THE ENERGY JOURNAL

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Endogenous Technological Change and the Economics of Atmospheric Stabilisation

Special Issue **IAEE**
International Association for Energy Economics

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Articles appearing in *The Energy Journal* are listed in both *Envir. Per. Bibliography* and *The Journal of Economic Literature* and are indexed/abstracted in *ABI/Inform, EconLit, JEL on CD*, *ISI Journal Citation Reports, Web of Science*, *SciSearch, Research Alert*, *Ei COMPENDEX, Trade and Industry Index, PAIS International*, *DOE Energy*, *Energy/Enviroline*, and *Wilson Business Abstracts*, and the following EBSCO databases: *Academic Search Premier* and *Business Source Premier*.

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ADVERTISING INFORMATION: For a complete media kit, contact Marketing Department, IAEE Headquarters, 28790 Chagrin Blvd., Ste. 350, Cleveland, OH, 44122-4630. Phone: 216-464-5365, fax: 216-464-2737. E-mail: iaee@iaee.org. Homepage: http://www.iaee.org.

International Standard Serial Number: 0195-6574. Printed in the U.S.A

ENDOGENOUS TECHNOLOGICAL CHANGE AND THE ECONOMICS OF ATMOSPHERIC STABILISATION

A Special Issue of
The Energy Journal

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THE ENERGY JOURNAL

SPECIAL ISSUE

ENDOGENOUS TECHNOLOGICAL CHANGE AND THE ECONOMICS OF ATMOSPHERIC STABILISATION

Table of Contents

Preface

The Energy Journal is pleased to present this special issue on the timely and crucial subject of atmospheric stabilization and endogenous technological change. The oft-quoted phrase—"necessity is the mother of invention"—comes to mind though one wonders whether invention will come in time. Moreover, if the most severe impacts of climate change are felt first in the poorest of countries, the initial "endogeneity" effect will surely be lesser than if these impacts occur first in countries that can afford the funds required for research and development of mitigating technologies.

The nature of technological change is extraordinarily difficult to predict. In technical jargon it might be said that it is neither stationary nor ergodic. It is not stationary because it is constantly evolving. It is not ergodic because simply observing the history of science is insufficient to predict the important characteristics that technology will have in the future. Still, the papers in this special issue attempt to shed light on how such technological change happens, a necessary first step if technologies for climate stabilization are to be supported by policy. It is my personal hope that their important work will continue.

Adonis Yatchew
Editor, *The Energy Journal*
March 29, 2006

Technological Change for Atmospheric Stabilization:

Introductory Overview to the Innovation Modeling Comparison Project

Michael Grubb, Carlo Carraro** and John Schellnhuber****

1. OVERVIEW OF THE ISSUES

1.1 Technology and the Sources of Innovation

As climate and energy issues continue their inexorable rise up policy agendas worldwide, there seems to be at least one core fact upon which almost everyone agrees: that the development and diffusion of low carbon technologies will be central to stabilizing the climate over the 21st Century. However, innovation is something that economists have long debated as an exceptionally complex area for economic theory.

Like a river, technology collects ideas from myriad sources. Under the force of gravity—the pull of market demand—technology can harness these ideas, through many tributaries of intermediate technologies, into viable products. The continuing advance of ideas in all walks of life, which help to flow into making an improved product, forms a general 'autonomous' advance. From a specific technology perspective it just happens; from a modeling perspective this is 'exogenous' technological change, built in by assumption.

Yet one feature of economic systems is the increasing pace with which the technology terrain evolves. Starting to understand and represent these forces is the domain of endogenous theories and models of innovation. The broad literature identifies several forces at play.

Seeking new markets, industry itself makes strategic decisions about R&D—where and how hard to try and break through barriers in the terrain, how

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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much to invest in what kinds of innovation. The extent and direction of this effort is influenced by the perceived opportunities and risks—the strength and nature of the demand-side forces.

Public funding is also important. Publicly funded, targeted R&D programs, along with the macroeconomic equivalent in terms of the publicly funded wider accumulation of knowledge, can themselves carve out new routes through the technology landscape. From an economic perspective, there is thus 'learning by searching' both funded directly by governments, and by industry in response to market incentives of various kinds.

Moreover, any technology also acts directly on its own surroundings. Just as a river carves out, deepens and extends its own channels, technology similarly modifies both itself, through experience and market feedbacks, and its surroundings. Technological streams act to reinforce their own competitiveness and dominance, unless other forces block the route or it is traversed by a deeper, better channel.

Technological advance is thus a product of at least three distinct forces-typically classified into public and private sector knowledge investment or 'learning by searching', and applied 'learning by doing'.

Reflecting and quantifying how these forces may act over time to shape the technology terrain is immensely complex. Nevertheless over the past few decades, economic analysis has made considerable progress, with endogenous growth theories beginning to enter mainstream economic thinking and diverse endogenous growth and learning-by-doing models being developed, as surveyed briefly in the Technical Review in this volume (Köhler et al. 2006)

1.2 Applying Theoretical and Empirical Insights

As in many areas of analysis, applying to practical questions the evolving theoretical ideas and models of innovation has proved an even greater challenge. For many areas of public policy—for issues that are short term, which involve marginal changes, or are purely local—this probably matters little. In such cases true innovation may be either not relevant on the scales and timescales considered, or left to events and decisions 'elsewhere'.

However, the problem of climate change is at the opposite end of the spectrum—long-term, deep and global. The goal expressed in the UN Framework Convention—to stabilize atmospheric concentrations of greenhouse gases—is decades away even under the most radical control scenarios: most scenarios suggest it will take until at least the end of the century and many remain skeptical the goal can be achieved even beyond that point. The intrinsically global nature of the problem also poses new challenges. Decisions taken in negotiations have an impact across the globe, and even decisions in relatively small countries—such as those which Denmark took with respect to wind energy in the 1970s and 1980s—can ultimately have major global repercussions, given a few decades for the resulting technology-industries to grow and spread internationally. How to model technological change is thus central to decision-making around climate change policy, and different perceptions about technological change processes help to explain differences in current national positions.

Theoretical models of endogenous change, however, are still far from fully applied models that can give quantified insights into the specifics of energy supply and demand and the impact of particular incentives. Moreover, endogenizing technological change in existing global energy-economy models has the potential not only to require different theoretical approaches, but can also vastly complicate the task of computation and interpretation. Applying insights from both theoretical and empirical studies on endogenous technical change in energy systems modeling was first initiated in the 1990s, but is only now beginning to mature as plausible and useable tools.

1.3 Innovation in Global Energy-environment Models

In the first generations of global energy-economy modeling applied to climate change, emerging from the late 1980s roughly up until the mid 1990s, technology entered through a series of exogenous assumptions. In true 'top-down' models, supply side technologies were reflected in assumptions about the elasticity of substitution between generic carbon and non-carbon sources (if any), whilst an "autonomous energy efficiency improvement" (AEEI) parameter was used to reflect an assumed degree of decoupling between GDP and energy consumption—a single, fixed parameter encompassing both structural change in the relationship between economy and energy and the development and diffusion of demand-side technologies.

Fully 'bottom-up' models, that represented the entire energy system in terms of specific technologies, were also developed and applied (the first global application being Goldemberg et al, 1988). These too had to rely on a series of exogenous assumptions about the future scale of energy demand and technology costs. Many of the models developed in the early 1990s combined top-down modeling of energy demand with bottom-up modeling of energy supply, disaggregated to various degrees, but still relied on essentially exogenous assumptions about both.

The most consistent finding to emerge from all these modeling studies was that technology mattered: the costs of deep emission reductions were almost entirely contingent upon the assumptions that the modelers built in about the pace of decoupling between GDP and energy demand on the one hand (the AEEI), and the cost of low-carbon energy sources on the other. Yet, as both the theoretical literature and empirical studies were already demonstrating, technology would itself be modified by climate policy.

From around the mid 1990s, two very different strands of analysis emerged seeking to endogenize technological change in energy-economy models. The 'top-down' modeling community began to explore incorporating both explicit knowledge functions using accumulated R&D, and learning-by-doing equations. At the same time, the 'bottom-up' community began building in learning-curves—explicit functions of how scale might be associated with cost reductions—into their analyses.

Unfortunately for policy, these two lines of enquiry appeared to lead to almost opposite conclusions about the implications of endogenous technological change. The initial studies using R&D in cost-benefit studies (in which the stabilization level is determined by the model) by Goulder and Schneider (1999) and by Nordhaus (2002) both highlighted the potential impact of 'crowding out' effects—the possibility that inducing more innovation in the energy sector could be at the expense of innovation elsewhere in the economy– and concluded that endogenizing technological change may make little difference either to the long term costs or the near term policy recommendations.

In sharp contrast, the MESSAGE studies pioneered at IIASA (Grubler, Nakicenovic and Victor, 1999), and related developments in the IEA technology program (IEA, 2000), appeared to show that learning-by-doing in the energy sector could, over the 21st century, revolutionize the system to such a degree that a very low carbon future could be just as cheap as a high carbon future, and that which emerged would be heavily dependent upon the policy choices taken early in the Century. Arguably, these initial efforts to endogenize technology change thus widened, rather than narrowed, the gulf in perceptions between different analytic communities in ways that perhaps also fed through to conflicting policy stances.

In the third generation of studies, from around the turn of the Century, both the 'top-down' and the 'bottom-up' lines of analyses have become more sophisticated and more circumspect. In the 'top-down' analysis, new models have been proposed in which the menu of effects of technological change that could be modeled was much richer and therefore the role of technological change more relevant than in Nordhaus (2002).[1] For example, as explained in the Technical Overview paper in this volume, strategic R&D investments and international R&D spillovers were introduced in Buonanno, Carraro and Galeotti (2002), crowding out effects between different R&D investments were introduced by Goulder and Matthai (2000), learning by researching and learning by doing were jointly modeled in Castelnuovo et. al. (2003), the dynamics of a backstop technology was endogenized by several authors. At the same time, the field has become more conscious of its heritage and the potentials to learn from mainstream developments in endogenous growth theories.

In the 'bottom-up' analyses, IIASA has similarly pioneered a recognition that the seemingly unambiguous empirical data on experience curves itself embody at least two very different components—direct knowledge investment, and actual learning-by-doing—and that incorporating this distinction in two-factor learning curves makes the results less strident, and more subtle, than earlier studies.

Now is thus an opportune time to assess the state of the art, with a comparative study traversing both 'bottom-up' and 'top-down' perspectives in relation to the most over-arching, long-term and global policy question in the field: the implications of trying to stabilize atmospheric CO_2 concentrations.

