other hand, the tax leads also to a reduction in output (and, hence, in cumulative output or 'experience') in other industries. This implies that in these other industries, the rate of technological change from LBD is lower than otherwise would be the case. Hence, climate policies that promote LBD in some industries also reduce the rate of LBD

[21] For a discussion of the cost implications of similar and other cases of inefficiencies in R&D markets, see Goulder and Schneider (1999). Unfortunately, however, Goulder and Schneider hardly analyse the implications of spillovers (or other R&D inefficiencies) for the performance of climate policies.

[22] For a discussion of other limitations of the study by Goulder and Schneider (1999) and a comparison with similar studies in the field of ITC and climate policy, see Weyant and Olavson (1999); Kverndokk et al. (2001); Sue Wing (2003), Gerlagh (2003); Gerlagh and Van der Zwaan (2003) and Gerlagh et al. (2004).

in other industries. However, as recognised by Goulder and Schneider, industries most harmed by a carbon tax - namely, the conventional energy industries - tend to be mature industries where LBD effects could be fairly small.

Nordhaus (2002)

In order to analyse the impact of induced innovations on the performance of climate policies, Nordhaus (2002) incorporates R&D-based ITC in an updated version of his globally aggregated DICE model, called R&DICE.[23] In the basic neoclassical DICE model, carbon intensity is affected by *substitution* of capital and labour for carbon energy, i.e. an increase in the price of carbon energy relative to other inputs induces users to purchase more fuel-efficient equipment or employ less energy-intensive products and services. In the R&DICE model, on the contrary, carbon intensity is affected by *induced technological change*, i.e. an increase in the price of carbon energy will induce firms to invest in R&D in order to develop new processes and products that are less carbon intensive. Nordhaus assumes that there is an initial rate of improvement in carbon energy-efficiency, or a rate of reduction in the elasticity of output with respect to energy carbon inputs. ITC is incorporated in the model by letting this rate of energy-efficiency improvement vary in proportion to the additional R&D investments in the energy sector. Hence, the mechanism of carbon abatement is through either energy-efficiency improving R&D (in R&DICE) or factor substitution of capital and labour for energy inputs (in DICE). By comparing the results of these two models, Nordhaus is able to compare the impact of ITC versus factor substitution in carbon abatement.

The primary conclusion of Nordhaus (2002) is that ITC is likely to be a less powerful factor in influencing the performance of climate policies than substitution of energy by capital and labour. Some other major findings and conclusions of this study include:

- The reduction in carbon intensity in the ITC case is quite modest in the early decades. The reduction in emissions from ITC is about 6 percent over the first five decades and about 12 percent after a century. At the beginning, the reduction in emissions from substitution is substantially larger than the reduction from ITC. The 'cross-over point', at which ITC becomes more important in reducing emissions than factor substitution, does not come until about 2230 (although the exact timing is sensitive to the model specification).
- The optimal carbon taxes for both the ITC and substitution cases are virtually identical as there is so little impact on the path of climate change.
- The benefits of positive welfare implications of ITC policies are a fraction (about 40 percent) compared to those of substitution policies. This result, however, depends highly on the assumption that the benefits from additional R&D investments in the energy sector (including spillovers) are fully offset by less R&D investments in other sectors.

According to Nordhaus (2002), the primary reason for the small impact of ITC on the overall path of climate change is that R&D investments are too small to make a difference unless the social returns to these investments are much larger than the already supernormal returns applied in the analysis. R&D expenditures are about 2 percent of output in the energy sector, while conventional investments are close to 30 percent of output. Even with supernormal returns, the small fraction devoted to R&D is unlikely to outweigh other investments.

Another, perhaps more important explanation for the outcomes of Nordhaus' study is its limited specification of ITC. The driving force for R&D investments and technological innovations is not so much emission abatement but rather energy conservation (i.e. improvements in energy efficiency). In fact, only departures from the assumed path of energy efficiency improvements are endogenised in the model, as there is only one energy input available characterised by a

[23] DICE (Dynamic Integrated model of Climate and the Economy) is an integrated assessment model developed by Nordhaus to analyse the economics of global warming. An updated, eight-region version of this model is RICE-99 (Regional Integrated model of Climate and the Economy). For a brief description of these models see Nordhaus and Boyer (1999) and Nordhaus (2002).

fixed (high) emission factor. Hence, the opportunity of developing and using alternative, low-carbon fuels is omitted. A richer specification of ITC opportunities would definitely enhance the modelling and data complications of Nordhaus' study but may result in a more significant impact of ITC on the performance of controlling climate change.

In addition, other limitations of Nordhaus (2002) are that it uses a highly aggregated (global) model, it assumes full crowding out of R&D, and it does not explicitly explore the implications of technological spillovers, for instance at the interregional level (although the study implicitly acknowledges the existence of sectoral spillovers by assuming that the social rates of return in R&D investments are far larger than the private rates of return).[24]

Buonanno et al.

The implications of ITC for climate policy have been a major topic for a group of scientists related to the Italian research institute Fondazione Eni Enrico Mattei (FEEM; see, for instance, Buonanno et al., 2000 and 2003; Galeotti et al., 2002 and 2003; Buchner et al., 2003; and Carraro, 2003). In order to explore these implications, they have developed a top-down model called FEEM-RICE.[25] This model is an extended version of Nordhaus' model RICE, the regionally disaggregated version of his DICE model (see above).

Compared to Nordhaus' RICE, which includes only exogenous technological change, FEEM-RICE is characterised by the extension of two factors. The first extension concerns the introduction of *endogenous* technological change (ETC), affecting the overall productivity of capital and labour at the firm level. This is done by adding a stock of knowledge in each production function and by relating this stock to R&D investments of profit-maximising firms. Secondly *induced* technological change (ITC) is introduced by allowing the stock of knowledge to affect also the emission-output ratio. Hence, more knowledge through profit-motivating R&D investments will help firms to increase their overall productivity (ETC) and to reduce their negative impact on the environment (ITC).[26] Therefore, in contrast to Nordhaus, who assumes that energy R&D fully crowds out other R&D, Buonanno et al. assume that policy-induced R&D enhances both environmental ITC and overall factor productivity (i.e. no crowding out).

In addition to these general factors, the FEEM-RICE model has usually been extended by specific factors depending on the application of the model to address specific issues. Examples of some major extensions concern:

- *Technological spillovers*. In order to account for the international spillovers of disembodied technological change, a stock of world knowledge is introduced in both the production function and the emission-output ration equation of FEEM-RICE (Buonanno et al., 2003; Buchner et al., 2003; Carraro, 2003).
- *Emissions trading*. In order to explore the potential impact of the Kyoto mechanisms, the opportunity of emissions trading has been introduced in the model by adding equations including regional emission targets and the net demand for emissions permits (Buonanno et al., 2000; and Galeotti et al., 2002 and 2003).

[24] For comments on Nordhaus (2002) and a comparison with other studies see Weyant and Olavson (1999); Goulder and Schneider (1999); Goulder and Mathai (2000); Gerlagh (2003); Gerlagh and Van der Zwaan (2003) and Zon and Yetkiner (2003).

[25] This model is also often called ETC-RICE or ITC-RICE in order to indicate two sub-versions that account for the difference made by the FEEM authors between endogenous and induced technological change (see main text). For a detailed explanation of the model, see Buonanno et al. (2000) and 2003; Galeotti et al. (2003); Buchner et al. (2003) and Carraro (2003).

[26] As outlined in Section 2.3, this distinction in FEEM-RICE between ETC versus ITC as the (overall) rate and the (specific) direction of technological change diverts from the more general definition of these concepts in which they are highly synonymous, except that the term ETC is mostly used in a modelling context.

- *Learning-by-doing*. In addition to R&D-based ITC in the basic version of FEEM-RICE, Galeotti et al. (2003) have added LBD-driven ITC to the model by assuming that learning - i.e. free knowledge accumulation - occurs as a side effect of the accumulation of new physical capital (in the production function) and by allowing for the emission-output ratio to depend upon this accumulated capacity. As a result, they have been able to compare the impact of R&D- versus LBD-based ITC, but they did not explore hybrid forms of knowledge formation, i.e. situations in which R&D and LBD are jointly present.

FEEM-RICE is basically a single sector top-down model disaggregated to 6-8 regions in the world. Within each region, a central planner maximises the utility or net present value of per capita consumption by optimally setting the value of four strategic variables (investments, R&D, abatement effort and demand for permits), subject to individual resource and capital constraints and the climate module for a given emission abatement strategy of all global players.[27]

The FEEM-RICE model has been used to explore the implications of ITC (and international spillovers) for a variety of short- and long-term issues, such as (i) the compliance costs of the Kyoto protocol, (ii) the effects on equity and efficiency of different degrees of restrictions ('ceilings') on emissions trading, or (iii) the consequences of the US withdrawal from the Kyoto protocol on the price of emission permits and abatement costs. Some of the main findings and conclusions of studies employing this model include:

a) Direct abatement costs generally decrease when ITC is allowed for regardless the emissions trading regime (Buonanno et al., 2003). However, abatement and R&D are substitutes in general, and R&D efforts are increased when environmental technical change is endogenised. Hence, according to Buonanno et al. (2003), the impact on total abatement costs, which include R&D costs, cannot be predicted a priori. In their simulations total costs of complying with the Kyoto protocol are higher with ITC.
b) Technological spillovers reduce the incentive to carry out R&D, thus increasing the price of a permit (Buonanno et al., 2003). As for the impact on total costs, the reduced R&D effort is offset by a greater increase in abatement costs. According to Buonanno et al. (2003), 'though a priori unclear, in our simulations costs turn out to be often higher when spillovers are present'.
c) When the environmental technology is endogenous, caps on CO_2 emissions prompt R&D investments, and trigger the 'engine of growth'. Kyoto mechanisms such as JI, CDM or emissions trading help in reducing the overall abatement costs, but actually slowdown the R&D accumulation of the most polluting high-income regions, while they spur Russia and Eastern European countries to strategically over-invest in R&D in order to provide the markets with a huge amount of permits, so performing large economic gains from emissions trading (Galeotti et al., 2002).
d) Restrictions (or 'ceiling') on the use of the Kyoto mechanisms are likely to increase R&D expenditures (relative to GNP) in OECD countries, i.e. countries which are going to buy permits, but they reduce them in the Former Soviet Union (FSU), China and other developing countries - the seller countries - where the greatest stimulus to carry out abatement R&D comes from the possibility to trade emission permits without restrictions. But even if the presence of ceilings stimulates R&D-based ITC, the overall impact on abatement costs and economic growth appears to be detrimental. According to Buonanno et al. (2000), the explanation is related to the relative importance of cost effects and innovation effects. In their model, the cost reduction achieved through unrestricted emissions trading seems to stimulate growth more than the increase of R&D-driven innovations achieved through trade ceilings. Moreover, in the presence of ITC, the Kyoto mechanisms increase equity, while the highest equity levels are achieved without ceilings, both in the short and in the long run. The main reason is that developing countries receive important transfers from developed countries through the trading of permits, and this tends to reduce income inequalities. In addition,

[27] As there is no international trade in the model, regions are interdependent through climate variables (Buonanno et al., 2000; and Buchner et al., 2003)

the introduction of R&D-based ITC offers developing countries the opportunity to use R&D strategically also to increase their sale of permits (Buonanno et al., 2000). Hence, these findings do not support proposals to impose restrictions on emissions trading for efficiency or equity reasons in the presence of R&D-driven ITC.

e) In the presence of ITC, the US withdrawal from the Kyoto protocol, by reducing the demand for permits and their price, lowers the incentives to undertake energy-saving R&D. As a consequence, emissions increase in other Annex I countries and feedback on the demand and supply of permits of these countries. As a result, the fall of the price of a permit after the US withdrawal is much smaller than the one identified in studies ignoring the impact of R&D-based ITC. Moreover, the presence of spillovers provides an additional contribution to this feedback effect. The US defection induces a strong reduction of domestic energy-saving R&D investments. This reduction spills over to other countries by reducing the world stock of knowledge, thus increasing the emission-output ratio resulting in an increase of the price of a permit. This feedback effect also partially offsets the initial fall of the permit price induced by the US defection. Hence, the final equilibrium price of a permit is higher than the one usually estimated in studies ignoring induced technological innovations and spillovers (Buchner et al., 2003 and Carraro, 2003).

A major strength of FEEM-RICE is that it is a regionally disaggregated model, accounting for ITC, international spillovers and/or (ceilings on) emissions trading. On the other hand, major limitations of this model concern its deterministic character - i.e. no uncertainty in ITC and environmental markets - and its restricted specification of the ITC function (i.e. modelling only one form of technology and not accounting for potential crowding-out effects).

Gerlagh and Van der Zwaan

An alternative top-down model to explore the role of ITC in controlling climate change has been developed by Gerlagh and Van der Zwaan. This macroeconomic model, called DEMETER, is a computable general equilibrium (CGE) model for the integrated assessment of global warming and induced technological change, characterised by the following features (Gerlagh et al., 2004; and Van der Zwaan and Gerlagh, 2002):[28]

- The model includes two competing energy technologies, one of which has net zero CO_2 emissions. This feature allows for emission reductions to be achieved by a transition towards a carbon-free technology (the energy transition option) in addition to those resulting from the substitution of energy by capital and labour (the energy saving option).
- It distinguishes old from new capital in such a way that substitution possibilities between production factors only apply to new capital stocks. This so-called 'vintage' or 'putty-clay' approach allows for different short and long-term substitution elasticities and can, in particular, describe a slow diffusion process.
- The model includes learning-by-doing through the use of learning curves. In this way, a transition towards alternative technologies leads to lower energy production costs for these technologies, and thereby enhances their market opportunities and accelerates the transition and learning process. This feature of the top-down model DEMETER is based on bottom-up models such as MESSAGE or MARKAL (see Chapter 6).[29]
- It includes niche markets, in which new technologies can relatively easily spread - even though costs are initially high - before these technologies are fully matured.

Gerlagh and Van der Zwaan have used DEMETER to analyse the impact of a stringent climate policy aimed at limiting the global average atmospheric temperature increase to two degrees Celsius in the presence of ITC on a variety of issues, including (i) the impact on abatement

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[28] DEMETER stands for the DE-carbonisation Model with Endogenous Technologies for Emission Reductions. For a description and specification of this model see Gerlagh and Van der Zwaan (2003); Gerlagh et al. (2004); Van der Zwaan et al. (2002) and Van der Zwaan and Gerlagh (2003).

[29] In recent (preliminary) working papers, Gerlagh (2003) has analysed the impact of R&D driven ITC, while Gerlagh and Lise (2003) have explored the implications of both R&D- and LBD-based ITC.

costs, energy use, gross world product and aggregate consumption (Gerlagh and Van der Zwaan, 2003), (ii) the impact on the optimal timing of CO_2 abatement, carbon tax levels and non-carbon subsidies (Van der Zwaan et al., 2002), or (iii) the impact of carbon taxes on emission levels when niche markets exist for new carbon-free technologies that experience LBD effects (Gerlagh et al., 2004).