1. See Clark and Weyant (2002), Carraro and Galeotti (2004) for a survey of how different climate economy models endogenise technical change.

2. THE INNOVATION MODELING COMPARISON PROJECT (IMCP)

This project represents a first systematic attempt to assess and compare the progress made through different modeling approaches, and to offer some first insights into what this may mean for the strategic economics of tackling the biggest long-term challenge in the energy sector, namely the goal of transforming energy systems in ways that could stabilize the atmospheric concentrations of CO_2. The project aims, for the first time, to 'open the black box' of endogenous innovation to scrutiny by comparing the results from different applied modeling approaches and the understanding the reasons for differences.

2.1 Background and Process

The IMCP arose out of recognition that the temporal, geographic and interdisciplinary scales of the climate change problem demand a more sophisticated kind of economics, and a more structured and collegiate international approach to analysis, than hitherto developed. Diverse researchers were invited to a brainstorming meeting in Utrecht in October 2003. This meeting marked the foundation of an 'international program on the economics of atmospheric stabilization', as a group of researchers with a common interest in pursuing such analysis. Participants debated various potential topics relating to the strategic economics of climate change particularly with reference to atmospheric stabilization. Out of the diverse range of topics discussed, the one universal element in the set of issues suggested by every participant was the need to understand better the representation of endogenous technological change. A follow-on meeting in Paris helped to define the resulting 'Innovation Modeling Comparison Project', and an open call was issued, including through the IAEE, for modeling groups interested in participating.

The project then developed through two main workshops. At the first, in Cambridge in November 2004, all modeling groups that had expressed interest presented the current state of their efforts and debated the criteria, issues and process going forward. At the second, at DIW in Berlin in late February 2005, groups presented their modeling results as far as possible on a common basis and critiqued the representation of technological change in more depth, together with a preliminary synthesis of results.

Over the subsequent months, the modeling groups submitted results according to the agreed common reporting format, and drafted papers that were then examined through a double review process—first by the Steering Committee, and then through a minimum of two external reviewers. The principal criterion was not that each paper individually had to represent methodological novelty. Rather, each paper had to show a qualitatively plausible representation of endogenous technological change in some form, together with some representation of the energy-carbon system sufficient to explore implications of ITC under different stabilization levels, and presented with sufficient clarity to enable comparison and interpretation of results. Of almost twenty groups initially expressing interest, the

10 studies set out in the papers here completed this extensive process.

2.2 Structure and Focus of the Analysis

The aim was to encompass a diversity of plausible approaches to modeling endogenous technical change and to compare them against common objectives. The guiding principle was that in each model, the analytic treatment of endogenous change should be consistent between a baseline run, and a set of runs with a constraint on atmospheric concentrations, so as to identify the impact of responses to the constraint in *inducing* technological change.[2]

The studies focus on atmospheric stabilization of CO_2, principally at levels of 450, 500, and 550ppm CO_2. Some models were also able to present results for 400ppm CO_2, others did not find this feasible given constraints on timescale of adjustment.

The decision to focus on CO_2 concentrations reflects a mid-point in a cascade of uncertainties, many of which complicate analysis without adding significantly to insights about the role of technological change.[3] Depending in part on the degree of action on other greenhouse gases, the range 450-550ppm CO_2 translates to a total atmospheric loading of roughly 500-650ppm CO_2-equivalent when the non- CO_2 gases are added.

The long-standing 'benchmark' of climate science studies of stabilizing radiative forcing at a doubling of pre-industrial CO_2 concentrations itself implies a projected CO_2 concentration probably below 500ppm CO_2, given the increase in other trace gases. However, 550ppm CO_2 has been more widely studied in the economics community, as a goal requiring less ambitious action, and one which some studies suggest would not require significant mitigation yet. Conversely, many scientists have argued for a goal to contain risks by aiming at low stabilization levels, with reference to physical indicators such as that now adopted by the European Council of Ministers of limiting temperature increase to 2 deg.C, which probably implies CO_2 concentrations at 450ppm CO_2 or lower.[4] Our chosen range aims to span these perspectives. Several models were able also to study 400ppm and these demonstrate that such levels would require action far more drastic than being contemplated in current implementation policies and negotiations, and they

2. Note that this terminology differs from that in Grubb et al.(2002), who refer to induced change as the process and endogenous change as a property of models that include induced technological change. In this study, we use endogenous change as the process, and refer to induced technological change as being the change in technological characteristics *induced by the policies or incentives associated with the stabilisation constraint.*

3. Both methane and N_20 are products primarily of land use changes and agricultural and waste practices, without a strong direct technological component, whilst the industrial trace gases are very sector and process specific and do not raise the same level of economy-wide issues that CO_2 raises. Given the dominance of CO_2, it is also apparent that overall greenhouse gas concentration cannot be stabilised unless CO_2 itself is brought close to stabilisation.

4. For example presented in Avoiding Dangerous Climate Change Conference hosted by UK Government (2005) and presented in Schellnhuber eds. (2006).

give a useful insight into what might be implied.[5]

The link between fossil fuel CO_2 emissions and concentrations itself depends on the assumed emissions from land-use change and the broader carbon cycle. These were not actively harmonized but the range from the models narrowed after initial comparison. Figure 1 shows the CO_2 emission trajectories across the models associated with (a) 450ppm CO_2 and (b) 550ppm CO_2 respectively. The 450ppm constraint requires global CO_2 emissions to peak soon—sometime in the period 2010-2030—and emissions by mid Century are generally between 5GtC/yr and the present level of 7GtC/yr, with cumulative emissions over the Century around 600GtC.[6,7]

The highest level in the comparison, 550ppm CO_2, displays a far broader range of trajectories. Three models use the extra 'headroom' to sustain a relatively flat emissions trajectory, between about 8 and 10GtC/yr across most of the Century. Others allows global emissions to continue rising sharply, peaking between 2030 and 2050, and then declining (in some cases precipitously), implying that in these trajectories the second half of the century sees removal, replacement or retrofit of much of the carbon emitting infrastructure constructed during the first half. Thus endogenizing change in these models does not itself appear to bring much alignment of the time-path of emissions (most but not all are dynamically optimized).

We designed guidelines attempting to reduce another major source of variation through proposing a common reference case, or 'baseline', around the 'Common Poles-Image' (CPI) baseline case which defines a 'business as usual' scenario. In practice, the models varied in their implementation of this—one feature of endogenous change being that the reference case itself becomes dependent upon other assumptions and features in the model and thus much harder to harmonize. Excepting one low and one high outlier,[8] the models have emissions (cumulative over the Century) in the baseline that are similar to within +/-20% around a mean of about 1400GtC, however, baseline GDP projections vary by much more as indicated below.

Figure 3 in the Synthesis paper in this volume (Edenhofer et al., 2006) illustrates the combined impact of the differences in carbon cycle and baselines,

5. Levels significantly below 450ppm CO_2 would also start to preclude use of conventional oil reserves, potentially driving costs up sharply but also underlining the fact that energy resource considerations will anyway require significant technological transitions in energy systems during this Century (IPCC, 2001)

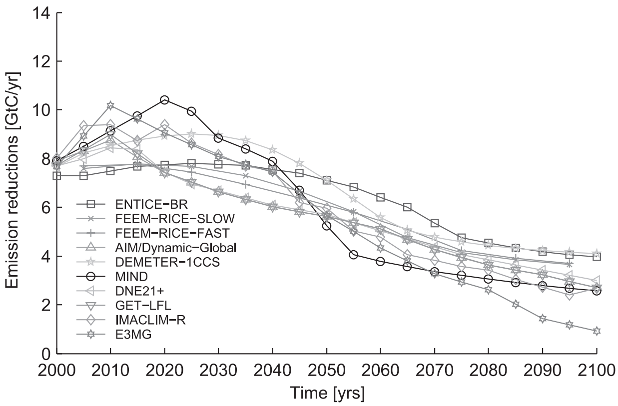
6. Specifically, the mean cumulative carbon emissions 2000-2100 across all the different models is around 600GtC for 450ppm, 780GtC for 500ppm, and 930GtC for 550ppm, with standard deviation about 7% for each level. Note these data also highlight the importance of assumptions around the global reserves and resources of conventional oil, which are generally estimated to contain under 200GtC together, with more than half of this in proven reserves.

7. Note that the rates of decline suggest that even 450ppm does not necessarily require premature retirement of existing capital stock, though it could severely limit the headroom for constructing new carbon intensive stock.

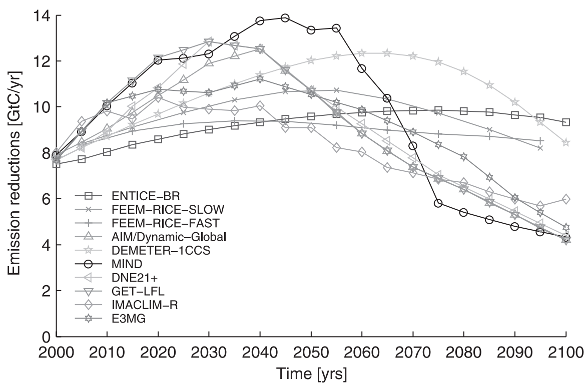
8. FEEM-FAST and MIND respectively.

Figure 1. CO_2 Emission Trajectories Associated with Stabilization Across the IMCP Models

(a) Stabilization at 450ppm CO_2



(b) Stabilization at 550ppm CO_2



in terms of the scale of the cumulative carbon reduction over the century implied by stabilization across the different models. This makes it plain that, particularly for the lower stabilization levels, the scale of the abatement task relative to baseline varies considerably. To some degree, this may be understood not only as indicating considerable genuine uncertainty about ‘business as usual’ trends, but also the considerable scope for different paths of global economic development. These different paths—potentially including land use policies—could do much to make the task of stabilization more or less difficult, even prior to the adoption of specific emission constraints. The far wider range of economic projections also highlight the extent to which atmospheric stabilization, for all its daunting scale, is a modest factor in the context of bigger influences on the pace and nature of global economic development—including the overall pace and capacity to handle technological change.

3. MAIN ECONOMIC FINDINGS OF THE INNOVATION MODELING COMPARISON PROJECT

The Synthesis paper in this volume examines and compares the influence and dynamics of technical change in the different models. This section aims simply to set all this in context, with a sense of the scale of the undertaking as indicated by the models. The discussion focuses upon the results from the models with endogenous change 'switched on', since there is no doubt that technical change is to some degree endogenous and the models themselves span a wide range of perspectives about how important it is. The Synthesis paper illustrates the impact also compared to scenarios in which endogenous change is 'switched off'.

(a) Marginal Carbon Prices

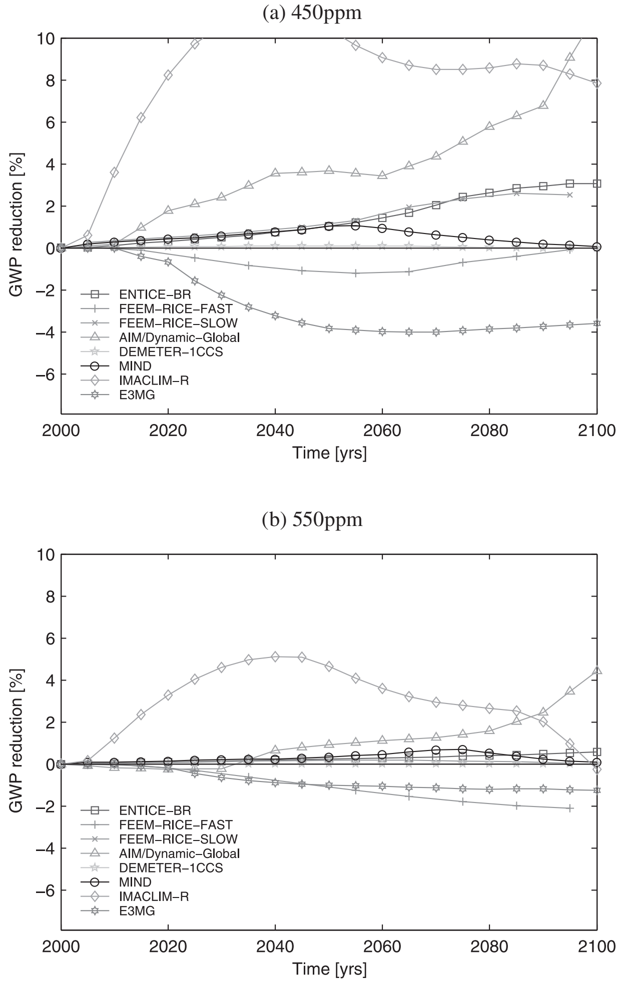
Most models represent incentives to change emissions trajectories in terms of the carbon price required, which not only changes specific investments according to carbon content, but also triggers technical change through the various mechanisms considered in the models (including through various forms of knowledge investment). The Synthesis paper (Figure 10) charts the evolution of carbon prices required to achieve stabilization and shows that they span a wide range, both in absolute terms and in the time profile. For stabilization at 450ppm, for most models carbon prices rise to c. US$100/tC +/- 50% by 2030 and are in the range US$50-250/tC by 2050. After that, they diverge enormously. Some go 'through the roof' as the allowable emissions shrink to low levels. Others rise more modestly, and one model echoes the results of some simpler studies based on learning curves which suggested that carbon prices might peak in the range US 100-200/tC and then slowly decline as new low-carbon technology systems come to dominate in the emerging economies (e.g. Anderson and Cavendish, 2001).

(b) Dynamics of GDP Impacts

Figures 2 (a) and (b) show the percentage impact over time on global GDP ('gross world product') of the constraints represented by the stabilization levels and corresponding emission trajectories in Figure 1. This reveals some striking differences between macroeconomic results that reflect fundamental methodological differences beyond those associated just with technological change.

Out of the eight models reporting global GDP results, four report losses that rise steadily to up to 1% of GWP by mid century under 450ppm, and subsequently diverge, whilst two report much bigger losses and two report gains in

Figure 2. Impact of Stabilization Constraint on %loss in Gross World Product over 2000-2100



Note: For comparison of total discounted economic impacts between models and at all stabilization levels see Synthesis report, Figure 1(a), which also includes cost metrics for participating models that encompass the energy sector only and not the whole economy (these metrics are less appropriate for mimicking the time profile of whole-economy impacts and hence are not included in this diagram).

GDP (negative loss)- one in particular reporting losses that peak over 10% and are sustained close to that under 450pp. The three energy-only models not illustrated in Figure 1 report costs equivalent to GDP impacts well within the central range.

The essential dynamic here is that in both energy sector and endogenous growth models, the early decades are characterized by a switch in *investment pat-*

terns. The associated GDP impacts are initially small for a number of reasons. First, mitigation policies per se initially target low-cost 'low hanging fruit' at low carbon prices, changing the *trajectory* of emissions without high costs. Second, the 'learning investments' are in emerging low carbon sectors. Because these sectors are initially relatively small, the scale of learning investment is also limited. Finally, in the growth models, additional investment can boost GDP. In most—but not all—of the models, these factors are ultimately overtaken by the sustained increased costs of the energy system, but again to widely varying degrees that depend largely upon the degree of endogenous technological response.

These dynamic mechanisms are not available in the highest-cost model, an equilibrium model in which carbon prices unavoidably depress GDP contemporaneously by raising an input factor cost (energy); additional features of this model are indicated below.

The mechanisms through which stabilization can increase economic output (without considering the climate-related benefits) differ between the two cases. In one, the negative costs originate from the Keynesian treatment of demand-side long-term growth; there are increasing returns to production and employment depends on relative prices, the recycling of carbon tax revenues therefore has potential to boost output. In the other model, the mechanism is directly to do with technical change considered below.

(c) Aggregate GDP Impacts and the Role of Endogenous Change

The Synthesis paper examines in depth the role of technology choice, endogenous change and macroeconomic linkages in these processes. Figures 1a and 2a in the Synthesis paper also summarize the GDP impacts in each model in terms of an aggregate comparable indicator, namely the discounted total difference between 'Gross World Product' in the stabilization scenarios and under the baseline projection. This is a global indicator defined as the discounted sum of GDP, aggregated across world regions and countries, over the next century. Therefore, it does not show differences across sector, countries and above all time periods. Nonetheless, it is a useful synthetic indicator of stabilization costs.

In one of these models accelerated development and diffusion of new technologies induced by climate policy has the potential to boost growth. The model was indeed designed to demonstrate the extent to which technical change can be effective in reducing stabilization costs if appropriate policies and investments are undertaken and if crowding out effects are limited. When these particular features of technical change dynamics are 'switched-off', costs become positive and consistent with those estimated by the other models.[9]

In all but two of the remaining models, discounted GWP is reduced but by less than one percent (relative to own baseline), even at 450ppm stabilization levels. The Synthesis paper analysis of the role of endogenous change in driving these cost impacts highlights big differences between the models. In some models, endogenous change makes a pivotal difference to the results. In others, the impact is modest.

Overall, the nature of the impact of endogenous technological change on stabilization costs may be usefully understood in terms of several different classes of observed impacts:

(i) *ITC makes little difference to already ‘modest’ costs.* In some models ITC makes a relatively small difference, but in the context of costs that are already relatively modest. In these cases, ITC does not necessarily lower costs much if major technological advances are projected to occur anyway in the base case. In such cases, low carbon technologies already make significant inroads into global energy and the effect of ITC is to slightly accelerate the process and reduce their costs further.

(ii) *Big ITC impact with backstop technologies.* In other models, ITC makes a large difference, in some cases reducing the costs of low stabilization levels (450ppm or 400ppm) from several percent to a fraction of a percentage loss in GWP. In general, this appears to be associated with models that have enough technological detail to allow substitution of higher by lower carbon options in supply, and responsiveness to the economic signals that enables the lower carbon supplies to ‘break through’ in markets on a large scale, leading to structurally different energy systems becoming established with various economies of scale now applying to low carbon instead of high carbon systems.

(iii) *ITC impacts insufficient to overcome relatively high costs.* In some models the above processes do not occur because the main mitigation option is energy efficiency, without options for substitution by low carbon supplies. As a result, tight carbon constraints can only be met by squeezing heavily on energy/carbon prices and forcing significant decline in energy-intensive processes. The two models for which discounted stabilization costs exceed 1% of GWP share this feature. In addition in the recursive general equilibrium model, the inflexibility of the core equilibrium assumption is exacerbated by the nature of macroeconomic linkages, and by the transport sector in which continued investment in carbon-intensive transport infrastructure in the early decades combines with a lack of viable substitution options. Although ITC does considerably reduce costs in some parts of the energy economy, this assumed lack of long-term foresight on the part of infrastructure investments and lack of substitution options in transport, combines with macroeconomic linkages that make the big rise in transport sector costs very expensive for the global economy.

In general therefore, one key determinant of the scope for induced technological change to lower costs is whether or not the models embody ITC with technological diversity: if they do, the improvement of low carbon “backstop” options limit stabilization costs; if they do not, costs are not capped in this way.

However, overall the studies also emphasize that the global economic impact of stabilization targets depends not just on technology, but also upon the nature of the assumed macro-economic linkage between the energy sector and the rest of the economy. As indicated, these can either ameliorate or exacerbate the costs incurred within the energy sector as a whole.

4. POLICY AND RESEARCH IMPLICATIONS

4.1 Policy Implications

Taken as a whole, the analyses give good grounds for believing that the atmosphere *can be* stabilized (or brought close to stabilization), at or significantly below a doubling of CO_2-equivalent concentrations (below 500ppm CO_2) at long-term macroeconomic costs that seem relatively modest—unlikely to exceed one year's foregone economic growth. However, this broad figure over a century hides many distributional impacts, across sectors, across countries and across generations. In particular, stabilization may require big changes in investment patterns in the short run, which would obviously provoke resistance to the implementation of effective climate policies. Whether or not the costs *are* actually small, will be a function of policy, and in particular, whether or not the policies adopted send the right signals and get the right mix of investment in R&D at one end, diffusion at the other—and of no lesser importance—all that lies between.

However, the policy implications that can be drawn from such analyses are not straightforward. Early discussions of ITC framed the issues as a stark choice between autonomous and government-led R&D on the one hand, versus inducement of innovation in the market through emission caps or carbon prices. Almost all the papers in this study emphasize that the situation is more complex, for several reasons.

ITC itself encompasses different elements from a policy perspective, the components of public R&D, private R&D and learning-by-doing all carry very different implications, but the models do not always distinguish between even these broad categories. And to the extent that technological change is driven by learning-by-doing, it still does not necessarily follow that emission caps are the only or best way of stimulating this, particularly for some of the less advanced technologies. Such instruments do increase the general prospect of profiting from innovation in low carbon technologies, but a far wider range of market-based policies may be required to stimulate the kind and degree of investment sought.