In general, Gerlagh and Van der Zwaan find that the inclusion of ITC in their model simulations has a large impact on the issues mentioned above (compared to scenarios excluding ITC as well as to other, similar ITC studies discussed in this chapter). More specifically, the main findings and conclusions of studies conducted by means of DEMETER concern:

a) Including ITC implies substantially earlier emission reductions to meet the stringent climate policy constraint, compared to efficient reduction paths calculated with models that do not include ITC. This can be achieved by imposing a carbon tax on fossil-fuel technologies and/or subsidising investments in non-carbon energy technologies such as wind or solar energy (Van der Zwaan et al., 2002).
b) During the entire simulation period, i.e. the 21st century, the optimal path of carbon taxes to meet the stringent CO_2 emissions constraint is substantially lower, compared to the case without ITC and niche markets (Gerlagh et al., 2004).
c) Over time, the induced transition towards a progressively cheaper non-carbon energy technology positively affects aggregate consumption and decreases the costs of the stringent climate policy. Overall cumulative abatement costs amount to only 0.06 percent of the net value of aggregate consumption, i.e. substantially lower than the estimated costs in case of no ITC or the costs estimated by similar studies (Gerlagh and Van der Zwaan, 2003).
d) The numerical results on the costs and timing of emissions reductions appear most sensitive to the parameters that characterise (i) the learning curve of the non-carbon energy source, and (iii) the substitution possibilities between this energy source and the fossil-fuel energy source. Compared to the central parameters of the model simulations, a relatively low (high) learning rate for the non-fossil energy technology increases (decreases) abatement costs, and implies a delay (acceleration) of a transition towards the non-carbon energy source and, hence a delay (acceleration) of emissions reductions. Similarly, a relatively low (high) elasticity of substitution between the two energy sources decreases (increases) the estimated abatement costs and decreases (increases) the potential of a transition policy towards the non-carbon energy source (Van der Zwaan and Gerlagh, 2002). Since limited empirical evidence is available to determine the proper value of the parameters, notably of the substitution elasticity, the empirical correctness of the numerical results generated by DEMETER is uncertain.

Strong points of the ITC studies conducted by Gerlagh and Van der Zwaan are the inclusion of niche markets, LBD-curves and two energy technologies in their top-down model and the extensive sensitivity analysis of their numerical results (which provides an indication of the uncertainty of these results). On the other hand, a major limitation of their approach concerns its highly aggregated, global character, which excludes the analysis of policy actions and effects at the sectoral or regional level (including international spillover effects). Moreover, as indicated above, the numerical results of the model simulations depend highly on the underlying assumptions and choices for the various parameters, for which there are only limited empirical data, notably with regard to the substitution of fossil-fuel energy sources for non-carbon energy technologies.

Popp (2004c)
In order to account for ITC in the energy sector, Popp (2004c) uses a modified version of Nordhaus' DICE model, called ENTICE (for ENdogenous Technological change). In this model ITC is channelled through R&D accumulations of knowledge that relates to improvements in energy efficiency. A distinguishing feature of ENTICE is that several R&D parameters have been calibrated by means of existing empirical studies on induced innovation in the energy sector. For instance, based on data of R&D expenditures by the US industries from 1972-1998, Popp as-

sumes a partial crowding out effect of energy R&D on other R&D of 50 percent. This is a key difference compared to Nordhaus, who assumes that there is a fixed amount of total R&D spending in the economy (100 percent crowding out) and Buonanno et al., who assume that policy-induced R&D accumulations enhance both environmental ITC and overall factor productivity (no crowding out).[30]

In first instance, Popp applies ENTICE to estimate the welfare costs of an optimal carbon tax policy in the presence of ITC.[31] Ignoring ITC overstates these costs by 8.3 percent. However, cost-savings - rather than increased environmental benefits - appear to drive the welfare gains, as the effect of ITC on emissions and mean global temperature is small. In fact, after a century the temperature is just 0.04 percent lower when the role of ITC is included.

Subsequently, however, Popp applies ENTICE predominantly to explore the sensitivity of his policy simulations to key assumptions on R&D parameters used to calibrate the model. The main findings and conclusions of this exercise with regard to the major R&D parameters include:

a) *The opportunity costs of R&D.* Completely removing crowding out of R&D increases the welfare gain from ITC in the optimal policy simulation from 8.3 percent to 43.6 percent. Similarly, simulations with complete crowding out lead to just 1.8 percent gain from ITC. These results suggest that assumptions about the opportunity costs of R&D are a key factor in explaining differences in outcomes among ITC models.
b) *Deviation between the private and social rate of return.* The base model sets the social rate of return on R&D to be four times greater than the private rate. Simulations removing this 'spillover gap' - for instance by granting government R&D subsidies to correct this market failure - suggest that the returns on such subsidies could be quite significant as the welfare gain from ITC for the optimal policy improves from 8.3 percent to 14 percent. Hence, internalising spillovers enhances welfare when ITC is present.
c) *Decay rate.* Many models of R&D assume that the stock of accumulated knowledge decays over time, due to obsolescence. The base model assumes no such decay. Not surprisingly, however, adding decay decreases the welfare gains from ITC, although the effect is not large.
d) *Return to energy R&D.* In the base model, it is assumed that each dollar of energy R&D leads to \$4 of energy savings. As expected, reducing potential energy savings in half reduces the potential welfare gains by about one-half.
e) *Elasticity of R&D.* The base model assumes that the elasticity of energy R&D with respect to energy prices, including carbon taxes, is 0.35 in 2005 and declines over time. Doubling this elasticity in the optimal policy case does not have a large impact on welfare, partly because some of the gains are cancelled by potential crowding out.

Although the results of the policy simulations and sensitivity analyses generated by ENTICE are quite insightful from a qualitative point of view, quantitatively they have to be treated with some prudence as the model is faced by some limitations. Firstly, by modelling the world as a single region, the ENTICE model simplifies policy dramatically as it ignores regional variation in innovative effects and technology diffusion. Secondly, the ENTICE model only includes innovation designed to improve energy efficiency but does not consider alternative, emission-free energy technologies. Finally, the ENTICE model does not include uncertainty (Popp, 2004c).

[30] A recently updated version of ENTICE - called ÉNTICE-BR – includes a backstop technology (see Popp, 2004a).
[31] In an optimal climate policy, the marginal costs of carbon abatement are equal to the marginal environmental benefits of reduced carbon emissions. In addition, Popp (2004c) estimates the welfare costs of a more stringent policy, i.e. restriction global emissions to 1995 levels.

Rosendahl (2002)

In his paper, Rosendahl (2002) investigates the implications of ITC for a cost-effective climate policy, if at least some of the induced learning effects are external to the emission source (i.e. if some of these effects spill over from a firm, industry or region to another firm, industry or region). In order to deal with this issue, the model structure used in this paper is based on Goulder and Mathai (2000). The main extensions are the inclusion of different emission sources and the presence of knowledge spillover effects.

Rosendahl assumes that ITC occurs through current abatement efforts, i.e. through learning-by-doing (LBD). By using simple numerical simulations, he investigates to what degree a cost-effective climate policy differs from a free, global quota market approach, assuming external LBD effects in the industrialised (Annex I) region that spill over to the developing world.

The results indicate that optimal carbon taxes may be significantly higher in the Annex I region than in the non-Annex I region. Hence, a cost-effective environmental policy does not imply equal taxes across emission sources, if external LBD effects exist (Rosendahl, 2002). Moreover, the Annex I share of global abatement may be higher in a cost-effective scenario than in a free quota market. In addition, global cost savings may be significant, at least if the international spillover effects are substantial.

As outlined above, Goulder and Mathai (2000) showed that introducing internal LBD effects implies that the optimal carbon tax is reduced. The simulations by Rosendahl on the contrary, indicate that with complete spillover effects in Annex I, the optimal carbon tax in this region is increased for the next 70 years. Even with partial spillover effects, the optimal tax level is increased for some decades. Hence, the impact of introducing LBD on optimal taxes depends crucially on the degree of spillover effects (Rosendahl, 2002).

Finally, Rosendahl shows that a fully flexible implementation of the Kyoto protocol may be far from cost-effective, as potential spillover effects of technological change in the industrialised world are not internalised in a free quota market. Some abatement in the non-Annex I region is optimal but the abatement share of Annex I should be significantly higher than what the free quota market generates. With diffusion of technology implemented into Rosendahl's model, the full flexibility regime is actually more costly than a regime with no abatement in non-Annex I, but full flexibility within Annex I. This is in contrast with the study by Buonanno et al. (2000), who conclude that emissions trade restrictions are not cost-effective even with endogenous R&D investments. However, they incorporate neither spillover effects nor diffusion in their model, which are essential in the study of Rosendahl (2002).

Bollen (2004)

In his thesis, Bollen (2004) analyses the impact of R&D spillovers on the production and income effects of carbon abatement. To estimate this impact, he uses Worldscan, i.e. a multi-regional, multi-sectoral and applied general equilibrium model, which can simulate long-term growth and trade in the world economy. ITC is included in the model by assuming that at the sectoral level R&D expenditures grow at an equal rate with production, implying that the R&D intensities stay constant over time. Accumulation of the knowledge stocks leads to enhancing the overall factor productivity of a sector and thus to lowering its unit costs of production. Moreover, accumulation of knowledge in one sector spills over to other sectors (sectoral spillovers), as well as to similar or even other sectors in other regions (regional or international spillovers).

In addition to different technology cases, i.e. with or without ITC/spillovers, Bollen (2004) distinguishes between different policy regimes, notably with or without full emissions trading, assuming that Annex I countries meet their Kyoto targets for the year 2010 (and kept constant beyond 2010).[32] Some of his major results include:

- The inclusion of induced technological change and spillovers magnifies the production and income effects of climate policies such as the implementation of the Kyoto protocol. Although these effects are generally negative (notably for Annex I regions such as Western Europe), they might be (slightly) positive for some sectors/regions (due to carbon leakage or other shifts in sectoral/regional production incurred by the Kyoto protocol). The magnification impacts due to ITC/spillovers are usually not huge, but significant (and tend to rise over time, because of the accumulation of the knowledge stock). In Western Europe, for instance, the presence of ITC/spillovers magnifies the income losses of the Kyoto protocol by some 5 percent in the year 2015 (in the case of no emissions trading) compared to 12 percent for the US (if they would participate in the Kyoto protocol).[33]
- The sectoral spillovers constitute the largest factor for the R&D magnification effect on the income losses of carbon tax. This directly follows from the values of the estimated parameters that link the knowledge stock to technological change. The second important factor is the accumulation of the own knowledge stock related to own R&D investments, and least important are the international spillovers.
- Emissions trading alleviates the magnification effect. Hence, the existence of ITC and spillovers offers an additional incentive to high cost countries to argue for efficient solutions of the climate problem.

The results of Bollen (2004) depend highly on some key assumptions of his model. Firstly, the model assumes that R&D intensities are fixed, implying that R&D expenditures are solely affected by production changes. However, if it is assumed that R&D investments are based on the optimal allocation of resources in order to maximise the profits of the firm, these investments may respond positively to climate policies such as higher energy prices or carbon taxes even if these policies lead to a decline in sectoral production. As a result, the presence of ITC and spillovers may not magnify but rather reduce the negative income and production effects of abatement policies.

Similarly, R&D expenditures on energy saving technologies are not included in the analysis, while R&D intensities are set to zero for energy sectors, because for these sectors data are hardly available or almost zero. Therefore, this study does not deal with energy efficiency improvements due to ITC. However, as noted, the presence of ITC with regard to energy saving technologies may reduce the negative production and income effects of CO_2 abatement.

Sue Wing (2003)

In his paper, Sue Wing (2003) investigates the potential for a carbon tax to induce R&D, and for the consequent induced technological change (ITC) to lower the macroeconomic costs of abating CO_2 emissions. To deal with these issues, he uses a multi-sector computable general equilibrium (CGE) model of the U.S. economy. This model numerically simulates the effects of a carbon tax on the level and composition of aggregate R&D investments, the rate of accumulation of an aggregate stock of knowledge, and the inter-sectoral reallocation and intra-sectoral substitution of the knowledge services derived there from.

[32] In addition, Bollen (2004) distinguishes two other policy cases, including and excluding the participation of the US in the Kyoto protocol (both with and without full emissions trading).

[33] In some sectors/regions, the production or income effects of the Kyoto protocol are positive and, hence, these positive effects are magnified by the inclusion of ITC (due to the assumed fixed relationship between sectoral production and R&D investments), but often partly nullified by the (negative) spillover effects from other sectors/regions.

A key feature of the model is that knowledge services are a homogeneous 'super factor' that substitute for all other commodities and factors - notably energy - in the economy. Hence, knowledge can move among sectors in response to relative price changes and differences in knowledge-energy substitution possibilities. ITC, therefore, results from two separate effects:

- An '*accumulation effect'* in which price-induced changes in R&D investments alter the rate of accumulation of the stock of knowledge and the aggregate endowment of knowledge services.
- A '*substitution effect*' in which price changes alter the allocation of the endowment of knowledge services among production sectors so as to reduce the costs of abatement. For instance, due to a carbon tax or an emission constraint, knowledge is reallocated away from output-constrained fossil-fuel sectors toward input-constrained sectors where its marginal product is greater due to its ability to substitute for limited energy inputs.

Contrary to other studies - such as Goulder and Mathai (2000) or Nordhaus (2002) - Sue Wing (2003) finds that the impact of ITC is large, positive and dominated by the above-mentioned substitution effect, which mitigates most of the welfare or 'deadweight' losses due to the imposition of a carbon tax. More specifically, the losses in income and output incurred by the carbon tax are slightly *exacerbated* by the accumulation effects as these losses *reduce* aggregate R&D investments, causing a slowing of knowledge accumulation and the rate of technological progress. At the same time, however, the relative price effects of the carbon tax induce substantial intra-sectoral substitution and inter-sectoral reallocation of knowledge inputs, enabling the economy to adjust in a more elastic manner. The consequent increase in gross input substitutability on the supply side of the economy ends up mitigating the bulk of the deadweight losses due to the tax. As the (positive) substitution effect far outweighs the (negative) accumulation effect, the overall impact of ITC on reducing the macroeconomic costs of CO_2 abatement is positive and large (Sue Wing, 2003).[34]

The outcomes of Sue Wing's model simulations depend highly on the underlying assumptions and parametrical estimates affecting the accumulation and substitution effects of a carbon tax on ITC. If, as applies to Sue Wing's study, the (direct) price effect of a carbon tax on R&D investments is less important than its (indirect) income or output effect, the accumulation effect of the carbon tax on ITC is, on balance, negative. However, depending on the parameterisation of the model, if the price effect turns out to be more important that the income effect (and the crowding-out effect of R&D is less than 1), a carbon tax may result in a positive impact on aggregate R&D investment and the accumulation of knowledge stocks (thereby further enhancing the positive substitution effect of a carbon tax on ITC).

On the other hand, it may be questioned whether knowledge services are a homogeneous 'super factor' that substitute for all other commodities and factors in the economy (as assumed by Sue Wing). If knowledge turns out to be rather sector or commodity specific, its substitutability across the economy will be significantly restricted, thereby reducing the substitution effect of a carbon tax on ITC accordingly.

Kverndokk et al. (2001 and 2003)

In their papers, Kverndokk et al. (2001 and 2003) investigate the implications of the presence of ITC and spillovers for the optimal mixture and timing of two policy instruments, i.e. taxing carbon emissions and subsidising carbon-reducing technologies. To address this issue, they use a simple dynamic general equilibrium model, including learning-by-doing with regard to the carbon-reducing technologies.

[34] Sue Wing adds that when the revenues of a carbon tax are recycled in order to subsidise R&D (or remove preexiting taxes on R&D), the sign of the accumulation effect becomes also positive. This issue, however, belongs more to the ongoing debate on the potential 'double dividend' of a carbon tax rather that its impact on ITC.

Although quite simple, the analysis of Kverndokk et al. produces some insightful results. Firstly, if the existing/new energy technologies do not create any positive spillovers, a subsidy on these technologies can not be justified and, hence, the optimal policy to deal with a negative environmental externality such as CO_2 emissions is just a carbon tax.

Secondly, a mixture of a carbon tax and a technology subsidy can be justified in the combined case of a negative externality (i.e. climate change) and a positive externality, i.e. the presence of spillovers from technological innovations to control climate change. Kverndokk et al. (2003) show that in such a case a technology subsidy, combined with an optimal carbon tax, has a big impact on improving the cost efficiency of CO_2 abatement. In addition, they show that the greatest return to learning-by-doing and, hence, the highest optimal subsidy occurs when a technology is first being applied. Moreover, compared to a uniform subsidy over time, the costs of CO_2 abatement are significantly reduced under an optimal subsidy policy, i.e. a subsidy which is highest when a technology is first being applied but declines steadily thereafter (Kverndokk et al. 2003).

However, in an earlier paper (Kverndokk et al. 2001), they found that even if there are positive spillovers from existing, carbon-reducing technologies, the granting of subsidies to these technologies may be questioned. Subsidising existing technologies may discriminate against new, less polluting innovations when spillovers from these innovations are not rewarded, resulting in a situation of 'locking-in' existing technologies and 'crowding- or locking-out' better performing innovations. This argument is strengthened in rigid policy schemes where it is hard to remove old subsidies, as well as to introduce new ones. Hence, in a second best world with uncertainty or incomplete information about nascent technologies or with rigid policy schemes, subsidising an existing technology amounts to 'picking a winner' (Kverndokk et al. 2001).

5.3 Major differences in performance of ITC top-down studies

The previous section has shown a wide divergence of the major results of top-down modelling studies on the impact of induced technological change and spillovers on the performance of climate policy (for a comparative summary, see Table 5.1 on pages 46-47). Whereas this impact is generally large and positive in some studies, it is relatively low or even negative in others. More specifically, with regard to the impact of ITC/spillovers on various performance indicators of climate policy, the major differences of the studies reviewed in the previous section include:

- Abatement costs. The impact of ITC/spillovers on total abatement cost *savings* varies from 'large and positive' (Sue Wing, 2000), 'substantial' (Gerlagh and Van der Zwaan) or 'significant' (Popp, 2004c) to 'relatively low' (Nordhaus, 2002) or even 'negative' in terms of magnifying the income losses of carbon taxation policies (Bollen, 2004). In Goulder and Mathai (2000), this impact varies from 'large' under their cost-effectiveness (CE) scenario to 'small' under their benefit-cost (BC) scenario.
- Carbon emissions. As most of the studies reviewed apply a CE scenario (with a given abatement target for a certain period), they have not analysed the impact of ITC on emission reductions or on similar environmental indicators such as carbon concentration ratios or changes in global warming or sea rise level. For those studies applying a BC scenario, this impact has varied from 'high' (Goulder and Schneider, 1999; Van der Zwaan et al. 2002) to 'low' or 'small' (Nordhaus, 2002; Popp, 2004c).
- Optimal timing of carbon abatement. When the channel for knowledge accumulation and ITC is learning-by-doing (LBD), it results in substantially earlier emission reductions in Van der Zwaan et al. (2002), whereas the optimal timing of carbon abatement is ambiguous in Goulder and Mathai (2000). However, if the LBD effect is strong enough, initial abatement rises (which in fact happens in most of the numerical simulations presented by Goulder and Mathai). On the other hand, when the channel for knowledge accumulation and ITC is R&D, it is preferable to shift some abatement from the present to the future (Goulder and Mathai, 2000).

- Optimal pattern of carbon taxation. Compared to a situation with no ITC, the presence of ITC implies that the level of carbon taxation over a certain time path to meet a certain abatement target is substantially lower in some studies (Goulder and Mathai, 2000; Van der Zwaan et al., 2002), whereas it is hardly changed for a long-term period in Nordhaus (2002) or even significantly higher in the Annex I region for the next 70 years (Rosendahl, 2002).
- Efficiency effects of emissions trading. In a situation with ITC/spillovers, restrictions on emissions trading between Annex I and non-Annex I regions appear to be inefficient in Rosendahl (2002), whereas they are not cost-effective in Buonanno et al. (2000).

Explaining the differences in modelling outcomes

In general, the above-mentioned differences in the major results of top-down modelling studies on the impact of ITC/spillovers on the performance of climate policies can be explained by the methodology and data used. More specifically, besides differences in ITC channel (R&D versus LBD) and in policy optimisation criteria (CE versus BC), these differences in outcomes can be mainly attributed to the following factors:

- The specification of some critical model functions, particularly the ITC or knowledge accumulation functions. A key factor in explaining differences in outcomes among ITC top-down models concerns the assumption about the 'crowding-out effect' or 'opportunity cost' of R&D. For instance, Popp (2004c) assumes a partial crowding out effect of energy R&D on other R&D of 50 percent compared to, on the one hand, Nordhaus (2002) who assumes that there is a fixed amount of total R&D spending in the economy (full crowding out) and, on the other hand, Buonanno et al. (2002 and 2003) who assume that policy-induced R&D accumulations enhance both overall factor productivity and environmental ITC (no crowding out). Moreover, whereas some studies assume that (all) R&D investments are either fully or partially fixed to output production (and, hence, may decline if output declines due to carbon taxation), other studies assume that (carbon-saving) R&D expenditures are responsive to price changes (and, hence, may increase due to carbon taxation). Finally, whereas some models are characterized by a poor or limited specification of their ITC function (with a limited set of energy/carbon-saving opportunities), other models have specified a broader ITC function covering a more extensive set of energy/carbon-saving technologies.
- Model parameterisation and data use. Due to a lack of reliable R&D/ITC data, the studies reviewed have used a variety of data assumptions, sources, indicators and numerical simulations in order to estimate the parameters and outcomes of their models. These outcomes are often quite sensitive to a few critical parameters such as the learning rate of new technologies (when LBD is the ITC channel), the elasticity of energy/carbon R&D investment with respect to energy/carbon prices (when R&D is the ITC channel), or the substitution rates between different energy sources or between energy and other production factors.
- The role of spillovers. The role and significance of spillover effects as an explanatory factor of the model outcome varies widely in the studies reviewed in Section 5.2. Out of the ten sets of studies reviewed, three sets - i.e. those of Goulder and Mathai; Gerlagh and Van der Zwaan, and Sue Wing - do not consider spillovers at all (see Table 5.1). Two studies - i.e. Nordhaus (2002) and Popp (2004c) - do not analyse spillovers explicitly in their models, although their presence is assumed implicitly (as it is assumed that the social rate of return on R&D is higher than its private rate, implying that abatement costs depend on technology policies addressing this market imperfection). In addition, two other studies - i.e. Goulder and Schneider (1999), and Kverndokk et al. (2001) - include sectoral spillovers in their (national) models, but these spillovers play a minor role in their analysis. Finally, two studies - Buonanno et al. (2002) and Rosendahl (2002) - include regional spillovers in their (global) model, while only one study - Bollen (2004) - covers both sectoral and regional spillovers in its WorldScan model. In the study of Buonanno et al. (2003), however, spillovers play a minor, less decisive role, whereas they play a major role in Rosendahl (2002) and Bollen (2004). In Rosendahl (2002), the prevalence of regional spillovers is crucial for the impact of LBD-channelled ITC on the efficiency of emissions trading and the optimal pattern of carbon taxation in the Annex-I region. For instance, Rosendahl shows that owing to the

presence of LBD and regional spillovers, restrictions of emissions trading may be efficient, in contrast to Buonanno et al. (2000), who do not include regional spillover and conclude that ceilings on emissions trading are inefficient. In addition, Rosendahl shows that owing to the incidence of LBD and regional spillovers, the optional carbon tax in the Annex-I region is increased for the next 70 years, in contrast to Goulder and Mathai (2000) who do not cover regional spillovers and conclude that due to the presence of LBD the optimal carbon tax is reduce over the whole time frame considered. Finally, as discussed in Section 5.2, Bollen (2004) finds that the presence of sectoral (or intra-industry) spillovers constitutes the largest factor for the R&D magnification effect on the income losses due to carbon taxation, while the second important factor is the direct effect on the own sectoral knowledge stock, and least important is the international spillover effect (i.e. almost zero)35. Hence, including the role of spillovers in ITC modelling studies may have a significant impact on the outcomes of these studies.

- The role of other modelling characteristics. In addition to the factors mentioned above, the differences in outcomes of the studies reviewed can be attributed to some other modelling characteristics varying among these studies such as (i) the scope or level of aggregation (sectoral, national, regional, global), (ii) the number and type of policy instruments covered, (iii) the stringency of the abatement target, (iv) the policy optimisation criterion used (i.e. a 'benefit-cost' or cost-effectiveness' framework) or (v) the time horizon considered (i.e. the impact of ITC is often more significant in the long term).

Evaluation of ITC top-down studies: strengths and weaknesses

As indicated above, top-down studies with regard to the impact of ITC/spillovers on the performance of climate policy show a wide diversity in outcomes, methodologies, models and data used. Over the past decade, these studies have made substantial progress in analysing this impact and, all together, they have offered some valuable contributions and useful insights to understanding this impact and its implications. The major strength of these top-down studies is that they are usually well-embedded in sound micro- and macroeconomic analysis, accounting for the economic behaviour of producers and consumers, the performance of markets and their imperfections, and the effects of policy interventions on this behaviour and performance, including the feedback effects at the macroeconomic level. Nevertheless, in their present state, these top-down modelling studies still suffer from some weaknesses and limitations, including:

- These studies often have a highly aggregated, abstract character with little technological detail and a poor, limited specification of knowledge accumulation, induced technological change and spillover effects.
- The empirical database for the parameterisation, calibration and estimation of the ITC model functions is still very weak.
- These studies are often very deterministic and hardly account for the major uncertainties of long-term policy issues in the field of global warming and technological change.
- These studies usually analyse only the impact of one ITC channel - mostly R&D, and occasionally LBD - but not both channels simultaneously within one model. Moreover, these studies generally explore only one sole policy instrument - mostly a carbon tax, and occasionally emissions trading or a technology subsidy - but not a mixture of climate and technology policies within one model. Therefore, it is usually hard to assess the full impact of ITC - including both R&D and LBD - on policy performance or to analyse and design a policy mix to optimise this impact. Finally, these studies usually analyse the impact of policies and ITC from a carbon abatement efficiency point of view but hardly from other socio-political considerations.

[35] A possible explanation for the major role of the intra-industry spillovers compared to the negligible role of the 'foreign' spillovers may be that the level of regional aggregation is high in the WorldScan model and, hence, the variable intra-industry spillovers picks up what other, less aggregated studies might measure as foreign spillovers.

5.4 Major lessons and implications

Despite the substantial progress made over the past decade, due to the present limitations of the ITC top-down studies and the diversity of their model outcomes, it is hard to draw firm lessons and implications from these studies. Nevertheless, a major lesson from these studies seems to be that even if climate policy induces technological change at the level of individual sectors or technologies, it does not imply that the social costs of such a policy will decline by necessity. There are two reasons for this (Sue Wing, 2003). The first reason concerns the opportunity cost or 'crowding out effect' of R&D expenditures, implying that the policy-induced response of carbon-saving innovations may result in reductions in other types of innovations, with adverse effects on aggregate knowledge accumulation and future productivity. The second reason is that climate policy may have a negative impact on output production and, hence, on R&D expenditures tied to this production, thereby further lowering future productivity (Goulder and Schneider, 1999; Sue Wing, 2003; Popp, 2004c; and Bollen, 2004). Hence, ITC studies that ignore these potential effects in the R&D market are likely to underestimate the gross social costs from climate policy. A major policy implication might be that, in order to reduce the potential crowding out effect of climate policy on R&D expenditures, this policy could be accompanied by other, technology or education policies to improve the supply of R&D facilities and well-trained scientists and engineers.

Another lesson is that, when analysing or generating ITC, not only its impact on gross social costs should be considered but also its potential environmental benefits. Since climate policy may induce cheaper abatement technologies, a higher optimal level of abatement can be achieved, resulting in an increase of environmental benefits. These benefits may even outweigh potential higher social costs of such a policy (Goulder and Schneider, 1999). Hence, ITC studies that ignore these environmental benefits are likely to overstate the net social costs from climate policy.

A final implication of the present state of ITC top-down studies is that further research is necessary in order to draw more firm policy lessons and implications. The major suggestions for further additional research include (i) improving the empirical database for ITC top-down modelling studies, (ii) improving the specification of the ITC model functions, for instance by broadening or diversifying the set of energy/carbon-saving technologies covered by these functions, (iii) including both ITC channels simultaneously in top-down analyses, and expanding or diversifying the number of policy instruments in these analyses, (iv) accounting for uncertainties in the field of global warming and technological change, and last but not least (v) disaggregating top-down modelling studies, including the analysis of spillover effects and diffusion of technologies at the (intra)sectoral and (inter)national level.

Table 5.1 *Overview of top-down modelling approaches on the impact of induced technological change and spillovers on climate policy performance*

Study	Model	ITC channel	Spillovers	Policy instrument	Focus of analysis	Major results (impact of ITC)	Comments
Goulder and Mathai (2000)	Partial cost-function model with central planner	R&D LBD	No	Carbon tax	Optimal carbon tax profile Optimal abatement profile	Lower time profile of optimal carbon taxes Impact on optimal abatement varies depending on ITC channel Impact on overall costs and cumulative abatement varies, but may be quite large	Deterministic One instrument High aggregation Weak database
Goulder and Schneider (1999)	General equilibrium multi-sectoral model	R&D	Yes (sectoral)	Carbon tax	Abatement costs and benefits	Gross costs increase due to R&D crowding-out effect Net benefits decrease	Lack of empirical calibration Focus on U.S. Full 'crowding out' effect
Nordhaus (2002)	R&DICE (global IAM, Top-down, neoclassical)	R&D	Implicit (social > private rate of return)	Carbon tax	Factor substitution versus ITC Carbon intensity Optimal carbon tax	ITC impact is lower than substitution impact and quite modest in early decades	Deterministic Full 'crowding out' of R&D High aggregation (global, one sector)
Buonanno et al (various)[a]	FEEM-RICE (6-8 regions, single sector) Top-down	R&D (and occasionally LBD)	Yes	Rate of carbon control Emissions Trading (plus ceilings)	Compliance costs of Kyoto protocol Impact of ET (+ restrictions)	Direct abatement costs are lower, but total costs are higher ET ceilings have adverse effects on equity and efficiency	Includes international spillovers No crowding-out effect
Gerlagh and Van der Zwaan (various)[b]	DEMETER One-sector Two technologies	LBD	No	Carbon tax	Optimal tax profile Optimal abatement profile Abatement costs	Costs are significantly lower Transition to carbon-free energy Lower tax profile Early abatement	Results are sensitive to elasticity of substitution between technologies as well as to the learning rate on non-carbon energy
Study	Model	ITC channel	Spillovers	Policy instrument	Focus of analysis	Major results (impact of ITC)	Comments
Popp (2004c)	ENTICE (based on Nordhaus' DICE)	R&D	Implicit	Carbon tax	Welfare costs Sensitivity analysis of R&D parameters	Impact on cost is significant Impact on emissions and global temperature is small	Partial crowding out effect
Rosendahl (2002)	Builds on Goulder and Mathai (2000)	LBD	Yes (industrial and regional)	Carbon tax Emissions trading	Optimal carbon tax (or permit price) over time in two regions Optimal ET + restrictions	ET restrictions are cost-effective Optimal carbon tax in Annex I region is increased with external spillovers	Outcomes are sensitive to learning rate, discount rate and slope of abatement curve
Kverndokk et al. (2001 and 2003)	Applied Computable General Equilibrium (CGE) model for small open economy	LBD	Yes (sectoral)	Carbon tax Technology Subsidy	Optimal timing and mixture of policy instruments Welfare effects of technology subsidies	Innovation subsidy is more important in the short term than a carbon tax Innovation subsidy may lead to 'picking a winner' and 'lock in'	
Sue Wing (2003)	Multi-sector CGE (U.S.)	R&D	No	Carbon tax	Macroeconomic costs Allocation of R&D resources	ITC impact is positive and large in reducing social costs	Outcome is due to the substitution effect of homogenous knowledge factor
Bollen (2004)	WorldScan (12 regions, 12 sectors)	R&D	Yes (sectoral, regional)	Carbon tax (+ recycling)	Income and production losses	ITC magnifies income losses	Sectoral R&D intensities stay constant overtime

a) See, for instance, Buonanno et al. (2000 and 2003); Galeotti et al. (2002 and 2003); Buchner et al. (2003); and Carraro, (2003).
b) See, for instance, Gerlagh and Van der Zwaan (2003); Gerlagh et al. (2003); Van der Zwaan et al. (2002) and Van der Zwaan and Gerlagh (2003).