Moreover, several of the models emphasize the crucial role of expectations. Whilst many of the models optimize dynamically—assuming that all actions look ahead to respond optimally to the stabilization target—others do not.

The importance of technological diversity also highlights the need for explicit technology policy to foster a diversity of options that can serve as 'backstops'. This already exists in power generation (whether or not it is represented in models), but far less so in the transport sector. The IMCP results therefore underline the importance of knowledge investments to broaden the base of options particularly for low carbon transport. Those few models that explicitly represent fossil fuel resources and technologies also highlight the importance of understanding and harnessing the associated interactions.

The policy implications are thus far more subtle than choosing between 'technology led' versus 'cap-and-trade' led approaches. Even with a strong role for ITC, future rounds of the Kyoto Protocol which duplicate the structure of sequential 5-year limits, without any clear and credible signals about the longer term evolution of the system, are unlikely to deliver the depth of innovation and adjustment to infrastructural investments required to minimize long-term costs. On the other hand, a purely supply-driven R&D strategy may generate ideas but not technology-based industries with the capacity to solve the problem, and with no signal at all to redirect ongoing investment and promote prior adjustment of infrastructure appropriate to a carbon constrained world. Thus both R&D, and carbon cap/pricing, appear necessary but in isolation insufficient instruments to deliver stabilization at low costs. What really matters may be combinations of these policies and all that lies between—together with the critical role of framing expectations that really influence the scale and direction of corporate investment in low-carbon knowledge, in learning-by-doing in the nascent technologies and industries, and in the infrastructure appropriate to low-carbon economies.

4.2 Future Research Needs

The studies in the IMCP reveal the complexity and richness of innovation issues. They demonstrate that our capacity to analyze one of the most thorny issues in economic theory has moved beyond abstract debates about stylized growth models, into a rich array of applied modeling approaches relevant to a problem in which technical change is central to solutions.

Compared to five years ago, the progress made is impressive, but so are the remaining challenges. Whilst growth models have a strong theoretical grounding, their empirical basis remains very limited, whilst the more energy-system oriented models embody relationships in which theory is weak and hence interpretation of observed data subject to controversy. Although there seems to be a trend to combine the two approaches, far more work is still required to develop tools and to apply empirical data in more theoretically grounded and comprehensive ways.

Moreover, although the models mostly concur that induced innovation can contain the costs of stabilization, they differ enormously in their representation of the different components of public knowledge investment, private knowledge investment and learning-by-doing, or indeed whether they distinguish these. Consequently it remains hard to derive from such modeling conclusions about the specific policy instruments—or mix of policies—that would stimulate optimal kinds of technology and infrastructural investment. In terms of application to the challenges of the global energy system, the extent to which they represent the structure of fossil fuel resources and the implications of moving beyond conventional oil and gas resources—on timescales parallel to those associated with transitions towards atmospheric stabilization—remain mostly very limited. And they do not yet shed light on the geographic dimension—whether and how technologies induced by action in some parts of the world may diffuse globally. These and other important questions remain to be explored in similar systematic ways.

Yet, developing models that start to reflect the reality that climate policy itself will mould the nature and direction of technology change is the essential precursor to such analyses. Really clarifying how best to represent this, and the more specific policy implications, remains a challenge. If our project has helped to open the door to a new generation of such studies, it will have been worth it.

ACKNOWLEDGMENTS

We are grateful to the funders of the IMCP project. The UK Department for Environment, Food and Rural Affairs and the German Bundesministerium fur Umwelt provided core funding. The UN Foundation and BP recognized the importance of the emerging work and provided funding for the production of this Special Issue. We are indebted to all of them, together with the team at the Energy Journal, and hope that they will consider their investment to have yielded adequate returns.

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The Transition to Endogenous Technical Change in Climate-Economy Models: A Technical Overview to the Innovation Modeling Comparison Project

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This paper assesses endogenous technical change (ETC) in climate-economy models, using the models in the Innovation Modeling Comparison Project (IMCP) as a representative cross-section. ETC is now a feature of most leading models. Following the new endogenous growth literature and the application of learning curves to the energy sector, there are two main concepts employed: knowledge capital and learning curves. The common insight is that technical change is driven by the development of knowledge capital and its characteristics of being partly non-rival and partly non-excludable. There are various different implementations of ETC. Recursive CGE models face particular difficulties in incorporating ETC and increasing returns. The main limitations of current models are: the lack of uncertainty analysis; the limited representation of the diffusion of technology; and the homogeneous nature of agents in the models including the lack of representation of institutional structures in the innovation process.

1. INTRODUCTION

The rise of climate change on national and international policy agendas has been accompanied by increased global efforts to develop policy instruments for controlling GHG emissions. In recent years, policy discussions have progressed beyond environmental standards, taxation and other environmental

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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economic instruments like permit trading. All parties to the debate, both political and academic, agree that the development of new, low carbon and energy saving technologies, together with their widespread adoption will be crucial for climate change mitigation. This has been addressed by developments in both national and international climate policy, including the Joint Implementation and Clean Development Mechanism structures introduced in the Kyoto Protocol.

There are two reasons why technology is important for climate change analysis. Firstly, it is the application of technology that has caused the anthropogenic contribution to climate change in the historical context; both coal and oil were part of processes of transformations of economies and societies. Understanding the history of technology then helps us to direct the course of future technical change. Secondly, a change to a low carbon society will require widespread development and mass deployment of new, low carbon technologies.

Energy economic modeling of climate policy also has to reflect the main features of the climate change problem. A timescale of the order of 100 years is necessary, because the Greenhouse effect of CO_2 changes the climate over a time period of 50-100 years or more. The climate system spreads the CO_2 throughout the atmosphere, making climate change a global issue and a public good in the broadest sense of the term. GHG emissions from one country affect the climate of all other countries. Representation of economic changes for such long-term horizon poses a wealth of challenges for modeling.

There is broad agreement in the literature that a reduction in emissions of 60%+ from the industrialized world (relative to current emissions levels) will be necessary to avoid dangerous rates of climate change associated with severe consequences to climate and ecosystems (IPCC, 2001). Moreover, countries that are becoming major world economies – such as China, India and Brazil– will have to follow a different technological path, if GHG emissions are not to increase, let alone decrease. Therefore, addressing climate change necessitates broad-ranging structural changes in global economic activity and technological changes that facilitate these activities. Technology policy therefore offers potential to overcome barriers to climate change mitigation, and modeling technologies is particularly important for the economic analysis of climate change mitigation.

In recent years, there have been considerable developments in macroeconomics and energy economics, both theoretical and empirical, on the theme of technological change. These have primarily been in the new macroeconomic endogenous growth literature and the application of the learning curve management literature to the energy sector. As a consequence, there has been a transition in the climate energy literature, such that endogenous technical change[1] is now a major feature of many analyses. As discussed below in Section 2, the processes of

1. ETC, where technical progress is dependent upon variables and processes within the model, leads to possibilities for policy to induce technical change (ITC) by influencing these processes. If ETC is included, policy operates through the ETC mechanisms of the model to generate ITC that would not otherwise occur. This is in contrast to exogenous or autonomous technical change, often represented through the autonomous energy efficiency improvement (AEEI) in climate-economy models.

technical change are complex; ETC is a much more realistic representation than the AEEI approach. However, the advance brings much more than increased realism. Economic analysis has shown that there are some significant market failures in R&D, which in the case of climate change are in addition to the environmental externalities. Therefore, there is a need to examine the case for policy intervention (the subject of a large literature outside climate policy). This cannot be done if the economic processes of technical change are not modeled.

The absence of ETC can significantly bias policy assessments. In the presence of ETC, a policy intervention can influence both the relative rates of technological change across industries/sectors as well as the aggregate rate. Given a policy that reallocates limited funds for R&D and/or investment between sectors, it is not obvious *a priori* how allowing for ETC affects the aggregate rate of technological change relative to models with exogenous technological change. A model with ETC should generate higher overall technological change only if the sectors that expand as a result of a policy intervention enjoy more spillovers, faster potential for learning by doing, or faster increasing returns (and associated cost-reductions) than the sectors that contract as a result of the policy. Otherwise the speedier technological change in the expanding sectors may be offset by the slower technological change in those sectors from which innovation resources are redeployed. Finally, models with ETC may give very different results to climate economy models with autonomous energy efficiency improvement (AEEI hereafter) (Grubb, Köhler and Anderson, 2002). The Synthesis Report of this special issue (Edenhoher et al., 2006a) demonstrates the new richness of results and issues that are raised by incorporating ETC.

The Innovation Modeling Comparison Project marks the first attempt at comparing different approaches to the incorporation of ETC (and consequently ITC (footnote 1) arising from related policies) into climate-economy models. The variety of models represented in the project that provides a cross-section of existing ETC climate economy models, demonstrates the range of methods and ideas in use. The ETC approaches used in the ten models represented in the IMCP are reported in the individual papers in this issue, while the Synthesis Report discusses the results obtained for a range of stabilization targets. Table 1 of the Synthesis Report also contains a summary of the ETC features in the IMCP models. Although there are a wide variety of formulations of ETC, underlying these models is a common intuition that knowledge capital and its growth is a fundamental driver of technical progress.

The objective of this paper is to review the theoretical and empirical literature on ETC and ITC, identify key insights and analytical methods that inform approaches to climate-economy modeling and assess the transition in modeling technical change in the IMCP models. The structure of this paper is as follows: Section 2 describes the advances in understanding of the economics of technical change and their application in the endogenous growth and the energy sector literatures and also examines the empirical evidence. Section 3 assesses the state of the art as represented by the IMCP models and shows the influence of emerging literature in the incorporation of increasing returns as a major feature of the IMCP models. Section 4 assesses the strengths and weaknesses of the various approaches when applied to ETC in climate mitigation economics, including particular difficulties faced by Computable General Equilibrium (CGE) models. Section 5 concludes.

2. ADVANCES IN THE THEORY AND MEASUREMENT OF TECHNICAL CHANGE

There are three literatures that have influenced climate economy models. The changes in modeling have been most heavily influenced by the new endogenous growth theory with its introduction of knowledge as a capital stock determining productivity, although the empirical evidence for these models is mixed. In contrast, the learning curve literature which describes the reductions in unit cost with increases in production in firms and sectors arose from empirical observations. Hence there are significant increasing returns to scale in sectors critical for climate policy such as power generation. The forms in which learning curves are used, however, have relatively weak theoretical underpinnings. Reflecting the ‘top-down’ and ‘bottom-up’ modeling approaches of climate/energy policy analysis, the two streams of literature combine to make important contributions by introducing increasing returns to scale in knowledge, with an explicit treatment of processes of technical change.. The current understanding of processes of technical change has come from a third source, the innovation literature, which emphasizes the role of spillovers, uncertainty and path dependence. Together, these three literatures take modeling into a world of imperfect competition as a result of spillovers.