6. INDUCED TECHNOLOGICAL CHANGE AND SPILLOVERS IN BOTTOM-UP APPROACHES OF CLIMATE POLICY MODELING

6.1 Introduction

As outlined in Chapter 2, bottom-up energy system models are usually characterised by a detailed analysis of energy technologies, including information on the costs and other performance characteristics of these technologies such as the energy efficiency or GHG emissions per unit input or output. Since the mid-1990s, technological change has been endogenised in some of these models by means of so-called learning curves that relate the costs of specific technologies to the accumulation of knowledge and experience during the innovation and diffusion stages of these technologies.

This chapter will assess the performance of some major bottom-up energy system models with regard to endogenising technological change and the implications for CO_2 abatement policies. Section 6.2 will first of all review briefly some methodological issues, while section 6.3 will discuss some results of major bottom-up models of endogenous technological change. Subsequently, Section 6.4 will give an example of the potential impact of a specific learning technology, namely carbon capture and sequestration, while Section 6.5 will discuss the impact of induced technological change in the presence of emissions trading and global technological spillovers. Next, Section 6.6 will compare a bottom-up approach on the analysis of international technological spillovers with the approach conducted by Grubb et al. (2002b) as discussed in Chapter 3. Thereafter, Section 6.7 will compare and evaluate the performance of the bottom-up studies reviewed in the present chapter. Finally, Section 6.8 will discuss some lessons and implications following from the assessment in this chapter.

6.2 Some methodological issues

Learning curves

Learning or experience curves describe how the specific investment costs of a given technology are reduced through one or more factors representing the accumulation of knowledge and experience related to the R&D, production and use of that technology. These factors are the cumulative installed capacity of a certain technology in the so-called one-factor learning curve (1FLC), as well as the cumulative R&D expenditures or knowledge stock with regard to that technology in the two-factor learning curve (2FLC).[36] A typical one-factor learning curve can be expressed simply as:

$$SC_t = a \times CC_t^{-b}$$

Where:

SC_t	Specific cost in period t
CC_t	Cumulative capacity in period t
a	Initial specific cost at unit cumulative capacity (t=0)
b	Learning index

[36] For a more extensive discussion of one-factor and two-factor learning curves, see Seebregts et al. (1999 and 2000), Kouvaritakis et al. (2000a and 2000b), Bahn and Kypreos (2003), Barreto and Kypreos (2004a), de Feber et al. (2003), Miketa and Schrattenholzer (2004), and Turton and Barreto (2004).

The *learning index* b can be used to calculate the *progress ratio* (PR = 2^{-b}) or its complementary *learning rate* (LR = 1–PR = $1–2^{-b}$), i.e. the rate at which the investment cost of a technology declines each time its cumulative capacity doubles. For instance, a progress ratio of 0.8 (or a learning rate of 0.2) means that the investment cost, per unit of a newly installed technology (e.g. a wind turbine) decreases by 20 percent each time its cumulative installed capacity is doubled.

A major shortcoming of a one-factor learning curve is that it does not adequately account for the variety of factors explaining cost reductions of technological innovations - notably the role of R&D - and, hence that it does not offer adequate, relevant insights and implications for policy makers. Therefore, some studies have developed a two-factor learning curve, where cumulative capacity and cumulative R&D (or 'knowledge stock') are used to represent market experience (learning-by-doing) and knowledge accumulated through R&D activities, respectively (Kouvaritakis et al., 2000a and 2000b; Bahn and Kypreos, 2003; Barreto and Kypreos, 2003; Miketa and Schrattenholzer, 2004; and Turton and Barreto, 2004).[37]

For a specific technology such a two-factor learning curve can be formulated as:

$$SC_t = a \times CC_t^{-b} \times KS_t^{-c}$$

Where:
SC_t Specific cost in period t
CC_t Cumulative capacity in period t
KS_t Knowledge stock in period t[38]
a Initial specific cost at unit cumulative capacity
b Learning-by-doing index
c Learning-by-searching index

Instead of the learning-by-doing and learning-by-searching indexes, corresponding rates of learning-by-doing (LDR) and learning-by-searching (LSR) can be defined as follows:

$$LDR = 1–2^{-b}$$
$$LSR = 1–2^{-c}$$

It should be noted that the LDR does not correspond to the learning rate (LR) described above for the 1FLC. In the 2 FLC, two variables - i.e. cumulative capacity and knowledge stock - are used to explain the cost trend that the 1 FLC tries to capture using only cumulative capacity as explanatory variable (Barreto and Kypreos, 2004b; Turton and Barreto, 2004).

Cluster of technologies and learning spillovers

Technologies often do not learn alone but in interaction with other technologies sharing common key components. In order to deal with this phenomenon of interdependent learning between technologies, the concept of *clusters of technologies* has been used in bottom-up energy modelling studies (Seebregts et al., 1999 and 2000; de Feber, 2002 and 2003; Barreto, 2003; Smekens, 2004; Turton and Barreto, 2004). A cluster of technologies is defined as a group of

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[37] Due to data and methodological problems (and the resulting disappointing performance of a 2FLC), an alternative approach to account for the role of R&D in the process of technological change has been suggested by de Feber et al. (2003). They propose to treat the impact of public R&D indirectly, i.e. exogenously to the model, by estimating the linear relationship between the learning rate of a 1FLC and the R&D intensity of a technology. R&D intensity is defined as the ratio between public R&D expenditures over a period and the turnover of a technology: R&D intensity = (amount of R&D/amount of R&D + turnover). This approach assumes that increasing R&D intensity will increase the learning rate of technology. It has been applied in the MARKAL model in order to assess the impact of an additional R&D budget (an *R&D shock*) on the penetration of emerging technologies (de Feber et al. 2003; see also Barreto and Kypreos, 2004a).

[38] An alternative variable would be the cumulative R&D expenditures is period t (CRD_t). The advantage of the variable KS_t is that it may account for the depreciation of the knowledge stock as well as for time lags between R&D expenditures and knowledge accumulation (Barreto and Kypreos, 2004a; and Miketa and Schrattenholzer, 2004)

technologies sharing a common essential learning component. This component, which can be a technology in itself, is called the 'key technology'. For instance, the gas turbine is a key technology used in a cluster of technologies such as the integrated coal gasification power plant, the gas combined cycle power plant or the gas turbine CHP plant. Other examples of key technologies are fuel cells, photovoltaic modules, wind turbines, burners and boilers (Seebregts et al., 2000).

For a single technology, the investment costs may consist of several learning components as well as a non-learning part. The learning components may have different learning rates, while the share of these components in the total cost structure may vary between technologies. Moreover, the learning does not necessarily have to take place through a specific technology. Due to the clustering of technologies, spillovers of learning between technologies may occur, as related or complementary technologies benefit from the learning processes of each other. These clustering and spillover effects may result in the (further) deployment and lock-in of certain technologies, while others may be locked-out from the energy system (de Feber et al., 2002 and 2003, Barreto, 2003; Smekens, 2004; and Turton and Barreto, 2004; see also Section 6.3 below).

Spatial dimensions of technological learning and spillovers
The impact of endogenising technological change in bottom-up energy system models depends partly on the assumptions made with regard to the spatial dimensions of technological learning and spillovers. For instance, the cost reductions and, hence, the deployment or diffusion of new technologies depend partly on assumptions concerning the scale or domain of technological learning (global, regional or national) as well as on assumptions whether technological learning at the regional or national level spill over to other regions or countries. As will be illustrated in Section 6.3 below, including spatial spillovers of learning in a bottom-up energy system model offers the possibility that the imposition of emission constraints in a given region may induce technological change in other regions, even when they do not face emission restrictions themselves, or that the effects of emissions trading on the process of induced technological change may be altered (see also Barreto, 2001 and 2003; Barreto and Kypreos, 2000 and 2004a; and Barreto and Klaassen, 2004).

Technological learning and uncertainty
Uncertainty is a pervasive element in the use of energy models in order to assess the impact of technological learning in long-term emission scenarios. This uncertainty refers specifically to the progress or learning rates, resulting from methodological shortcomings and lack of adequate data to estimate these rates properly. But even if the historical values of the learning rates could be estimated adequately, their long-term future values would remain uncertain. Besides this specific 'learning' uncertainty, other uncertainties (with perhaps more impact) are present in bottom-up energy models dealing with long-term emission scenarios and technical change. The most pronounced and often mentioned sources of uncertainty concern future energy demand, fuel resources, fuel prices, economic/environmental policies, discount rates and various technology characteristics such as the availability and efficiency of new technologies.[39] In order to account for these uncertainties and to assess their potential impact on the model's outcomes, a variety of methodological practices and techniques have been used such as developing different scenarios, sensitivity analyses, stochastic programming, or specific methods to analyse data uncertainty in scientific models, e.g. the Monte Carlo Analysis (de Feber et al., 2003).

Emission scenarios and policy cases
Bottom-up energy system studies have used a variety of emission scenarios and policy cases to analyse the impact of endogenising technological change in their models. In addition to a reference or baseline scenario, for instance one of the emission scenarios developed by IPCC/SRES (2000a), these studies have assumed one or more policy constrained emission scenarios based on either the Kyoto protocol, the achievement of a long-term abatement target or the imple-

[39] For a discussion of these and other uncertainties in climate-energy-economic models see Van der Zwaan and Seebregts (2004), Grübler and Gritevski (2002), and Grübler et al. (1999a and 1999b).

mentation of specific policy measures such as the imposition of an energy or carbon tax. Moreover, some studies have included emissions trading in their models at the regional/global level. By both including and excluding technological learning in these different emission scenarios and policy cases, these studies have been able to illustrate the impact of endogenising technological change in their models (see Section 6.3).

Models used

In order to endogenise technological change, a variety of bottom-up energy-system models have been used. The major versions of such models include:

- ERIS (Energy Research and Investment Strategies). ERIS is a multi-regional bottom-up energy-systems optimisation model that endogenises technological change by means of learning curves. The model has been developed as a joint effort between the International Institute for Applied Systems Analysis (IIASA), the Paul Scherrer Institute (PSI) and the National Technical University of Athens (NTUA) during the EC-sponsored TEEM and SAPIENT research projects. Originally, ERIS provided a simplified multi-regional representation of the global electricity generation system, including thirteen different electricity generation technologies in each region (of which six technologies were characterised by endogenous learning). Gradually, however, the model has been extended and restructured by, for instance (i) including a cluster approach to technological learning, (ii) adding the non-electric sector in a detailed and disaggregated way, (iii) adding an energy carrier production sector, including hydrogen (iv) incorporating non-CO_2 emissions and abatement options, notably for CH_4, N_2O and SO_2, and (v) including geological and terrestrial carbon storage (for details on ERIS, see Kypreos et al., 2000; Barreto and Kypreos, 2000; Barreto and Klaassen, 2004; and Tuton and Barreto, 2004).
- MARKAL (acronym for MARKet ALlocation). MARKAL is a widely applied bottom-up, dynamic energy system model developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA). It actually covers a large family of models for analysing the role of technology in energy planning and policy strategies to reduce the environmental impacts - notably of carbon emissions – from energy and materials consumption. In addition to the standard linear programming model, which provides extensive detail on energy supply and demand technologies, the MARKAL family has been enlarged over the past two decades by models to deal with material flows, uncertainties, multiple regions, emissions trading, macroeconomic feedback effects, and endogenous energy demand responsive to price changes (Seebregts et al., 2001). Experience from MARKAL models with endogenous technological change has been gained by including learning parameters for a selected set of technologies in a compact multi-regional model of the global energy system (Barreto, 2001; Barreto and Kypreos, 2004a) as well as in a large-scale model covering Western Europe (Seebregts et al., 2000; de Feber et al., 2003; Smekens, 2004).
- MERGE (Model for Evaluating the Regional and Global Effects of GHG reduction policies). MERGE is a multi-region, multi-technology model for analysing regional and global climate policy issues. It actually combines a top-down and bottom-up approach of climate policy modelling. The top-down part of MERGE covers the macroeconomic linkages between the demand side of the energy system and the rest of the economy, while the bottom-up part provides some technological detail of the energy supply sector in a given region, particularly the generation of electricity and the production of non-electric energy (fossil fuels, synthetic fuels and renewables). Originally, MERGE has been developed in the 1990s at the Stanford University by Manne et al., who recently have added endogenous learning-by-doing to a few power generating technologies of the model (see, for instance, Manne and Richels, 2004 and 2003, or Manne and Barreto, 2004).[40]

[40] For a description and documentation of MERGE, see the website: http://www.stanford.edu/group/MERGE.

- Similarly, Bahn and Kypreos of the Paul Scherrer Institute (PSI) have also added endogenous technological learning (ETL) to a new version of MERGE (called MERGE-ETL), through either a one-factor learning curve (Kypreos and Bahn, 2003a) or a two-factor learning curve (Bahn and Kypreos, 2002 and 2003).[41]
- MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact). MESSAGE is a bottom-up system engineering optimisation model used for medium- to long-term energy system planning and policy analysis. It determines how much of the available resources and technologies are actually used to satisfy a particular end-use demand, subject to various constraints, while minimising total discounted energy system costs. MESSAGE has been developed by the International Institute for Applied Systems Analysis (IIASA). It exists in many versions, including one that provides a wide variety of detailed information at both a multi-technology and multi-regional level, one that is linked to a top-down macroeconomic model (MESSAGE-MACRO), one that incorporates endogenous technological learning (ETL), one that accounts for uncertainties, and versions that merge ETL with uncertainties or ETL with MESSAGE-MACRO (for details, see Messner, 1997; Grübler and Messner, 1998; Grübler et al., 1999a and 1999b; and Riahi et, al., 2004).

6.3 Some illustrative results

Learning rates

In order to explore the impact of induced technological change, bottom-up energy system models have used a variety of learning rates for different individual energy technologies (notably electricity generating technologies; see Table 6.1). These rates have been either assumed or estimated econometrically, based on expert knowledge or empirical studies.[42] Estimates of learning rates may show a large range of values, even for the same technology, depending on the methodology and data used. For instance, Table 6.1 shows that the estimates of the learning rate for wind power vary from 8 to 15 percent, and for solar PV from 18 to 28 percent.[43] On the other hand, the variance of the learning rate for other technologies mentioned in Table 6.1 is often smaller, while there seems to be some consensus that this rate is relatively low for new nuclear (4-7%), and for advanced coal-based power generating technologies, notably the integrated, combined cycle gasification system (5-7%).

Table 6.1 *Learning rates of electricity generating technologies in bottom-up energy system models: one-factor learning curve*

[%]	ERIS	MARKAL	MERGE-ETL	MESSAGE
Advanced coal	5	6	6	7
Natural gas combined cycle	10	11	11	15
New nuclear	5	4	4	7
Fuel cell	18	13	19	-
Wind power	8	11	12	15
Solar PV	18	19	19	28

Source: Messner (1997), Seebregts et al. (1999), Kypreos and Bahn (2003a), and Barreto and Klaassen (2004).

41 In MERGE-ETL, endogenous technological progress is applied to eight energy technologies: six power plants (integrated coal gasification with combined cycle, gas, turbine with combined cycle, gas fuel cell, new nuclear designs, wind turbine and solar photovoltaic) and two plants producing hydrogen (from biomass and solar photovoltaic). Furthermore, compared to the original MERGE model, Bahn and Kypreos (2002 and 2003) have introduced two new power plants (using coal and gas) with CO_2 capture and disposal into depleted oil and gas reservoirs.

42 For a review of the literature on learning curves, including 42 learning rates of energy technologies, see McDonald and Schrattenholzer, 2002.

43 For a discussion and explanation for similar (and even wider) variations in estimated learning rates for wind power, see Söderholm and Sundqvist (2003) and Neij et al. (2003a and 2003b).

The learning rates in Table 6.1 are all derived for one-factor learning curves. Similar rates for two-factor learning curves (2FLCs) are more scarce. Some available estimates of learning rates for energy technologies derived from 2FLCs are presented in Table 6.2.[44] For each technology and model considered, the learning-by-searching rate (LSR) is significantly lower than the learning-by-doing rate (LDR). Note that the LDRs used by the MERGE-ETL model are similar to the comparable learning rates from the 1FLCs while the LDRs used by the ERIS model are even higher than the comparable 1F learning rates (although one would expect intuitively that the LDRs would be lower than the comparable 1F learning rates as the LDRs are designed to explain only part of the specific technology cost decreases explained by conventional 1F learning rates).

Investment costs

When considering induced technological change, the specific costs of a given technology decrease with the accumulation of knowledge that occurs through the increase of the cumulative installed capacity (in 1 FLC), and through as well as the increase of the cumulative R&D expenditures (in the 2FLC). As an illustration, Table 6.2 reports on the reduction of specific investment costs as a learning process for electricity generating technologies over the period 2000-2050 in both a baseline scenario and a CO_2 mitigation scenario.[45] For instance, in case of a 1FLC, the investment costs for a fuel cell power plant decreases from 5096 US$/kW in 2000 to 884 US$/kW in 2050 under the baseline scenario and even to 856 US$//kW under the mitigation scenario (as the total installed capacity of fuel cell power plant increases even further under the latter scenario). Owing to the accumulation of R&D expenditures, these costs decline even more in case of a 2FLC, i.e. to 826 and 819 US$/kW in 2050 under the baseline and emission scenario, respectively. Note that in case of the 1FLC baseline scenario the investment costs of a solar PV plant do not decline (as no capacity is installed under this scenario), while under the mitigation scenario these costs are higher in the 2FLC case than in the 1FLC (as the other power plants benefit more from R&D spending than solar PV, resulting in less installed capacity of solar PV in case of the 2FLC mitigation scenario).

Table 6.2 *Learning rates of electricity generating technologies in bottom-up energy system models: two factor learning curves*

	ERIS		MERGE-ETL	
[%]	LDR	LSR	LDR	LSR
Advanced coal	11	5	6	4
Natural gas combined cycle	24	2	11	1
New nuclear	4	2	4	2
Fuel cell	19	11	19	11
Wind power	16	7	12	6
Solar PV	25	10	19	10

Source: Barreto (2001). Barreto and Kypreos (2004b), and Bahn and Kypreos (2003).

Mix of primary energy use

As illustrated in Table 6.3, accounting for induced technological chance (ITC) implies a decline of energy production costs over time, as knowledge and experience in the different learning technologies builds up. In other words, the production factor energy becomes less expensive over time and, thus, it can substitute partly for other production factors such as labour or capital. Consequently, as illustrated by Bahn and Kypreos (2003), primary energy use is higher in the baseline and mitigation scenarios including ITC compared to similar scenarios excluding ITC.

[44] For additional estimates of learning rates from 2FLCs, see Kouvaritavis et al. 2000a; Söderholm and Sundqvist, 2003; and Miketa and Schrattenholzer, 2004.

[45] According to the baseline scenario, the global amount of energy elated CO_2 emissions increases from 6.55 GtC in 1990 to 15.6 GtC in 2050, whereas the mitigation scenario implies a reduction of these emissions to a level of 10 GtC in 2050 (Bahn and Kypreos, 2003). Similar illustrations of cost reductions for learning technologies are reported by Messner (1997), Seebregts et al. (2000), and Nakicenovic (2002).

Comparing the 1FLC and 2FLC cases, primary energy use is lower under the 2FLC baseline scenario (B2F) compared to the 1FLC baseline scenario (B1F), whereas the opposite takes place under the mitigation scenarios (i.e. primary energy use is higher in M2F than M1F). This is due to opposite variations in overall GDP (see Bahn and Kypreos, 2003, and the discussion below on the impact on abatement costs). Moreover, the reduction of primary energy use due to carbon mitigation is lower when considering ITC: 15% reduction in the mitigation scenario compared to the baseline scenario (both excluding ITC), 9% in the M1F case compared to B1F, and only 7% in M2F compared to B2F (Bahn and Kypreos, 2003).

Table 6.3 *Reductions of specific investments costs as a learning process for electricity generating technologies over the period 2000-2050 (in US dollars at constant 2000 prices per unit installed capacity*

	2000	Baseline scenario 2050		Mitigation scenario 2050	
[US$/kW]		1FLC	2FLC	1FLC	2FLC
Advanced coal	2020	1355	1254	1349	1252
Gas combined cycle	713	513	503	514	505
New nuclear	3999	2454	2366	2460	2371
Fuel cell	5096	884	826	856	819
Wind power	887	564	525	562	520
Solar PV	6075	6075	5022	1775	5022

Source: Bahn and Kypreos (2003).

ITC affects also the primary energy mix, as illustrated by Bahn and Kypreos (2003). Firstly, the share of fossil fuels decreases, notably coal in the baseline cases and oil in the carbon mitigation cases (where coal is already significantly reduced compared to the baseline). Secondly, the share of nuclear increases, particularly in the baseline cases. Thirdly, the share of renewables increases, especially biomass and wind, to reach 22 percent by 2050 in the M2F case. Finally, these trends are stronger when considering also knowledge accumulated through R&D spending (i.e. the 2F cases).

Electricity generation: output and technology mix

The impact of ITC on primary energy use in the cases mentioned above is similar on electricity generation, i.e. it is higher in the learning (ITC) cases compared to the no-ITC cases. Electricity generation is also always higher in the 2F cases compared to the 1F cases. This means in particular that in the B2F case, where primary energy use is slightly lower than in B1F, electricity substitutes partly for non-electric energy following relative price changes in energy markets. Moreover, similar to primary energy use, the reduction of electricity generation due to carbon mitigation is lower when considering ITC. Indeed, power generating costs decrease over time for learning technologies, as do non-electric energy production costs. Electricity (and non-electric energy) can thus substitute partly for capital and labour as production factors (Bahn and Kypreos, 2003).

With regard to the technology mix for generating electricity in the cases mentioned above, ITC favours the deployment of the advanced learning power plants, largely at the expense of using conventional coal and other, non-learning technologies. In the baseline learning cases, these plants include particularly integrated coal gasification with combined cycle (IGCC), gas combined cycle (GCC), new nuclear (NNU) and wind turbine (WND), whereas in the mitigation cases they refer mainly to GCC, NNU and WND (Bahn and Kypreos, 2003).

The above findings regarding the power generating technology mix in the study of Bahn and Kypreos - who used the MERGE-ETL model - confirm largely similar results of a previous study by Messner (1997), applying the MESSAGE model. However, in contrast to Bahn and Kypreos (2003), the output demand for generating electricity is fixed in the study of Messner, while she compares the technological learning case with two alternative ways of modelling technological change. The first variant, the 'static' case, is the least realistic of the three cases (and comparable to the 'no-ITC' or 'no-learning' case of Bahn and Kypreos). 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 second variant, the 'learning' case, assumes that the investment costs of the new technologies decline over the years 1990-2050 according to the progress ratios provided in Table 6.1 for the MESSAGE model.[46] Finally, the 'dynamic' case assumes the same degree of cost reductions over the period 1990-2050 as in the 'learning' case, but the reductions are exogenous ('autonomous'), occurring at continuous rates between 1990 and 2050. This dynamic case corresponds to the most common approach of dealing with technological change in long-term energy system modelling (Nakicenovic, 2002).

According to the static case of Messner (1997), the technology mix of global electricity generation in 2050 relies primarily on established technologies such as standard coal and nuclear power plants. In the dynamic case, however, these standard technologies are largely replaced by natural gas combined-cycle, new nuclear, solar and wind technologies. As these latter technology improvements are exogenous in the dynamic case, the shift in investments from traditional to new technologies changes in line with the evolving cost reductions. Compared to the dynamic case, the technology mix in the year 2050 is hardly different in the learning case, except a slight shift from new nuclear and solar thermal systems to solar PV systems. This outcome is hardly surprising as a similar structure in cost reductions for the new technologies in the year 2050 has been assumed for both cases. In contrast to the dynamic case, however, in the learning case investments in new technologies have to 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. Hence, in the decades preceding the year 2050, there might be a significant difference between the dynamic and learning cases, depending on the timing and speed of investments in new, promising technologies (Messner, 1997; Nakicenovic, 2002; see also Grübler and Messner, 1998 and Grübler et al., 1999a and 1999b, as well as the sections below on the timing of abatement investments).

Clustering of learning technologies

The importance of clustering learning technologies has been illustrated by the Energy research Centre of the Netherlands in a MARKAL model for Western Europe (Seebregts et al. 2000; de Feber et al., 2002; Smekens, 2004). The database of this model covers detailed information of some 500 technologies used in different supply and demand sectors of the energy system. In a first set of experiments, clustering was restricted to 28 learning technologies, of which 21 technologies in the power generating sector and 7 end-use technologies in the transport sector (Seebregts et al. 2000). These 28 technologies were clustered to 5 'key technologies': wind turbines, solar PV modules, fuel cells, gasifiers, and gas turbines. The cluster fuel cells combines 3 technologies applied in the power sector and 7 applications in the transport sector, while the other clusters refer to technologies applied in the power sector only.

In the first run by the MARKAL model, the fuel cell transport applications were not included in the cluster of fuel cell power technologies. As a result, fuel cells become not cost-effective over the period 1990-2050 and, hence, they are 'locked-out' from the technology mix to generate electricity during this period (both in the baseline and carbon mitigation scenarios). In the second run, however, when the fuel cell technologies in the power and transport sectors are clustered to one key technology, fuel cell applications in the power sector become cost-effective in the carbon mitigation scenario - due to the widespread application of fuel cells in the transport sector - and account for a major share in the power generating technology mix in 2050. This ex-

[46] In addition to the technologies recorded in Table 6.1, Messner (1997) assumes a learning rate for solar thermal of 15 percent.

ample illustrates the importance of clustering learning technologies as the experience (i.e. cost reductions) gained by some applications in one sector may benefit the deployment of related applications in other sectors.

In a second set of experiments, the number of clusters of key technologies was enlarged from five to ten (representing 59 individual MARKAL learning technologies). During these experiments, the number of clusters included in the model runs was varied from 2 to 10 in order to assess the impact on the cumulative installed capacity of key technologies such as solar PV or fuel cells (de Feber et al., 2002). Depending on this number of clusters, these key technologies were either 'locked-in' or 'locked-out' from the energy system. This finding further illustrates the complex interactions in a detailed energy technology model such as MARKAL and the importance of a proper and balanced identification of clusters of learning technologies.

The timing of investments

Messner (1997) has analysed differences in timing (or pathways) of investments in new electricity generating technologies in two alternative cases: the dynamic case with exogenous cost reductions and the technological learning case with endogenous cost reductions (see also Grübler and Messner, 1998). The most striking differences are that, compared to the dynamic case, the learning case shows higher up-front investment costs in the period 1990-2015, but lower investment costs in the years 2015-50, while over the total period 1990-2050 the discounted systems costs are lower. This finding illustrates a generic difference between the two approaches of modelling future technology costs and performance (Nakicenovic, 2002). In the dynamic case, it pays to postpone some investments in new technologies until the costs are reduced (exogenously). In the learning case, there is no time to waste. Higher levels of costly investments are made immediately to accrue sufficient experience to be able to reap the benefits of cost reductions at some point further along the learning curve. Nevertheless, as mentioned above, despite higher initial investments, the overall discounted costs are lower in the learning case compared to the dynamic case. This result implies that early actions to promote new technologies may be able to reduce the overall discounted costs of long-term mitigation strategies even if similar rates of 'autonomous' technological improvements are assumed in the case without learning. In reality, however, the exogenous cost reductions are unlikely to occur unless someone else invests instead (Nakicenovic, 2002).

The timing of CO_2 abatement

The above findings of Messner, Grübler and Nakicenovic, with regard to the optimal timing of investments in new (abatement) technologies seem to contradict comparable findings of Manne and Richels (2004) as well as Kypreos and Bahn (2003b) regarding the optimal timing of carbon abatement, notably when the mitigation target is to reach cost-effectively a certain CO_2 concentration level at a certain point in time (say 550 ppmv in 2100).[47] According to Manne and Richels (2004), the inclusion of learning-by-doing (LBD) does not have a significant impact on the overall timing of carbon abatement in order to reach a concentration level of 550 ppmv in 2100, while Kypreos and Bahn (2003b) even conclude that LBD postpones strong actions in carbon abatement to later periods in the 21st century. These differences in findings between 'bottom-up' studies seem to confirm the 'top-down' approach of Goulder and Mathai (2000), who

[47] It will be clear that if the mitigation target is specified as a certain (declining) limit of CO_2 emissions per 5 or 10 year period (starting in 2010), the inclusion of endogenous learning does not have an impact on the timing of carbon abatement (as this is fixed per period), but only on the costs of reaching this target. In addition, it may also be clear that if there are no mitigation targets at all, the inclusion of endogenous learning does not have an impact of the 'optimal timing' of carbon emissions as such but rather of the actual outcome of these emissions in the baseline scenario, depending on the difference in assumptions between exogenous and endogenous technological change. For instance, in the baseline scenario of Kypreos and Bahn (2003b) global CO_2 emissions in 2100 are 44 percent lower when endogenous learning is included (compared to the baseline excluding technological learning). In Manne and Richels (2004), the reduction in baseline carbon emissions varies roughly between 10 and 70 percent, depending on whether learning-by-doing (LBD) will result in low or high cost savings of electricity generating technologies, compared to the no-LBD case. In Grübler et al. (1999a and 1999b), baseline carbon emissions in 2100 are 66 percent lower due to the inclusion of technological learning.

found that the timing of abatement is analytically ambiguous when the channel for knowledge accumulation is LBD (see Section 5.2).

To some degree, these differences in findings may be due to differences in model specification and parameterisation, notably of the learning curve. When the cost reductions due to LBD are high, early investments are warranted (and initial abatement rises), whereas there is less inducement for early investments (and abatement) when these reductions are low (Manne and Richels, 2004; Goulder and Mathai, 2000).

However, the above mentioned differences in findings may also be partly due to differences in meaning and interpretation of 'timing of abatement action', where one party is primarily focused on ' timing of investment' and the other on 'timing of emission reduction'. Actually, there seems to be some consensus on the timing of abatement policies. For instance, according to Grübler and Messner (1998), abatement action needs to start in the short run, but this does not necessarily mean aggressive short-term emissions reductions but rather enhanced research & development and technology demonstration (R&DD) efforts that stimulate technological learning. On the other hand, Kypreos and Bahn (2003b), who conclude that LBD postpones strong actions in carbon abatement by a few decades, notice that early policies in form of R&DD support for the new and carbon-free technologies are implicitly assumed in their approach. Hence, there seems to be some consensus between 'bottom-up' approaches on LBD with regard to the need of early timing of R&DD abatement policies. Nevertheless, there still seems to be some obscurity and controversy with regard to the meaning and interpretation of the 'timing of abatement actions' and, hence, further research and clarification on this issue seems to be warranted.

Abatement costs

Compared to the abovementioned issue on the timing of CO_2 abatement, there seems to be much more consensus among bottom-up approaches with regard to the impact of induced technological change on the costs of carbon abatement. In general, technological learning has a very significant impact on the reduction of these costs, with the size of this impact depending on the assumed rate of technological learning (compared to the assumptions on technological change in the baseline), the number of learning technologies included in the analysis, the year or period considered, the stringency of the mitigation target, the opportunity of emissions trading, as well as the discount rate and the indicator used to express abatement costs, i.e. either in terms of marginal costs or as an amount/percentage of total (discounted) costs/GDP losses.