This section briefly reviews the insights from the innovation literature to describe the current understanding of technical change. We consider the theoretical and empirical contributions to show how the adoption of ETC has required significant innovation in modeling. The common underlying idea of a ‘stock of knowledge capital’ opens up the possibility of combining the theoretical and empirical insights from these literatures to provide an improved understanding of the implementation of technical change. The innovation literature also demonstrates that there are pervasive market failures in technical change. Increasing returns through learning-by-doing (experience) and learning-by-searching mean that there will be imperfect competition in technical change. These increasing returns can cause path dependency, with the possibility of lock-in to sub-optimal technologies. Knowledge spillovers mean that private R&D and investment may be considerably less than the social optimum. This may be amplified by barriers to technology diffusion through trade restrictions and limitations to foreign direct investment (FDI). The uncertain returns to R&D may also result in socially sub-optimal expenditures, if society can accept or spread risk more efficiently than private firms. These considerations give an efficiency justification for public support for R&D, for example through subsidies and expanded patent rules.

2.1 Insights from the Innovation Literature

Spillovers

The innovation literature has developed a sophisticated understanding of the economics of technical change. However, in its application to economic analysis, technical change presents difficult challenges.

Technology is partially a public good, but of a complex sort. Technology is embodied in physical goods but is fundamentally knowledge. Knowledge may be of practices, scientific understanding and of supporting institutions, such as educational or market institutions. It is clearly important to understand the process from which knowledge arises – whether by learning, by research and/or by doing. Technology is also non-rival in character: once the technology is developed, its use by one agent does not diminish its availability to others. Knowledge, as represented in specifications and patents, can be communicated almost at zero cost, and can often be inferred from publicly available sources such as products, patents and published material. However, transfer of technology requires that recipients of knowledge have the ability to apply the information. Also, part of any technology is tacit knowledge that cannot be transferred. Hence in practice, technology is partly non-excludable. These properties result in spillovers such that technical change is characterized by non-linearities.

The innovation literature also emphasizes the impact of uncertainty. By ignoring different strategies from heterogeneous firms and path dependence in technological development and adoption, the theoretical approach with a single 'typical' firm will leave out important factors in technical change. Technology is also embodied in physical capital. This leads to a similar set of considerations: Are externalities also a feature of physical capital accumulation and what is their relationship to R&D investment? R&D is the process of invention and innovation – of learning by searching for new ideas and developing them. Diffusion is mainly triggered by investment in physical capital. Hence there is the classical distinction between invention, innovation and diffusion as different parts of the innovation process.

Weyant and Olavson (1999) briefly review the literature on innovation. Schmookler (1966) emphasized the role of market pull factors: under the environment where major innovations create new markets and developing new products is relatively easy, the challenge to entrepreneurs lie in assessing market needs. In contrast, Rosenberg (1976) emphasized the supply of innovations: production capacity evolves over time, as a result of unpredictable product and process innovations. Many product and process innovations are appropriable without patents – a combination of learning/learning curves, lead-time effects and tacit knowledge. Innovations are mainly (private) profit led, since firms' knowledge is a vital and appropriable part of new technologies.

Spillovers are a major theme of the energy technology literature. Reflecting the analytical methods of Archibugi and Michie (1997), Weyant and Olavson (1999) distinguish between intra- or inter-sectoral spillovers, as well as local and international spillovers. Furthermore, spillovers may be embodied or disembodied in the production process i.e. whereas some spillovers reduce input costs or resource requirements, knowledge spillovers are the application of ideas from one production process to another. Spillovers may occur in many directions: up–down spillovers in a value chain for a single product; horizontally between firms within an industry; between firms in different industries; and across countries, for example where there is international trade and FDI.

Since spillovers are not only a geographical phenomenon and they possess public good characteristics, it is the relationship between different agents along the knowledge chain that determine the direction and intensity of spillovers. Sijm (2004) reviews ITC in climate-economy models and spillovers. In energy-economy models with learning curves, spillovers most naturally come from the cost reductions being assumed to take place in more than one industry or more than one region. However, the representation of spillovers across industries is often limited. A common simplification for incorporating spillovers is to assume that learning is dependent on R&D, investment or production cumulated over regions. The extreme case is to assume that all (global) expenditures contribute to cost reductions that apply to all regions. The no spillover case would assume zero correlation between technology costs across regions. This is in contrast to heterogeneous prices across regions, although the two forms of imperfect competition – regional variations in costs and regional variations in prices – are related.

How frequent and important are these spillovers? Empirical studies show that spillovers from R&D are prevalent and often large (e.g. Griliches, 1992). Studies such as Mansfield (1977, 1996), Pakes (1985), Jaffe (1986), Hall (1995) and Jones and Williams (1998) typically find that social rates of return are approximately four times higher than private rates of return for R&D. Nevertheless, spillovers are difficult to model as processes, because they depend on the diffusion of knowledge, rather than sales in markets or even patents. Because spillovers generate positive externalities, the incentives for R&D may be too low from an efficiency point of view, because they reduce appropriability for the private firm. These sound theoretical arguments for policies to support R&D are reflected in current policy debates about supporting new technologies such as power generation from renewables which by themselves, cannot compete in current main energy markets. Given the history of commercial failure in government R&D programs (e.g. supersonic aircraft and nuclear power), however, there is strong reluctance among policymakers to 'pick winners' and cultivate technology paths.

Uncertainty

The return to investments in new knowledge is, by definition, uncertain. Since the objective of R&D and innovation lie not only in discovering new technologies and products, but also to develop new markets for those products, uncertainty is pervasive. This clearly has important implications for the financing of R&D: how can uncertainty (hence investment risk) be minimized to attract finance? This has been a particular problem for new or alternative energy technologies faced with fierce competition from cheap fuel sources such as coal. Investment in wind, for example, is viable only where continuing policy support is guaranteed. Other investment factors are also critical, in particular, uncertainties about the availability of resources and security of supply.

Freeman and Soete (1997), in their discussion on the history of industrial organization of R&D, also emphasize the role of uncertainty. They argue that firms' strategies for innovation centre around the management of uncertainty – firm innovation behavior is dependent upon 'competencies' in R&D, manufacturing and marketing. The heterogeneity between firms allow for the empirical assessment of the role of uncertainty, as firms in the same sector respond differently to market conditions. At an aggregate level, this requires either a descriptive approach based on historical analysis, or a stochastic approach if the model is to be general. From a macroeconomic perspective, if the innovations are to be adopted on a large scale, clusters of innovations can be identified which follow a diffusion pattern through sectors and economies. Weyant and Olavson (1999) also stress heterogeneity and discontinuity in technology development. Freeman and Soete (1997), following Schumpeter (1939), emphasize competition among heterogeneous technologies in the early stages of new technologies. This requires modeling the switching processes to new technologies, such as non-linear dependence on relative prices of fossil fuel vs. new low carbon technologies.

Montgomery and Smith (forthcoming) point out a distinct problem associated with climate R&D: the lack of market preference for low carbon energy or transportation products. Given that conventional (high-carbon) products are priced below their social cost, low-carbon substitutes are more expensive partly because the externality is not included. Low carbon technologies therefore attract socially sub-optimal levels of investment from profit maximizing private firms. Where externalities exist, it is therefore necessary for policy to correct price signals such as to internalize the costs of carbon into private decision-making. However, with long time horizon and high scientific uncertainty associated with climate change, the degree of policy uncertainly for investors in energy/carbon technologies is exceptionally high. Hence the uncertainty and lack of guarantee of policy prevents firms from undertaking large scale, long term investments required to drive rapid diffusion of low carbon technologies.

These uncertainties have some important implications for climate policy analysis. The technological uncertainties mean that future (relative) costs of different technologies are uncertain, so it is necessary to characterize these in order to develop cost effective policies that will provide strong enough signals to overcome the reluctance to invest in new energy technologies.

Path Dependence

Following Rosenberg (1976) who pointed out the need to go beyond initial conditions and view the path of technological change as a sequence of events, Freeman and Soete (1997), Weyant and Olavson (1999) and other authors emphasize the importance of path dependence that lead to inertia in the technology system. A corollary of this is technological lock-in (David, 1985) – the processes by which a particular technology establishes dominance by growing exploitation of increasing returns to scale. New competing technologies then face institutional, infrastructural and cultural barriers in addition to any initial cost disadvantage. With increasing returns, it is not by default that the 'best' technologies become dominant and markets may indeed lead production locked into inferior technologies. This can be thought of as a form of temporal spillover.

Howells (2005, ch3.) gives empirical demonstrations of the process of path dependence – once a particular technology shows a clear competitive advantage, widespread adoption enables the benefits of increasing returns-to-scale to be appropriated. Namely, for both civil aircraft in the 1930s and wind turbines, an initial wide variety of technologies and competing approaches to innovation led to success for a small group of manufacturers. A series of incremental developments resulted in a defining product in both cases that led the way to mass adoption – the DC3 aircraft in the 1930s and Danish wind turbines in the 1980s. The theoretical implication is the need to differentiate between competing technological solutions and their cost dynamics over time.

Technology Diffusion

Modern economies are subject to a continuing process of globalization. Archibugie and Michie (1997, ch.1) discuss how technological change is dependent on the economic, social, political and geographical context. They argue that the national system of innovation is critical in determining technological performance, while processes of globalization tend to magnify the success or lack of success of national industries. For modeling, this implies that models need to differentiate between different economic regions, while incorporating the international process of cross-country technology diffusion and knowledge transfer or spillovers. Keller (2004) surveys the literature on international technology diffusion. He concludes technology diffusion is a major determinant of economic growth in many countries, yet the effects are country specific and requires microeconomic analysis and disaggregated data. However, Keller is caution in drawing explicit policy messages as many factors are at play here – trade, FDI and the ability of receiver countries to 'absorb' new knowledge are all important, but the literature is mixed about the strength of the effects.