In terms of reducing marginal abatement costs, the impact of endogenous learning has been estimated at 20-40 percent for the years 2020-2050 (Seebregts et al., 2000; Manne and Richels, 2004; Bahn and Kypreos, 2003). For the year 2100, this impact has even been estimated at 60-80 percent (Grübler and Messner, 1998; Kypreos and Bahn, 2003b). For instance, in the static technology case of Grübler and Messner (1998), the marginal abatement costs of the carbon constraint increase continuously from 10 US$/tC in the year 2002 to some 1200 US$/tC towards the end of the 21st century. In the endogenous learning case, these costs are much lower, levelling off at US$500/tC.[48] In terms of total (discounted) abatement costs/GDP losses, estimates of cost reductions due to technological learning vary by period (and study) considered, i.e. 10 percent for the period 1990-2050 (Seebregts et al., 2000), 40-60 percent for the period 2000-2050 (Barreto and Kypreos, 2000), 40-70 percent for the period 2000-2100, in case of a maximum concentration level of 550 ppmv (Manne and Richels, 2004), and 50-70 percent for the year 2050 only (Bahn and Kypreos, 2003).

[48] Notice that these marginal abatement costs compare to a carbon tax or price of an emission permit at the same level. Notice also that for long-term time intervals such as the 21st century it would be more realistic to compare the difference in marginal abatement costs between an endogenous learning case and an exogenous technology dynamics case (rather than a static technology case).

As LBD implies investment costs in early periods and (rising) benefits in later periods, the rate of cost reductions due to technological learning is generally higher when later periods are considered. In addition, the cost impact of LBD is higher if the discount rate is lower. Moreover, according to the estimates of Barreto and Kypreos (2000), cost reductions due to endogenous learning are higher in case of full emissions trading (60%), compared to no trading (40%). As expected, these cost reductions are also higher in case of technologies characterised by higher learning rates, compared to lower learning rates (Manne and Richels, 2004). With regard to stringency of the mitigation target, the impact of LBD on cost reductions seems analytically ambiguous. If the CO_2 concentration level is lower (i.e. more stringent), cost reductions due to technological learning are higher in an absolute sense. However, in a relative sense (i.e. expressed as a % of abatement costs without LBD), they may either decline (Manne and Richels, 2004) or rise (Kypreos, 2003) if the concentration level is lower.

Finally, in the cases studied by Bahn and Kypreos (2003), induced technological change has a dual impact on GDP. Compared to the baseline scenario without learning, ITC yields GDP growth in the baseline cases including either one-factor or two-factor learning (as the production of energy becomes cheaper due to LBD/ITC). Compared to the baseline cases (both including and excluding learning), ITC reduces GDP losses in the mitigation cases (both including and excluding learning). For instance, Bahn and Kypreos (2003) estimate the GDP loss in 2050 due to carbon abatement at 1 percent in the mitigation case without learning (compared to the baseline without learning), at 0.5 percent in the mitigation case with 1FL (compared to the baseline with 1FL), and at 0.3 percent in the mitigation case with 2FL (compared to the baseline with 2FL). Hence, due to technological learning, abatement costs are reduced by 50% in case of 1FL and even by 70% in case of 2FL (compared to the mitigation case without learning). Notice, however, that total GDP in the mitigation cases with learning may be higher than the baseline scenario without learning, as the (reduced) GDP losses due to carbon mitigation may be surpassed by the growth in GDP due to technological learning.

The allocation of R&D expenditures

Recently, two studies using two-factor learning curves within the ERIS model have explored the role and allocation of R&D expenditures in energy technology processes (Barreto and Kypreos, 2004b; Miketa and Schrattenholzer, 2004). Based on estimated learning-by-doing rates (LDRs) and assumed learning-by-searching rates (LSRs) for solar PV and wind, Miketa and Schrattenholzer (2004) present the optimised levels of R&D for these learning technologies up to 2080 in the hypothetical situation of an unlimited R&D budget. Additional sensitivity analyses show that the learning rates affect the optimised R&D levels in opposite ways. Higher LSRs result in higher optimised R&D expenditures, implying that more R&D investments pay off. Accordingly, investment cost reductions are steeper when LSRs are high. In contrast, higher LDRs lead to lower optimised R&D expenditures. This is because when learning-by-doing is more effective than learning-by-searching, cost reductions can be achieved better through capacity accumulation while R&D funds can be saved rather than being spent to reduce costs (Miketa and Schrattenholzer, 2004).

Another interesting finding of Miketa and Schrattenholzer is that the optimised R&D allocation for one technology is independent of the presence and learning parameters of the other technology. Hence, they identified a situation in which the often-cited phenomena of ‘lock-in’ (i.e. the dominance of one learning technology at the expense of the other as a consequence of increasing returns to scale) and ‘crowding-out’ (i.e. a limited R&D budget that leaves room for supporting only one technology) were not observed.

Similarly, Barreto and Kypreos (2004b) have estimated the optimal allocation of R&D expenditures for six learning technologies based on assumed LDRs and LSRs (see Table 6.2) and a fixed R&D budget up to 2050 (although the total available budget was not fully spent in most years and cases considered). As expected, the technologies with the highest LSR - such as solar PV, gas fuel cells and wind turbines - appear to be more attractive for expending R&D resources than other learning technologies (such as the gas combined cycle, clean coal or new nuclear technology). However, other factors such as the LDR, the maximum growth rates allowed and the presence or absence of a constraint on emissions, which may force low-carbon technologies into the solution, play also an important role. Moreover, sensitivity analyses reveal that a higher depreciation rate of the knowledge stock may favour allocating more R&D funds to currently competitive technologies in order to avoid or mitigate their 'forgetting-by-not-doing' process -implying that if no R&D efforts are made on a given technology its investment cost may increase - rather than allocating these funds to currently expensive technologies that are promising in the long run (Barreto and Kypreos, 2004b).

Uncertainty and sensitivity analyses

Most of the results presented above are highly uncertain due to the interaction of a variety of modelling, methodological and parameter uncertainties (Van der Zwaan and Seebregts, 2004). In order to assess the sensitivity of the results to these uncertainties and the assumptions made, several authors have conducted uncertainty and sensitivity analyses. In addition to some findings of such analyses already recorded above, a few other outcomes are recorded below:

- In the deterministic case with no uncertainty, a new technology enters the market earlier and diffuses faster. In the stochastic case, however, when learning is uncertain, diffusion is more gradual and market entry is later. Moreover, experiments with the stochastic version of MESSAGE have shown that, if the uncertainties concerning future technology performance are incorporated, the model tends to spread risks by diversifying investment strategies over more technologies (Messner, 1997; Grübler and Messner, 1998; Grübler et al., 1999a and 1999b; and Barreto and Kypreos, 2000).
- The impact of technological learning depends highly on the future learning rates of new technologies that, as indicated above, are highly uncertain. As illustrated by, for instance, Capros and Chryssochoides (2000) or Seebregts et al. (2000), if the learning rate turns out to be higher (or lower) than assumed, it may have a major mutually reinforcing impact on trends in cost reduction deployment, installed capacity and experience (i.e. cost reduction) of a technology and hence on the technology mix of an energy system and the level/costs of carbon abatement. Moreover, as shown by Capros and Chryssochoides (2000), each technology has a different sensitivity with respect to the learning rate.
- Capros and Chryssochoides (2000) have also analysed the sensitivity of the benefits from endogenous technological learning with respect to fluctuations in fuel prices. They show that this sensitivity is noticeable, but not very high, as a 100% change in prices resulted in a 25% change in the carbon cost savings of learning.

6.4 An example: endogenous learning for carbon capture technologies

In a recent paper, Riahi et al. (2004) have analysed the impact of technological learning for carbon capture and sequestration technologies (CCTs) on the performance of different CO_2 mitigation scenarios by including (learning) CCTs for power plants in the energy supply optimisation model MESSAGE-MACRO (in which MACRO calculates the macroeconomic feedback effects of mitigation measures on energy prices and the demands for energy and other production factors). For this purpose, they selected two baseline scenarios of the IPCC Special Report of Emissions Scenarios (SRES) as their reference scenarios, called A2 and B2 (IPCC, 2000a). For each, they developed two carbon mitigation scenarios (one with and one without CCT learning) aiming at the stabilisation of atmospheric carbon concentrations at about 550 ppmv by the end of the 21st century.[49] A major difference between the baseline scenarios A2 and B2 is that the estimated figures on population, GDP and GHG emissions in 2100 are higher in A2 than B2. Hence given the same abatement target for each scenario (i.e. 550 ppmv in 2100), the mitigation

[49] For a comparable study, see Riahi et al. (2003), which analyses the impact of introducing (learning) CCT in the baseline scenario A2 only (without any specific mitigation target).

scenario A2-550 can be considered as implying more stringent carbon abatement policies than under mitigation scenario B2-550.

In order to design a learning curve for CCTs, Riahi et al. (2004) calculated the initial total carbon reduction costs of CCTs at 196 US$/tC for a standard coal power plant and 137 US$/tC for a natural gas combined cycle power plant. Moreover, due to a lack of data, they assumed a learning date for the investment costs for CCT of 13 percent, based on an estimate for a comparable technology, i.e. capture of sulphur dioxide (SO_2) emissions from coal-fired power plants.

In addition to carbon storage and sequestration, Riahi et al. (2004) considered two other mitigation options to meet the required stabilization target, namely fuel switching and energy demand reduction (through enhanced energy conservation). The carbon reductions of these options as well as other characteristics and results of the emission scenarios analysed by Riahi et al. (2004) are summarised in Table 6.4. More specifically, their major findings and conclusions with regard to the impact of learning CCTs on the performance of carbon abatement scenarios during the 21st century include:

- In all mitigation scenarios, the comparatively largest contribution to carbon reductions comes from fuel switching, notably shifting away from coal. The second most important contribution is due to carbon capture and sequestration, where the emissions reductions are particularly high in the case of learning CCTs.
- During the 21st century, total carbon reduction costs of CCTs remain constant in the mitigation scenarios with static CCTs (A2-550s and B2-220s), while they decline in the mitigation scenarios with learning CCTs (A2-550t and B2-550t) from 196 to 41-61 US$/tC for a standard coal power plant and from 137 to 34-38 US$/tC for a natural gas combined cycle power plant (Table 6.4).
- Comparing the diffusion of CCTs in scenarios with declining costs due to learning with those assuming costs of static technologies shows that the market penetration of CCT is accelerated due to technological learning. Particularly, the carbon capture from coal technologies benefits considerably from the learning effect, leading to global market shares of more than 90 percent in 2100, compared to 60-70 percent in the case of static costs. At the end of the century, almost all fossil power plants are equipped with carbon capture technologies in the case of learning (Riahi et al., 2004).
- A major characteristic of all four mitigation scenarios is the comparatively late diffusion of CCTs. It requires decades for them to diffuse widely. Large-scale applications first emerge as late as in the 2030s. In all scenarios, the entire diffusion of CCTs, from the initial introduction to saturation, spans about 50 years.
- Cumulative carbon sequestration is higher in the case of the A2 mitigation scenarios compared to the B2 mitigation scenarios, and higher in scenarios with learning CCTs than in those with static cost assumptions. In the case of learning, CCT's cumulative carbon emissions over the years1990-2100 range between 137 and 243 GtC (compared to 90 and 167 GtC in the scenarios with constant CCT costs).
- In the mitigation scenarios, the marginal costs of carbon abatement rise steadily from 20 US$/tC in 2000 to about 400-500 US$/tC in 2100. Although these costs are lower in scenarios with learning CCTs, compared to those with static technologies, a remarkable finding is that these cost differences are relatively small, notably in the A2 mitigation scenarios (with static versus learning CCTs). A similar striking result was found with regard to total abatement costs/GDP losses, where the differences in GDP losses are particularly small in the B2 mitigation scenarios (see Table 6.4).[50]

[50] The explanation for this striking result offered by Riahi et al. 2004) is vague and demanding: 'There seems to be no direct relationship between total amounts of cumulative carbon sequestration and GDP losses, indicating that the macroeconomic stabilization cost is the result of a more complex price formation, in which CCTs are just one influencing factors among many. CCT cost contribute to the progression of prices, but do not completely determine them.' (Riahi et al., 2004). An additional, alternative explanation might be that their analysis includes only CCTs as learning technologies, whereas differences in marginal/total abatement costs between scenarios with different technology assumptions may become larger if more learning technologies are included.

Table 6.4 Major characteristics and results of emissions scenarios with different assumptions regarding carbon storage and sequestrations technologies (CCTs, 1990-2100)[a]

	Year	Baseline scenarios (without CCTs)		Mitigation scenarios (550 ppmv in 2100)			
				Static CCTs		Learning CCTs	
		A2	B2	A2-550s	B2-550s	A2-550t	B2-550t
Global GDP [trillion US$$_{1990}$]	2100	242.8	234.9	236.4	230.8	236.6	230.9
Population [billion]	2100	15.1	10.4	15.1	10.4	15.1	10.4
Primary energy [EJ]	2100	1921	1357	1571	1227	1636	1257
Cumulative carbon emissions [GtC]	2100	1527	1212	992	948	990	950
Cumulative carbon sequestration [GtC]	1990-2100	-	-	167	90	243	137
Carbon concentrations [ppmv]	2100	783	603	550	550	550	550
Carbon reductions [GtC] by:							
• energy conservation	2100	-	-	3.6	1.3	3.7	1.5
• fuel switching	2100	-	-	12.5	3.9	9.5	4.0
• carbon sequestration	2100	-	-	5.8	3.0	8.9	4.0
• total	2100	-	-	21.9	8.2	22.0	9.5
Carbon reduction costs [US$/tC]							
• coal-based CCTs	2100	-	-	196	196	41	61
• gas-based CCTs	2100	-	-	137	137	34	38
Abatement costs:							
• marginal [US$/tC]	2100	-	-	496	447	490	406
• total/GDP losses [trillion US$$_{1990}$]	2100	-	-	6.4	4.1	6.2	4.0

[a] Compare with 1990 values for GDP (20.9 trillion US$), population (5.3 billion), primary energy use (352 EJ). and carbon concentrations (354 ppmv).

Source: Riahi et al. (2004).

Based on their findings, Riahi et al. conclude that ''*climate policies need to be extended to include technology policies, in order to make the diffusion of environmentally sound technologies operational in the long run... This calls for early action to accomplish the required cost and performance improvements in the long term, including the creation of niche markets, the development of small-scale demonstration plants, and targeted R&D*'' (Riahi et al., 2004). This conclusion, however, may be questioned as the authors did not study the performance of mitigation scenarios excluding CCTs (or other 'environmentally sound technologies'), while the comparison of the mitigation scenarios with static versus learning CCTs shows that the differences in marginal/abatement costs are relatively low, thereby raising doubts whether early action and investment in these technologies can be justified.

6.5 Emissions trading and spatial learning spillovers

In most bottom-up energy systems studies, the impact of endogenous technological change is analysed in the context of a scenario assuming global learning. This means that capacities of energy technologies deployed across all regions considered are added up to obtain the global cumulative capacity, which is used for the computation of corresponding investment costs. Assuming global learning, however, has an important implication for the diffusion of the learning technologies (Barreto and Kypreos, 2002). With all regions contributing to the cost reduction, deploying an energy technology in one of them translates into a reduction of the specific investment costs to all of them. Hence, through these so-called 'spatial learning vestment costs to all of them. Hence, through these so-called 'spatial learning spillovers' investments in expanding the installed capacity of a learning technology in a given region will contribute to render this technology more cost-effective also in other regions, thereby affecting the energy technology mix and the corresponding system costs and carbon emissions in these regions. In a different, but comparable way, CO_2 emissions trading affects not only abatement costs and carbon emissions at the regional level but also the development, diffusion and deployment of new, carbon-saving technologies. Moreover, through the deployment of these technologies, emissions trading also influences their regional learning and spillover effects, while these effects may in turn affect emissions trading at the regional level, resulting in a complex, but intriguing interaction of the impact of spatial learning spillovers and emissions trading on the diffusion and deployment of new technologies and the corresponding carbon emissions at the regional and global levels.

Recently, two bottom-up energy system studies have analysed the above-mentioned interaction and impact of emissions trading and learning spillovers on the regional performance of technology deployment in the global electricity generating sector (Barreto and Kypreos, 2004a; and Barreto and Klaassen, 2004).[51] Although the focus and methodology of these studies are highly comparable, there are some differences as well, notably:

- Both studies use a multi-regional bottom-up energy-systems optimisation model. However, while Barreto and Kypreos (2004a) use a 5-region MARKAL model of the global energy system, Barreto and Klaassen (2004) apply an 11-region ERIS model.
- While both studies are focussed on analysing the impact of emission trading and learning spillovers on technology deployment in the global electricity sector, Barreto and Klaassen explore also the effects on regional emission patterns and mitigation costs.
- Both studies cover 6 learning technologies, out of 13 power-generating technologies in Barreto and Kypreos (2004a) and out of 14 such technologies in Barreto and Klaassen (2004).
- Both studies consider an unconstrained baseline (or reference) scenario and a CO_2 constrained mitigation scenario. However, the 'Kyoto-for-ever' mitigation scenario of Barreto and Klaassen is less stringent for the *Annex B region* (excluding the US) than the 'Kyoto-trend' mitigation scenario of Barreto and Kypreos for the *Annex I* regions (including the US).[52] In the latter scenario, the Annex I regions are compelled to reach their Kyoto target in 2010 and to follow, from this target, a linear reduction of 5% per decade until the end of the horizon. In both studies, the other regions (called either 'non-Annex B' or 'non-Annex I'), are not subject to emissions reduction but they cannot exceed their emissions in the unconstrained case (implying that both studies exclude the opportunity of 'carbon leakage').
- In both studies, the mitigation scenario distinguishes between three variants of emission trading, namely (i) no emissions trading across regions, (ii) restricted inter-regional emissions trading, i.e. only between the regions of 'Annex B' or 'Annex I', and (iii) full-free emissions trading between all regions.[53]
- Besides a global learning scenario, the studies consider cases of regional learning, in which regions learn separately, i.e. technologies in one region cannot benefit from capacity accumulating in another region. However, whereas Barreto and Klaassen (2004) explores only one case of regional learning (i.e. Annex B versus non-Annex B), Barreto and Kypreos (2004a) considers three cases of regional learning that represent a geographical fragmentation of the learning process in (i) Annex I/non-Annex I, (ii) IND/EIT/DEV, i.e. industrialised, economies-in transition and developing countries), and (iii) single-region learning domains, respectively.

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51 These papers build on previous work of Barreto (2001) and Barreto and Kypreos (2000 and 2002).

52 Officially, Annex I refers to the developed countries listed in Annex I of the United Nations Framework Convention on Climate Change (UNFCCC), while Annex B concerns the developed countries mentioned in Annex B of the Kyoto protocol (i.e. those developed countries that accepted an emission limitation target at the Kyoto conference). Annex B includes all countries recorded in Annex I, except Belarus and Turkey.

53 Notice that an emission trading refers to all trade in emission permits generally and does not distinguish particularities of the flexible mechanisms considered under the Kyoto protocol (ET, JI and CDM).

As noted, besides some differences, the focus and methodology of the two studies are highly similar, resulting in a set of findings and conclusions that on the one hand are highly comparable, but on the other hand supplement and, to some extent, qualify each other as well. The major findings and conclusions of these two studies will be discussed briefly below.

Firstly, the presence and geographical scale of learning spillovers affect the deployment and ranking of different technologies in individual regions and, hence, the resulting technology mix in these regions. For instance, Barreto and Klaassen (2004) show that in the reference case with global learning, technologies such as solar PV or advanced coal plants are widely used by the end of the 21st century in the Annex B regions, while with regional (Annex B/non-Annex B) learning, these technologies remain ‘locked out’ of the electricity generating mix. For solar PV, a similar pattern of ‘lock-in’ versus ‘lock-out’ is observed in the ‘Kyoto-for-ever’ mitigation scenario under full emissions trading with global versus regional learning. Similar differences in technology deployment due to differences in learning spillovers were found by Barreto and Kypreos (2004a) for the year 2050, although for solar PV in the Annex I region they observed this difference in deployment only for their ‘Kyoto-trend’ mitigation scenario (for both the full trade and Annex I trade cases, however), but not for their reference scenario. It should be noticed, however, that in most other cases analysed by these two studies the differences in technology deployment between global versus regional learning were either absent, small or less pronounced (‘lock-in’ versus ‘lock-out’) than in the case of solar PV in the developed regions.

Secondly, the emissions trading regime may not only have a direct effect on technology deployment in different regions, but also an indirect effect as it may affect the relationship or impact of the presence and geographical scale of learning spillovers on the deployment and mix of different technologies in individual regions. For instance, Barreto and Kypreos (2004a) show that under the ‘Kyoto-trend’ mitigation scenario with global learning the deployment of solar PV in the non-Annex I region for the year 2050 is much higher in the full trading scheme than the no-trading regime. Besides, in both trading schemes this deployment is much higher in the case of global learning than in the three cases of regional learning (which, in turn, also show major differences in solar PV deployment).

Thirdly, the imposition (and stringency) of a carbon constraint may not only have a direct effect on technology deployment in different regions, but also an indirect effect as it may affect the relationship or impact of the presence and geographical scale of learning spillovers on the deployment and mix of different technologies in individual regions. For instance, Barreto and Klaassen (2004) show that in case of regional learning the deployment of solar PV in the Annex B region for the year 2050 is much higher in the ‘Kyoto-for-ever’ mitigation scenario than the reference scenario. Besides, in both emission scenarios, this deployment in higher is the case of global learning, compared to regional learning.

Fourthly, the presence and scale of learning spillovers may not only affect technology deployment at the regional level but, hence, also the amount of carbon permits traded. For instance, as illustrated by Barreto and Kypreos (2004a), the volume of CO_2 permits sold by the region Asia in the ‘Kyoto-trend’ scenario is significantly higher in 2050 in case of IND/EIT/DEV regional learning (compared to global learning), while it is significantly lower in the case of Annex I/non-Annex I learning.

Fifthly, the presence and scale of learning spillovers may also affect the total abatement costs of the different mitigation cases. In general, as illustrated by Barreto and Klaassen (2004), these costs are highest in the case of no trading, less in the case of Annex B trading only and lowest in case of full global trading (although the cost differences in the trading cases of Barreto and Klaassen are relatively small as the mitigation target of their ‘Kyoto-for-ever’ scenario is weak). In addition, however, they show that for each case considered, the abatement costs are lower in the case of global learning, compared to regional (Annex B/non-Annex B) learning.

Finally, the presence and scale of learning spillovers may also have an impact on the amount of emissions at the regional level - notably in the non-Annex B regions - and, depending on the trade regime, at the global level as well. As illustrated by Barreto and Klaassen (2004), this impact is in relative sense the largest in case of the 'Kyoto-trend' scenario with no emissions trading. In this case, the Annex B regions have to deploy low-carbon technologies in order to curb their emissions (except the US as it remains outside the Kyoto protocol). Such deployment leads to cost reductions of these technologies that, assuming global spillovers, are shared by the non-Annex B regions. As a result, these technologies become more attractive in the non-Annex B regions and, hence, they become more deployed, resulting in less CO_2 emissions in this region. However, in case of no emissions trading and no or regional (Annex B/non-Annex B) learning spillovers, mitigation efforts in the Annex B regions do no lead to cost reductions of technology deployment in the non-Annex B regions and, hence, to no changes in the technology mix and corresponding emissions of the non-Annex B regions. Therefore, owing to the presence of global learning spillovers, the imposition of emission constraints in the Annex B regions may induce carbon-sharing technological change and, thus, less CO_2 emissions in the non-Annex B regions, even when the latter regions do not face carbon constraints. However, although of all cases considered by Barreto and Klaassen (2004) the impact of the presence of global learning spillovers on non-Annex B emissions is the largest in the case of the 'Kyoto-trend' scenario with no emissions trading, the size of this impact is limited to approximately 1 GtC in 2100 (about 10 percent of the non-Annex B baseline emissions in the late 21st century) because the reduction target of this scenario is weak and the learning mechanism can be observed only in electricity generation technologies.

In contrast, in the case considered above, the impact of the presence of global learning spillovers is much smaller (or almost absent) on Annex B emissions. This is due to the fact that for the Annex B regions (except the US), the level of emissions is determined by the mitigation target of the 'Kyoto-trend' scenario and, hence, the presence or absence of global learning spillovers has little impact on the carbon emissions of these regions (although, as indicated above, it may affect the costs of achieving the emission target). Therefore, in the case of no emissions trading, the impact of global learning spillovers on total, global carbon emissions is hardly determined by its impact on Annex B emissions but predominantly by its effect on non-Annex B emissions, as outlined above.

However, when global emissions trading is introduced, the impact of global learning spillovers on non-Annex B (and global) emissions becomes much smaller (or even zero). This is due to the fact that emissions trading lowers the amount of (high-cost) emission reductions in the Annex B regions, resulting in less deployment of carbon-saving technologies in these permit-buying regions and, hence, to less learning spillovers to non-Annex B regions. Moreover, any emission reduction realised in non-Annex B regions (either due to emissions trading or global learning spillovers) can be traded to Annex B regions, thereby leaving global emissions unaffected.

6.6 Comparing two approaches on induced technological spillovers

The section above has discussed some major findings by Barreto et al. (Barreto and Klaassen, 2004; Barreto and Kypreos, 2004a) on the impact of induced technological spillovers on carbon emissions in (unconstrained) developing regions, while Chapter 3 has dealt with comparable findings by Grubb et al. (2002a and 2002b). A comparison of these two approaches of induced technological spillovers offers some useful insights on this issue, notably with regard to the implications of the underlying assumptions and methodologies for the major findings of these studies.

Firstly, as noted above, of all cases considered by Barreto and Klaassen (2004), the impact of induced technological spillovers on carbon emissions in (unconstrained) developing regions is the largest in the case of the 'Kyoto-for-ever' scenario with global learning spillovers and no emissions trading, in which case this impact is approximately 1 Gt in 2100 (i.e. about 10% of the assumed baseline emissions of these regions). In contrast, as indicated in Chapter 3 (Figure 3.1), Grubb et al. (2002b) estimate this impact in their case of full spillover (σ = 1) at about 11 Gt in 2100 (i.e. some 85% of the assumed baseline emissions of the non-Annex B regions). These differences in impact of induced technological spillovers on carbon emissions in (unconstrained) developing regions can be attributed to the following factors:

- *The character of the two studies.* The findings of Barreto and Klaassen (2004) are based on a sound analysis of the interaction between emissions trading and induced technological spillovers by means of a well-established scientific model, whereas the results of Grubb et al (2002b) are based on simple, hardly tested assumptions on the presence of international spillovers in order to provide a numerical illustration of the potential role and significance of these spillovers.
- *The assumed baseline scenario.* Barreto and Klaassen (2004) base their estimate of the reference emissions in developing regions for the year 2100 on the SRES-B2 scenario (developed with the MESSAGE model), while Grubb et al. (2002b) take as their baseline the SRES A2 scenario of the IPCC (2000a). However, this factor can explain only a small part of the difference in impact of induced technological spillovers found by these studies as the reference emissions in developing regions for the year 2100 are estimated at approximately 11 GtC in the SRES-B2 scenario and about 13 GtC in the SRES-A2 scenario.
- *The stringency of the carbon constraint in the developed regions (i.e. either 'Annex B' or 'Annex I' regions).* In Barreto and Klaassen (2004), the mitigation target for the year 2100 is relatively weak ('Kyoto-for-ever'), while in Grubb et al. (2002b) it is rather stringent (i.e. Kyoto until 2012 followed by a decline in Annex I emissions by 1% per year thereafter). Moreover, in the analyses of Barreto and Klaassen (2004), the US remains outside the Kyoto Protocol, whereas in the illustrative example of Grubb et al. (2002b), it participates in the stringent mitigation commitments for the Annex I regions. Therefore, compared to Barreto and Klaassen (2004), the incentives for induced technological change in developed regions are much larger in Grubb et al. (2002b).
- *The meaning and implication of the concept 'global/international technological spillovers'.* As outlined in Section 2.2, Grubb et al. (2002b) employ a broad definition of this concept, including (i) spillovers due to economic substitution ('carbon leakage'), (ii) spillovers due to diffusion of technological innovations, and (iii) spillovers due to policy and political influence of developed countries' mitigation efforts on developing countries' abatement actions. In their case of full spillover (σ = 1), this definition covers the full, global diffusion of all energy/carbon-saving innovations at both the supply and demand side of the whole economic system, including cost reductions and other performance improvements of these technologies such as enhancing energy/carbon efficiency. On the other hand, in Barreto and Klaassen (2004; as well as in almost all other bottom-up energy system studies), the concept of global technological spillovers refers particularly to the fact that the benefits of technological learning (i.e. cost reductions) due to the deployment of a given technology in a certain region also spread to other regions, thereby improving the attractiveness of deploying this technology also in these regions. More specifically, in the case of global technological spillovers studied by Barreto and Klaassen, this concept refers only to the cost reduction effects of a few learning technologies on the supply side of the electricity generating system, while ignoring all other energy/carbon technologies of the economic system as well as all other aspects of improving the performance of these technologies besides cost reduction, notably enhancing carbon/energy efficiency. Moreover, in the study of Barreto and Klaassen, the diffusion of carbon-saving technologies in developing regions may be restricted due to cost-competitive considerations and, hence, the power-generating technology mix in these regions may divert significantly from this mix in developed regions (see also the discussion below). In the study of Grubb et al., however, it is assumed that in case of full global technological spillovers the average carbon intensity in developing regions converges to the same level of the (declining) carbon intensity in the developed regions by the end of the 21st century.

Hence, whereas in Grubb et al. (2002b), the average carbon intensity in the year 2100 is assumed to be the same in developing and developed regions, in Barreto and Klaassen (2004) this intensity may be substantially higher in developing, carbon-unconstrained regions than in developed, carbon-constrained regions due to different cost considerations in these regions. Therefore, the concept global/international technological spillovers has a far broader meaning and implication in Grubb et al. (2002b) than in Barreto and Klaassen (2004).

Together, these factors - notably the multiplication of the third and fourth factor mentioned above - explain the large difference in impact of induced technological spillovers on carbon emissions in developing regions for the year 2100 as estimated in the considered cases of Barreto and Klaassen (at approximately 1 Gt) and Grubb et al. (about 11 GtC).

Secondly, another useful insight offered by comparing the studies of Grubb et al. and Barreto et al. concerns the role of incentives in deploying emission-saving technologies in case of no emissions trading between developed, constrained regions and developing, unconstrained regions. In the studies of Barreto et al., these technologies are deployed in developed regions as far as they become more attractive than alternative, more carbon-intensive technologies due to endogenous, global learning effects (i.e. cost reductions) of emission-reducing technologies as well as endogenous, climate policy induced effects of raising the costs of alternative technologies, while in the developing regions only the global learning effects apply. In the study of Grubb et al., however, emission-saving technologies are diffused in developed regions due to autonomous and endogenous factors, notably stringent policy-induced carbon constraints.