Market failures associated with technology diffusion therefore provide a considerable challenge for economic analysis of GHG mitigation. Increasing returns mean that there will be imperfect competition in technical change. These increasing returns can cause path dependency, with the possibility of lock-in to sub-optimal technologies. The uncertain returns to R&D may also result in socially sub-optimal expenditures. The public good character of spillovers means that, without policy intervention, private industry will under-invest in R&D compared with the socially optimal levels. The under-investment may be amplified in the global context by barriers to technology diffusion through trade restrictions and limitations to foreign direct investment. Imperfect information and search costs of available knowledge may also impede technological diffusion, and addressing these market failures may generate large returns to society.

2.2 The Endogenous Growth Literature

In this section we review the endogenous growth literature, to show how ‘top-down’ climate economy models have adopted the macroeconomic literature on ETC. The macroeconomic literature on growth has turned again to technological progress in recent years. Solow (1957) was for a long time the basis of thinking about the economics of technological change in macroeconomics. He argued that the unexplained element of increased productivity in his econometric analysis of US data on economic growth was due to technological progress. This became known as the ‘Solow residual’.

The next major step was to explain technological change. The recent endogenous growth literature, surveyed by Aghion and Howitt (1998), has been built on the concept of knowledge capital, starting with Romer (1986, 1990). Romer (1986) rediscovered the *‘Y=AK’* endogenous growth model, in which production is dependent on knowledge, a function of physical capital. The knowledge stock *A* is a global public good, introducing positive spillovers from incomplete appropriability i.e. increasing returns to scale to the production function. Romer (1990) extended the model to include imperfect competition through increasing returns to scale, through a fixed cost element in an intermediate goods sector. This extra form of increasing returns then generates a model of oligopolistic competition. The treatment of knowledge stock is usually similar to physical capital – it is assumed to be dependent on cumulated R&D expenditures – thus these models incorporated ETC.

Grossman and Helpman (1994) point to international interdependence through trade, introducing yet another form of spillover. As Aghion and Howitt (1998) argue, these theoretical developments revitalized the economic literature on growth, leading to insights for the analysis of business cycles, sustainable development, international income distribution and a renewed awareness of the fundamental role of industrial innovation in macroeconomic growth. The authors further developed these ideas to incorporate ‘Schumpeterian’ growth – the idea otherwise known as Schumpeter’s idea of ‘creative destruction’ – which implies that firms search in an uncertain world for innovations that qualitatively improve the production technology and make previous technologies obsolete. This is yet to be applied to climate-economy models,

2.2.1 Empirical Assessments of the Endogenous Growth Models

The empirical evidence for these imperfect competition endogenous growth models is mixed. For ETC, there were several critiques of the Schumpeterian innovation models. Aghion and Howitt (1998) discuss several of these critiques. Growth accounting studies, in particular for East Asian countries, suggested that growth came from capital accumulation, rather than technical change (Young, 1995; Jorgenson, 1995). Jones (1995) found that, for OECD countries, substantial increases in R&D activity, measured by numbers of scientists and engineers engaged in R&D, did not lead to faster total factor productivity growth. Jones argues that this is due to decreasing returns to scale in knowledge generation. Long run growth then becomes proportional to the rate of population growth and is independent of structural characteristics of the economy, a return to the conclusions of the Solow model. This is in contrast to the innovation literature on spillovers discussed above. Agion and Howitt argue that there are two reasons for Jones' result. Firstly, the increasing complexity of technology makes it necessary to raise R&D over time, in order to keep the proportional innovation rate constant for each period. Secondly, as the number of products increases, each innovation has a smaller proportional impact. These two arguments mean that a constant percentage rate of growth in total factor productivity requires increasing levels of R&D activity to maintain a constant percentage growth rate.

The '*AK*' models were challenged by Mankiw, Romer and Weil (1992) who augmented the Solow growth model with a human capital factor in the production function. Mankiw, Romer and Weil (1992) find evidence to suggest that growth rates are converging in line with the results of Solow-Swan growth models, yet as Evans (1996) highlights, this is incompatible with the Schumpeterian growth models. Technical change, however, remained exogenous within these discussions by Mankiw, Romer and Weil and Evans.

Temple (1999) is highly critical of the findings by Mankiw, Romer and Weil (1992), that 80% of international variation in per capita incomes can be explained by population growth, physical and human capital investment rates, with little role for technological progress. He questions the assumption that investment rates are exogenous to the level of income and uncorrelated with efficiency. He is also critical of the methodology used to measure schooling that ignores primary schooling, as it tends to exaggerate the variation in human capital across countries.

Aghion and Howitt (1998) extend their Schumpeterian growth model to include population growth and consequent growth in the number of products, together with a multi-country framework. This enables them to find results that are consistent with the evidence from growth accounting, scale effects and cross-country growth. Schumpeterian growth models do indeed deliver testable hypotheses: R&D intensity displays similar properties to the long run growth rate; the long run growth rate should be positively correlated with the flow of patents; and entry of new firms and flow of new products and negatively correlated with exit and the rate of capital obsolescence. Aghion and Howitt caution that there has been little empirical work on testing the implications of Schumpeterian growth models. They give ambiguous predictions on the relation between competition and growth. However, there is some supporting evidence from microeconometric studies that structural parameters can affect productivity growth. Blundell et al.

(1994) found that the arrival rate of innovations has a significant positive correlation with firms' market share and a significant negative correlation with a measure of market concentration. Nickell (1996) found evidence of strong positive correlation between the levels of competition and productivity growth.

Aghion and Howitt also discuss a fundamental problem of measurement – the data from national accounts is collected in a way that assumes that knowledge is fixed and common. Yet as there are no commonly accepted empirical measures for the fundamental concepts in the new theories (e.g. the stock of technological knowledge, the stock of human capital, resource cost of knowledge acquisition, the rate of innovation and the obsolescence of knowledge), it is difficult to test the Schumpeterian theories and thus to reach conclusions about their applicability.

Temple (1999) surveys empirical research on macroeconomic growth across countries that use reduced form models, where the mechanisms of growth are not made explicit.. This is a much-criticized literature partly due to methodological problems in the use of time series econometrics, and Temple puts forward arguments for the use of panel analysis. The inconclusive empirical results also undermine the credibility of the literature – with a range of estimates of convergence rates of 0-30% a year it gives little insight into whether there is convergence in growth rates. Coe and Helpman (1995) find large effects of foreign R&D on domestic total factor productivity (TFP). Eaton and Kortum (1994) found that half the US productivity growth depends on foreign technology improvements, suggesting that evidence for a common long run growth rate is consistent with endogenous growth models where international spillovers would make technical progress common across countries.

Temple finds mixed evidence for convergence of efficiency in OECD manufacturing in the 1970s and 1980s suggesting convergence in growth rates can be attributed to services. He finds some evidence of decreasing income dispersion between countries linked through trade, which may reflect technology transfer through trade. Furthermore, robust correlation is found between investment rates and growth, and strongest econometric result that returns to physical capital are diminishing is in accordance with the Solow-Swan model. The survey implies developing countries, investment in equipment, possibly incorporating technology transfer, is important in determining growth, less so in OECD countries.

Temple (1999) also argues that macroeconomic data is too aggregated to address the issues of interest in human capital, such as schooling quality or health. Macroeconomic studies on human capital find that it explains little of the variation in changes in output. This is problematic, because it contradicts the microeconomic evidence that schooling does lead to higher wages. There is widespread agreement that human capital accumulation is not a sufficient condition for growth. The question here is: under what circumstances is human capital accumulation beneficial and what are the constraints that need to be included in models?

Temple suggests that R&D has an important role in growth, with a wealth of microeconomic evidence e.g. private rates of return as high as 30-50% for R&D in the US in the 1950s and 1960s. There is also evidence of significant knowledge spillovers, so that social returns to R&D may be even higher (Griliches, 1992). However, whether there are increasing returns to research is a question for which the evidence is mixed. Given the difficulties in measuring knowledge and ideas, the challenge posed here is immense. Even the model of Jones (1995) mentioned in the discussion by Aghion and Howitt (1998) above allows research to have significant level effects on output, so R&D would remain an important policy variable. This point does not, however, address the contradiction between the microeconomic and the macroeconomic evidence. The debate thus remains open. The macroeconomic empirical issue of structural transformation has not been adequately addressed, although the development literature is extensive. Temple (1999) concludes that macroeconomic data on factor accumulation and efficiency change has given unconvincing results, such that disaggregate analysis using structural models to examine the mechanisms of growth is probably more fruitful. Scott (1991) shows that gross investments in physical capital are a good explanatory variable to capture the unexplained part of growth in the Solow model.

To summarize, the theoretical endogenous growth literature has emphasized the role of knowledge capital spillovers in technical change and hence economic growth. However, empirical analyses have failed to conclusively demonstrate their importance. Criticisms of the theory of spillovers in the empirical literature have serious limitations; the argument is made problematic by the difficulties in measuring knowledge or human capital and their contribution to innovation in a meaningful way at the aggregate level. Part of the challenge is in identifying the relationship between knowledge capital and physical capital. Physical capital accumulation is assumed to embody new knowledge, but differentiating between physical and knowledge capital and their relative contribution to productivity improvements remain. Knowledge capital is hence fundamental to productivity growth rates, but empirical analysis at microeconomic level gives more convincing conclusions. It is to this we turn next.

2.3 Microeconomic Evidence on Technical Change – Learning/Experience Curves

Many climate economy models incorporate knowledge indirectly through learning using experience curves. Such curves relate investment and/or R&D expenditures to cost reductions. In practice, we find the terms ’learning curves‘ and ’experience curves‘ used interchangeably throughout the literature. Our review of the literature suggests that while such curves document the correlation between cumulative experience with a technology and falling costs, questions remain as to the causal links between experience and costs. As such, we refer to such models as ‘experience curves’ in this section, to make clear that work remains to be done to explain the causal links between learning and cost reductions. Here, we briefly review the experience curve literature in industry in general and its application to energy technologies in the context of climate change mitigation.