In case of full global technology spillovers and no emissions trading between developed and developing regions, these technologies are assumed to be widely deployed in developing regions regardless their cost implications compared to alternative technologies that might be more carbon-intensive, but cheaper. However, why should developing countries in such a case deploy emission-reducing technologies, for instance carbon storage or fuel switching technologies for generating electricity, if cheaper, but more carbon-intensive alternatives are available? Of course, incentives to encourage the diffusion of emission-saving technologies in developing regions could be enhanced by introducing carbon constraints in these regions and/or allowing emissions trading between developed and developing regions. However, allowing such trading has a variety of counteracting effects on the performance of climate policy and induced technological change (as discussed below), while introducing effective carbon constraints in developing countries may be politically hard to realise, particularly in the short and medium term (and it discharges the politically attractive statement that, owing to global technology spillovers, emissions in developing regions can be reduced substantially without introducing carbon constraints in these regions).

Finally, an additional useful insight offered by comparing the studies of Grubb et al. and Barreto et al. refers to the interrelated effects of emissions trading on the performance of climate policies and induced technological change. More specifically, these effects can be distinguished into:

- The impact of emissions trading on technology deployment and learning effects. As discussed above, emissions trading lowers the amount of high-cost emission reductions in constrained regions, resulting in less deployment of carbon-saving technologies in these permit-buying regions and, in case of (global) learning effects, in less cost reductions of these technologies (and less spillovers to other regions). In the permit-selling regions, however, the deployment of (other) carbon-saving technologies is encouraged, including their potential (global) learning effects.
- Hence, emissions trading has two counter-acting effects on the process of technology deployment and learning at the regional level, and the final outcome depends, among other

things, on the relative weights of these two effects (Barreto and Klaassen, 2004; Barreto and Kypreos, 2004a).[54]

- The impact of emissions trading on regional and global carbon levels. In the absence of technological spillovers, emissions trading has no impact on the total amount of global carbon emissions but only on its distribution among participating regions. However, when technological spillovers are present, emissions trading between constrained and unconstrained regions does have an impact on the total amount of global carbon emissions as any carbon reduction in unconstrained regions due to technological spillovers can be traded to constrained regions, thereby enhancing emissions in these constrained regions as well as at the global level, compared to the case when such trading is not allowed. Actually, the potentially high impact of full global technological spillovers on global emissions, as illustrated by Grubb et al. (2002b), depends critically on the assumption of no emissions trading between constrained and unconstrained regions (although, paradoxically, CDM-based emissions trading might be a major channel to promote full international technology spillovers to unconstrained regions). If they would have allowed such trading, global carbon emissions would have been much higher (the same applies to the technology spillovers explored by Barreto and Klaassen, although the size of these spillovers are much smaller). Hence, in the presence of global technological spillovers, global emissions are lowest when emissions trading between constrained and unconstrained regions is not allowed.
- The impact of emissions trading on abatement costs. In general the (static) costs or GDP losses of achieving a given mitigation target are lowest when full, unrestricted emissions trading is allowed on a global scale (Weyant and Hill, 1999; Sijm et al. 2000). This implies that an abatement strategy that does not allow such trading ends up in higher costs. This applies particularly for the strategy illustrated by Grubb et al. (2002b) as its abatement target for the year 2100 is rather stringent for the constrained regions while it does not allow emissions trading between constrained and unconstrained regions. Hence, the costs or GDP losses of this strategy could most likely be reduced substantially if such trading would be allowed. However, as explained above, allowing emissions trading between constrained and unconstrained regions implies that global emissions levels will be higher (as it allows unconstrained regions to trade their emission reductions resulting from global technological spillovers). Therefore, in the presence of global technological spillovers, there seems to be a trade-off between an abatement strategy with full, unrestricted emissions trading - which implies lower costs - and an abatement strategy with no or restricted emissions trading (which implies lower global emissions). The optimal outcome of this trade-off may be hard to determine as it depends on the size of the global spillover effects versus the amount of cost savings owing to full emissions trading. Hence, further research on the optimal trading regime in the presence of global technological spillovers seems warranted.
- The impact of emissions trading on dynamic efficiencies. It is sometimes stated that forbidding or restricting emissions trading would stimulate induced technological change (ITC) in constrained regions, which may lead to dynamic efficiencies such as lower abatement costs and/or higher abatement levels in the long run. However, some counter-arguments to this statement can be raised. Firstly, as discussed above, with regard to the process of technology deployment and learning, emissions trading has counter-acting effects in constrained versus unconstrained regions, but the final outcome is ambiguous. Secondly, a similar argument can be applied with regard to R&D-based ITC, in the sense that emissions trading may discourage R&D-based ITC in constrained regions, while encouraging it in unconstrained regions. However, according to Buonanno et al. (2000), even if restrictions on emissions trading stimulate, on balance, R&D-based ITC, the impact on overall abatement costs and economic growth appears to be detrimental as the cost savings achieved through unrestricted emissions trading seems to stimulate growth more than the increase of R&D-driven innova-

[54] For instance, in case of no emissions trading, a carbon constraint in developed regions may encourage the deployment of wind or nuclear technologies in these regions (and through global learning effects also in developing regions), while allowing CDM-based emissions trading may encourage the deployment of solar PV in developing regions (with potential learning spillovers to developed regions).

tions achieved through trade ceilings (as discussed in Section 5.2). Finally, as emissions trading lowers the short-term (static) costs of an abatement target, governments may be willing to accept a more stringent target, which may enhance the inducement of developing and diffusing carbon-saving innovations.

To conclude, emissions trading has a variety of counter-acting and counter-balancing effects on the performance of abatement policies in the presence of induced technological change and international spillovers. Although insights in these effects have grown over the past years, little is still known about the final, empirical outcome of these effects and, hence, additional research seems to be warranted.

6.7 Major similarities in performance of ITC bottom-up studies

In contrast to the ITC top-down studies (see previous chapter, notably Section 5.3), the ITC bottom-up studies reviewed in the present chapter show some major similarities in performance, in terms of both methodological approach and major findings of the models used. In order to explore the interaction between climate policy and induced technological change (ITC), these studies have used a detailed, bottom-up energy technology system model in which learning curves have been added to the cost functions of (some) energy technologies covered by these models. The major findings of these studies are that, due to the presence of ITC (i.e. 'learning technologies'), (i) the investment costs of these technologies decline if they built up capacity ('experience'), (ii) the energy technology mix changes in favour of those technologies that built up the relatively highest rate of learning (i.e. cost reduction), and (iii) the total abatement costs of a given abatement target decline significantly.[55]

However, although there is a large degree of agreement among bottom-up studies with regard to these results, the size of the impact of ITC on, for instance, the technology mix or abatement cost may vary substantially between these studies depending on the assumed rate of technological learning, the number of learning technologies included in the analysis, the time frame considered, the stringency of the mitigation target, etc.

Evaluation of ITC bottom-up studies: strengths and weaknesses

The major strength of ITC bottom-up studies is that they provide a detailed, and rather concrete picture of the process of induced technological change, particularly of the diffusion and deployment of energy and carbon-saving technologies due to learning-by-doing (in contrast to the often highly aggregated, and rather abstract paintings generated by ITC top-down studies that are often focussed on technology innovation through R&D). Moreover, some recent bottom-up studies have offered valuable contributions and useful insights with regard to analysing the interaction between ITC, emissions trading and learning spillovers.

On the other hand, bottom-up ITC studies are usually faced by some weaknesses and limitations, including:

- While the number of energy technologies included in bottom-up models is often relatively large, the number of technologies characterized by endogenous learning is usually limited to a few (electricity) supply-side technologies, thereby neglecting other technologies, particularly at the demand side of the energy system (Laitner and Sanstad, 2004). This leads to biased results and an underestimation of the full potential impact of ITC.
- The empirical database for estimating learning curves in general, and two-factor learning curves in particular, is often weak. Moreover, the estimation of (two-factor) learning curves is often faced by statistical problems and econometrical shortcomings, leading to biased re-

[55] In general, bottom-up ITC studies assume a given abatement target in their mitigation scenarios and, hence, they do not analyse the impact of ITC on emission reductions or similar global warming indicators (although they sometimes explore this impact in their baseline scenario by comparing this scenario with and without ITC).

sults. In addition, despite some growing insights, the technology learning phenomenon remains largely a ‘black box’ and sound models, able to identify the factors that underlie the learning effects, are still missing (Barreto, 2003). As a result, it is often hard to draw firm, relevant policy implications from bottom-up studies based on estimated learning curves.
- Bottom-up studies are usually focussed on analysing mainly the diffusion of technologies (‘learning-by-doing’) and less on technological innovation through R&D investments (‘learning-by-searching’). The latter channel of ITC, however, is covered by some recent bottom-up studies, although - as indicated above - these studies often suffer from statistical and econometrical shortcomings. In addition, bottom-up studies are usually focussed on analysing the ITC impact of only one or two policy instruments, particularly an energy/carbon tax or a technology subsidy. As a result, it is often hard to draw firm, relevant policy implications with regard to the choice and optimal mix of instruments, either within the field of technological innovation or the field of technological diffusion, or between these fields of technological change.
- Bottom-up studies are characterised by a limited specification of the behaviour of producers and consumers, the performance of (imperfect) markets, and the feedback effects of this behaviour and performance at the macroeconomic level. Therefore, their estimates of GDP losses or social costs due to climate policy or ITC have to be interpreted with some prudence.

6.8 Major lessons and implications

Despite significant progress made in endogenising technological change in bottom-up modelling studies over the past decade, the present state of these studies is still characterised by too many weaknesses and limitations to draw a set of firm, specific policy lessons and implications. Nevertheless, a few general lessons and implications can be formulated. Firstly, according to Gielen et al. (2003), *'the most important policy message from technology learning is that new technologies require markets to become commercial…. The outstanding feature of technology learning is that there are no substantial cost reductions without market interaction'*. Hence, as it takes time to build up capacity (i.e. ‘learning’ or ‘experience’) and to reduce costs until a market break-even point is reached, there is a need for early policy action *'to accomplish the required cost and performance improvements in the long term, including the creation of niche markets, the development of small-scale demonstration plants, and targeted R&D'* (Riahi et al., 2004). In addition, the (temporary and declining) subsidization of promising technologies may be considered, although the dangers of ‘picking a winner’ and becoming ‘locked-in’ an inefficient technology system have to be reduced by broadly supporting a general package of renewable energy and carbon saving technologies rather than heavily subsidizing a specific technology. Even then, however, there is still the risk of ‘rent-seeking’ and ‘rent-keeping’, i.e. the incidence of political lobbies to introduce and maintain subsidies at a fixed level.

Another lesson is that, owing to the presence of spillovers, the imposition of emission constraints in the Annex I region may induce technological change and, hence, emission reductions in the non-Annex region even when the latter region does not face emission constraints itself (Barreto and Kypreos, 2004a; Barreto and Klaassen, 2004). A major policy implication is that Annex I governments may improve the operation of spillovers and the resulting diffusion of technologies to non-Annex I countries, for instance by means of an open, fair international trading regime - including emissions trading - or by upgrading the absorptive capacity in non-Annex I countries for the transfer, deployment and further development of new technologies. It is hard, however, to draw more firm, specific policy implications given the trade-offs and still limited knowledge with regard to the intriguing, but complicated interaction between emissions trading, induced technological change and the presence of spillovers, including the impact of this interaction on total abatement cost and global emission reductions.

A final lesson or implication is that further research is needed in order to draw more concrete, firm policy conclusions from ITC bottom-up modelling studies. More specially, the major suggestions for additional research include:

- Improving the empirical database for bottom-up studies, particularly to improve the estimation and interpretation of (two-factor) learning curves.
- Expanding the number of learning technologies in bottom-up modelling studies, including technologies at the demand side of the energy system.
- Enlarging the focus of analysis from technology diffusion and a few related policy instruments to technology innovation and other instruments in order to draw firm, relevant policy implications with regard to the choice and optimal mix of policy instruments, either within the field of technological innovation or the field of technological diffusion, or between these fields of technological change.
- Intensifying the analysis of the impact of climate policy on international spillovers, including the interaction between emissions trading, induced technological change and the presence of spillovers, as well as the impact of this interaction on total abatement cost and global emission reductions.

7. IMPLICATIONS FOR POST-KYOTO CLIMATE AND TECHNOLOGY POLICIES

The discussion in the previous chapters raises some major considerations and implications for the post-Kyoto agenda on climate and technology policies.[56] Firstly, as argued in Chapter 4, the market for developing and diffusing environmental technologies is characterised by two related sets of imperfections (i.e. environmental externalities and technology market failures). Moreover, both the greenhouse effect and the spillover externality of technological change have a highly international, global character. Therefore, a well-balanced package of internationally co-ordinated climate and technology policies is necessary to deal with these two sets of market imperfections, in particular as long as climate policy alone is not able to address the greenhouse externality in an adequate way. In addition, it should be noted that technology policy alone will not be able to cope adequately with the issue of global warming, since an incentive - for instance a carbon tax or emission limit - is necessary to induce technological change in the direction of developing and diffusing emission-saving technologies.[57]

Secondly, it is sometimes suggested that technology diffusion should be used as an incentive in the international climate negotiations, for instance by excluding certain countries from the climate coalition and, thus, from the benefits of technology diffusion (or by including these countries by exchanging these benefits for the willingness to accept emission limitations). It may be questioned, however, whether such a strategy - notably the 'exclusion option' - will be feasible and efficient, because technological knowledge has a highly public (international) character, while restricting technology diffusion is not in the interest of the climate coalition for both environmental and technology learning (i.e. cost reduction) reasons (Tol et al., 2000 and 2001; Golombek and Hoel, 2003, and Koops, 2003). Indeed, Tol et al. (2000 and 2001) show that this strategy of 'issue linkage' is not cost-effective, or even counter-productive, since nobody will benefit. Rather than excluding other countries from the knowledge on emission-saving technologies, it is better to pursue an optimal diffusion of such technologies.

Thirdly, the considerations above raise the question how the innovation and diffusion of emission-saving technologies can be stimulated internationally by the climate coalition. The major options include:

- International co-operation on Research, Development, Demonstration and Deployment activities (summarised as RD3; see Barreto and Klaassen, 2004). For instance, De Groot and Tang (2001) suggest the option of an international subsidy fund for the innovation and diffusion of renewable energy technologies.
- Encouraging technology diffusion through trade and other, general policies. Since diffusion of technology often occurs through international trade and foreign direct investments, it can be promoted through general policies such as pursuing a fair open trading system or taking care of adequate financial and legal means in developing countries (IPCC, 2000b; Koops, 2003).
- Stimulating technology diffusion through emissions trading, notably the Clean Development Mechanism (CDM), and sound technology transfer strategies emphasizing, among others, local activities and sound technology capacity building that enables countries to assimilate and adapt experience accumulated somewhere else (Barreto and Klaassen, 2004).

[56] Besides the previous chapters, the discussion of the present chapter is based particularly on Koops (2003), as well as relevant contributions made by IPCC (2000b), Tol et al. (2000 and 2001), Groot and Tang (2001), Buchner et al. (2002b), Grubb et al. (2002a and 2002b), Golombek and Hoel (2003), and Barreto and Klaassen (2004).

[57] Moreover, as shown recently by Buchner and Carraro (2004), international technological cooperation without any commitment to emissions control may not lead to a sufficient abatement of greenhouse gas concentrations.

- Promoting the innovation and diffusion of carbon-saving technologies by means of voluntary agreements ('covenants') between governments of the climate coalition and a few international firms that dominate R&D and technological change in certain areas, for instance the international automobile industry or the international 'bulk power' technology generating industry (Grubb et al., 2002b; Koops, 2003). If such covenants turn out to be not effective, the imposition of well-designed international technology standards could be considered.

These options should be part of the post-Kyoto agenda in order to enhance the potential positive interaction between climate policy, induced technological change and international spillovers, including the potential positive impact of this interaction on mitigating global greenhouse gas emissions and reducing total abatement costs.

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