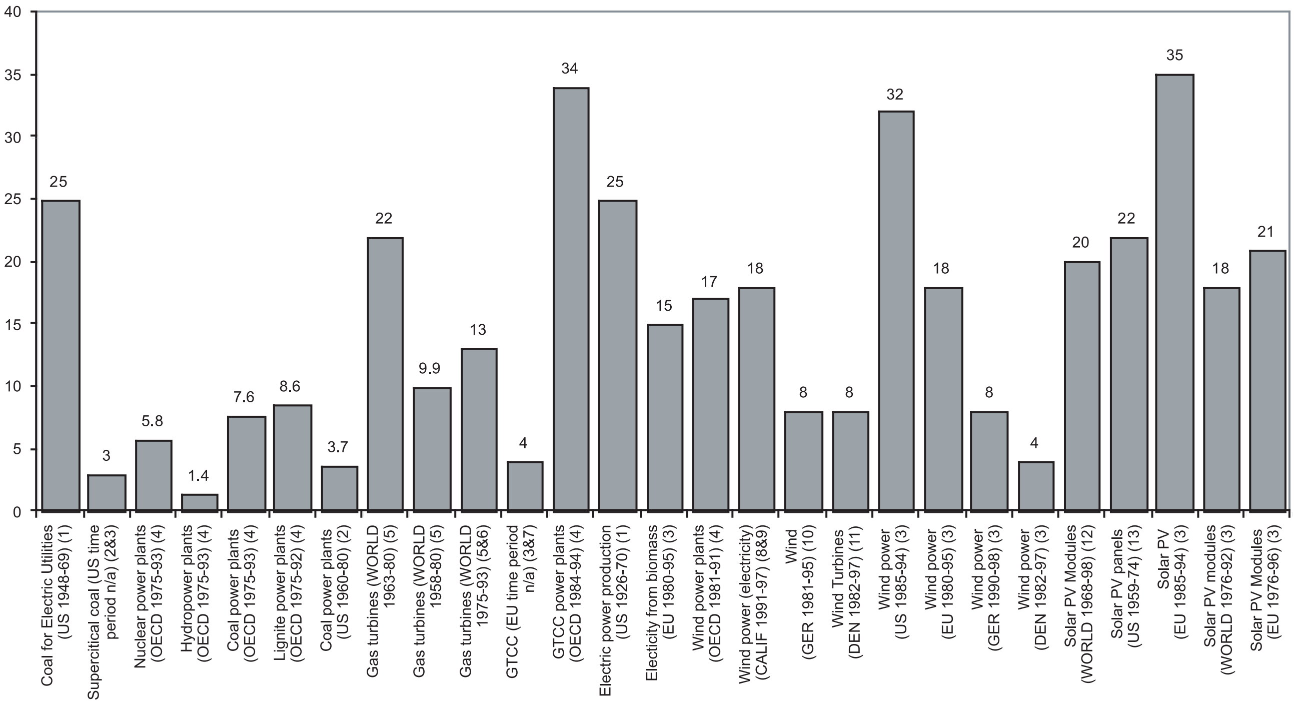
Incorporating experience curve relationships in analysis can allow a far richer set of possible scenarios and introduces strong path dependence: the costs of future technologies and systems are intimately bound up with the investments made in earlier decades. The incorporation of experience curves into modeling also creates great complexity and has significant impact on not only numerical results, but also qualitative aspects of conclusions drawn from economic modeling. For these reasons, their use and their empirical basis necessitate careful examination. The literature on experience curves has little discussion on theoretical explanations, although as explained above, the innovation literature thoroughly examines increasing returns in manufacturing evident from decreasing costs of production which are observed as an experience curve in a firm.

2.3.1 'Learning rates' in the Literature

The literature on observed experience curves frequently summarizes observations in terms of a single parameter – the 'learning rate'. Argote and Epple (1990) survey the literature in manufacturing which go as far back as studies by Wright (1936) on aircraft production in the 1930s and by Rapping (1965) on shipbuilding. Positive experience curves have been found both in manufacturing and service sectors. Recent contributions to this literature consider the learning processes that lead to experience curves e.g. Thornton and Thompson (2001) for shipbuilding. Furthermore, it extends the idea to production processes e.g. Jaber and Guiffrida, (2004) for reductions in defects and in current industries, and Hatch and Mowery (1998) for new industries such as semiconductors. Argote and Epple (1990) draw attention to the considerable variability in learning, not only across industries, but even within different plants of the same company. Variability is also observed in studies of international technology diffusion and its effects on growth in different countries (Keller, 2004). Dutton and Thomas (1984), quoted in Argote and Epple (1990), provides a frequency distribution of progress ratios (% cost reduction for a doubling of cumulative output) for 108 cases, with a range of 55% to 96% for the progress ratio and a case where the ratio is over 100%, i.e. where costs increase with cumulated output. The mode of this distribution is 81-82%, which has led to the common assumption of an 80% progress ratio i.e. a 20% reduction in unit cost/doubling of output.

As part of the IMCP, we surveyed the literature quantifying experience curves in the energy sector, with results as presented in Figs 1-3. The literature dates back at least to the early 1980s (Zimmerman, 1982; Joskow and Rose, 1985). The great majority of published learning rate estimates relate to electricity generation technologies. As illustrated in Figure 1, estimates associated with different technologies and time periods span a very wide range, from around 3% to over 35% cost reductions associated with a doubling of output capacity. Negative estimates have even been reported for technologies when they have been subject to costly regulatory restrictions over time (e.g. nuclear, and coal if flue gas desulphurization costs are not separated), and for price-based (as opposed to cost-based) learning rates in some periods reflecting aspects of market behavior.

Figure 1. Learning Rates in Electricity Production Technologies



Sources: Adapted from McDonald & Schrattenholzer 2001

(1) Fisher (1974); (2) Jaskcow & Rose (1985); (3) IEA (2000); (4) Kouvaritakis et al. (2000); (5) MacGregor et al. (1991); (6) Nakicenovic et al (1998); (7) Claeson (1999); (8) CEC (1997); (9) Loiter.

Notes: World GTCC data from Claeson (1999) excluded due to outliers (negative learning rates); possibly explained by oligopolistic pricing behavior.

The data suggest some broad yet useful patterns. For many energy technologies, learning rates appear higher in earlier stages. Thus early coal development (US 1948-1969) showed rapid learning in contrast to later evidence (US 1960-1980). Gas turbine data also suggest some evidence of learning depreciation (either kinked or smooth). However, wind energy has demonstrated a wide range of learning rates with no obvious pattern across locations or even time periods (early versus late development stages). Solar PV in general has enjoyed faster rates of learning than other renewable technologies. Grübler, Nakićenović and Victor (1999b), IEA (2000) and McDonald and Schrattenholzer (2001) survey the evidence for energy technologies, showing that, in line with the more general results mentioned earlier, unit cost reductions of 20% associated with doubling of capacity has been typical for energy generation technologies, with the exception of nuclear power.

This learning rate literature has led, in some cases, to the use of a general "rule of thumb" learning rates of 20%. This is a plausible proxy of the observed rates for many electricity generation technologies, but – in addition to the issues of interpretation discussed below – the evidence on the decline of learning rates over time suggests it may err on the high side, if treated generically across these technologies as a constant in long-run modeling exercises. Indeed, the application of such learning rates has led to cost reductions so high that some studies have artificially imposed a 'floor price' to prevent technologies like wind energy from becoming absurdly cheap, which then changes the effective assumed average learning rate.

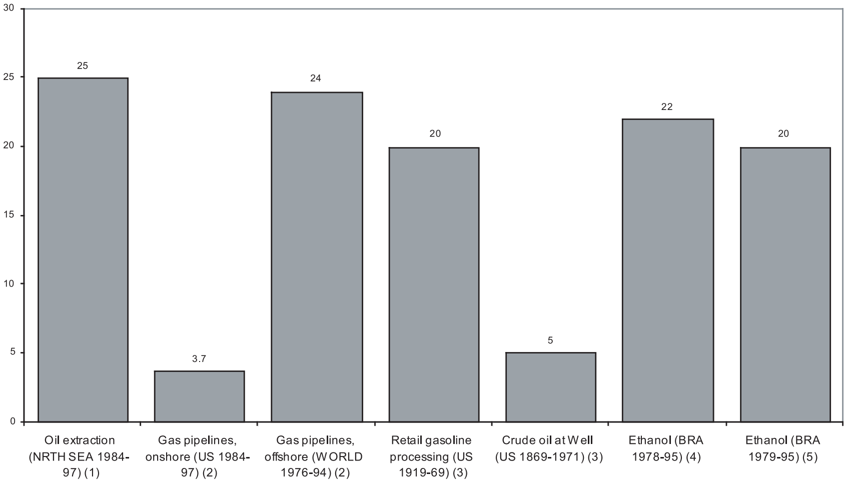
Amongst the non-electric supply technologies (for liquid fuels see Figure 2), the difference in learning rates between offshore and onshore gas pipelines is striking – 3.7% versus 24%. There is also marked difference between Oil at Well and North Sea Extraction (25% versus 5%).

It is notable that those technologies enjoying exceptionally high learning rates – like photovoltaics – have been able to benefit directly from advances made in electronics and silicon technology in general. The pattern for rapid learning in electronics technologies is carried through to the End-Use technologies (Fig 3). End-use technologies appear to display higher learning rates in general, and particularly so within electronics based technologies (diodes and DC converters).

2.3.2 Interpreting Experience Curves and Learning Rates

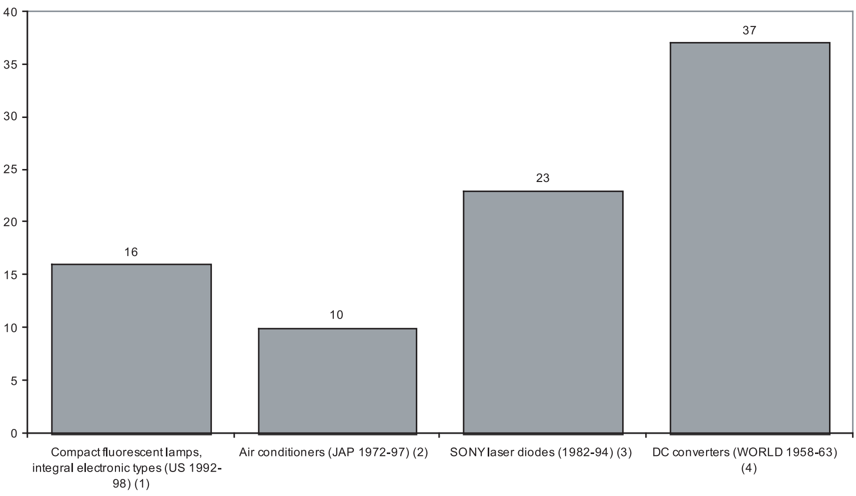
The fact that the magnitude of learning rates seems to depend to a large extent on both the technology and the choice of data points/time period (e.g. with low R^2 values) illustrates the need to understand better the underlying elements and issues in experience curves. Although some of the variability in published analyses is slightly reduced for those relating to costs – avoiding the additional variability induced by diverse market pricing strategies – there is clearly a need to understand better the influence of other explanatory variables. To what extent do experience curves give us insights into technological change, and how robust are the conclusions when applied in models?

Figure 2. Learning Rates in Liquid Fuels



Sources: Adapted from McDonald & Schrattenholzer 2001
(1) Blackwood (1997); (2) Zhao (1999); (3) Fisher (1974); (4) IEA (2000); (5) Goldemberg (1996)

Figure 3. Learning Rates in Energy End-use-related Technologies



Sources: Adapted from McDonald & Schrattenholzer 2001
(1) Iwatune (2000); (2) Akisawa (2000); (3) Lipman & Sperling (1999); (4) Rabitsch (1999)

Cost reductions may come from cross-sectoral learning (spillovers), R&D undertaken to develop new products and develop new markets, or from learning by doing e.g. incremental improvements in the technical performance of machinery or production processes as engineers and the workforce gain experience with new machines and products. There may be increasing returns to scale in investment, which is difficult to separate from learning by doing in production. Even after excluding market pricing effects, there are several important issues to be disentangled in interpreting cost-based experience curve data. The relationship between cost and 'learning' is indirect in the sense that both are plotted over time, hence many factors may come into play over that time. We distinguish three major issues.

The Role of Direct R&D

Firstly, in general, direct R&D expenditure come from both public and private sources. To what extent can learning be attributable to this? The 'two factor' experience curve analysis explores this question by its attempt to separate cost reductions that result from R&D expenditures and capital investment. Unfortunately, this decomposition poses new problems, and sometimes leads to unstable results. Furthermore, the causal relationship between increased R&D expenditure and greater market scale (and hence overall level of finance flowing into the sector), remains uncertain. Robust conclusions from the market application of this analysis cannot be drawn therefore, without establishing the extent to which R&D expenditure, market scale and R&D productivity are interrelated. A key problem is predicting (from history) what the return will be on future investments in R&D.

The Role of Time and Cross-sectoral Spillovers

Secondly, the role of time in the learning process (separate of any increased deployment) must be understood. As time passes, technologies will be able to exploit developments in other sectors. For example, huge improvements in offshore oil reservoir mapping in the 1980s and 1990s first drew on advances in medical three-dimensional scanning techniques and later on the evolution more specific to oil. Cost reductions in photovoltaics must in part be attributable to wider developments in the semiconductor industries.

The Direction of Causality

The final important issue around experience curves is the question of causality. Whilst it is entirely reasonable to assume that greater market scale leads to cost reductions, it is equally plausible that cost reductions lead to greater market scale. Sufficient econometric decomposition of panel data might be able to decompose at least some of these factors, but we did not find such analyses in the literature.

These three categories of caveats indicate that applying experience curve data in modeling projections through the use of a single implied 'learning rate' is prone to the exaggeration of effects. The strongest reason for applying them in long-run modeling is not that these issues have been resolved, but rather that the evidence for *some* degree of experience-based cost reduction is overwhelming. Assuming a learning rate determined exogenous of the model is problematic and there remains little consensus on the 'genuine' learning rate – only that zero, the implicit assumption in models that do not incorporate endogenous change, is a number that we can be most confident is wrong. Learning rates are valid but incomplete data, which need to be better explored, but not ignored, in economic analyses..

2.4 Microeconomic Evidence of Incentive-driven Technological Change: Patent and Other Data

While many studies have examined the relationship between experience and costs, this work is descriptive in nature, and does not attempt to address the causal links between incentives and technological change. In contrast, empirical work linking these incentives asks how prices and/or policies affect the evolution of technological change. It is useful here to make a distinction between reduced form and structural models. Reduced form models (e.g. Newell et al., 1999) examine how the rate and direction of technological change is related to price changes, but do not make explicit the mechanisms by which this happens. Structural models, on the other hand, link prices to variables such as R&D expenditures, or knowledge changes to R&D effort.

Much of this work makes use of patents or R&D spending as proxies for technical change. An example of the structural approach is given by Popp (2002) in which energy patents are regressed on energy prices and other control variables. Popp calculates a 0.35 elasticity of energy patents with respect to energy prices, and finds evidence of diminishing returns, so that less R&D is induced by a price change over time. Lichtenberg (1986, 1987) finds that the share of R&D devoted to energy increases as energy prices increase. Newell et al. (1999) use an approach closely related to hedonic techniques to study the effect of both energy prices and energy efficiency regulations on technological advances in energy efficiency for air conditioners and natural gas water heaters. They find that energy prices have the largest inducement effect. However, because their data focuses on the results of innovation rather than inputs to the research process, it provides no estimates of elasticity between research and energy prices. Other researchers have studied the links between environmental policy and innovation, often by regressing R&D or patents on pollution abatement control expenditures (PACE). Examples include Jaffe and Palmer (1997) and Brunnermeier and Cohen (2003). In general, these papers find a positive link between prices and innovation, although the magnitudes are often small. While these papers do not directly estimate the returns to the induced R&D, other work (e.g. Popp 2001) finds social returns comparable to the studies cited in Section 2.1. Combined, such studies allow the modeler to calibrate both the response of R&D to climate policy, as well as the potential impact of induced R&D.

2.5 Summary: What are the Connections Between the Modeling Literatures?

To summarize, the endogenous growth literature considers knowledge capital accumulating through either R&D expenditures and/or physical capital investment. This knowledge accumulation is then assumed to lead to productivity improvements. The two factor experience curves model reductions in production costs through cumulated R&D and physical capital investment. Hence a two factor experience curve has the same variables and underlying idea generating technical change as the knowledge capital growth models. The common idea of a stock of knowledge capital opens up the possibility of combining the theoretical and empirical insights from these literatures to provide an improved understanding of the implementation of technical change. In principle, the theoretical formulations of the growth models could be used to estimate experience curve parameters, providing a stronger theoretical base for experience curve parameterizations.

However, the case-based nature of the experience curve literature makes it difficult to generalize to aggregated industries often employed in top-down models. This problem is made clear by the current understanding of the complexity of the innovation process (Montgomery-Smith, forthcoming). Different levels of aggregation in different models make common parameterizations problematic, except where models consider the same technologies at similar levels of detail. This is already the case among energy system e.g. hybrid models that have some detailed renewable energy technologies.

Technical change comes through the development of knowledge and human capital, also embodied in physical capital. There is a useful distinction to be made between invention, innovation and diffusion, which involve different processes within technical change. There are positive spillovers of knowledge, such that innovation is characterized by increasing returns and imperfect competition. The experience curve literature provides empirical evidence of rates of cost reduction with experience, which vary widely. There is even more variation in the macroeconomic evidence on growth rates and technology. These uncertainties lead to the conclusion that ETC is fundamental to economic growth, but the mechanisms by which this happens and the strengths of the effects not yet clear.

The different literatures on innovation open up a very complex picture of multiple factors influencing innovation and technical change. Innovation is characterized by uncertainty in new discoveries, the need to consider new markets and the partly non-rival and non-excludable nature of knowledge about technologies. Market failures are pervasive. Increasing returns mean that there will be imperfect competition in technical change. These increasing returns can cause path dependency, with the possibility of lock in to sub-optimal technologies. The uncertain returns to R&D may also result in socially sub-optimal expenditures. The public good character of spillovers means that, without policy intervention, private industry will under-invest in R&D compared with the socially optimal levels. The under-investment may be amplified in the global context by barriers to technology diffusion through trade restrictions and limitations to FDI. Imperfect information and search costs of available knowledge may also impede technological diffusion, and addressing these market failures may generate large returns to society. There is heterogeneity in firms' innovation behavior and in national systems of innovation. This points to two market failures in particular that should be considered in climate economy models with ETC: environmental externalities and R&D market failures. This provides a considerable challenge for economic analysis of GHG mitigation. The positive externalities of spillovers and firms' response to policy uncertainty mean that, without policy intervention, private industry can be expected to under-invest in R&D.

3. ETC IN THE NEW CLIMATE ECONOMY MODELS

This section considers how insights about endogenous technical change have been incorporated into the climate-economy literature and models, using the IMCP models as a representative cross section of the existing state of the art. The response has been dramatic: there has been a transition in climate energy modeling, such that ETC is now a feature of many leading models. However, the expansion of models into the inclusion of processes of technical change brings new, serious empirical challenges.

Several recent surveys reflect the increasing interest in this area. Azar and Dowlatabadi (1999) discuss technology diffusion, demand pull in technology development and experience curve models. They further emphasize the extent to which policy results and prescriptions are dependent on technical change assumptions made in modeling work. Grübler, Nakićenović and Victor (1999a,b) describe the breakthrough made in the energy sector modeling literature in which experience curves were applied to energy and climate policy analysis. Buonanno et al. (2000) reported one of the first applications of ETC in an optimal growth model. Goulder (2004), Jaffe, Newell and Stavins (2000), Weyant and Olavson (1999) and Löschel (2002), Nordhaus (2002) and van der Zwaan et al. (2002) also review the application of ETC in the climate economy literature. Grubb, Köhler and Anderson (2002) include a survey of the approaches to modeling ETC in climate energy models and the policy implications of ETC. Manne and Richels (2004) consider the optimal timing of abatement with ETC. There are also various combinations of top-down and bottom-up models, as well as the incorporation of both macroeconomic and energy system models in climate policy integrated assessment models (IAMs). Clarke and Weyant (2002) have an extensive discussion of the issues of induced technological change in the climate economy literature. Grubb, Köhler and Anderson (2002) show that ETC can give very different results compared to models with autonomous technical change. The overriding conclusion from the literature is that the way in which technical change is represented matters. Positive spillovers may dominate leakage effects, costs of stabilization may be relatively small and early policy action can give higher overall welfare than delayed action.

Climate economy models have produced widely differing estimates of the economic implications of policies. The analysis by Barker, Köhler and Villena (2002) provide insight into the implications of the different underlying theoretical assumptions and structures of models to their outputs. One important contrast has been between the results of bottom-up energy system models and top-down macroeconomic models. For years, an "energy efficiency gap" has been identified in the analysis of existing and potential technologies. In particular, there are heated discussions on low-cost or no-cost options and the role of energy-efficiency in reducing fossil energy.

The Stanford Energy Modeling Forum project on "Technology and Global Climate Change Policies" (overview provided by Weyant, 2004) marked the first comprehensive model comparison with specific focus on energy technologies. A range of climate-economy models were compared for the costs of stabilization at 550ppm CO_2 and a range of carbon tax trajectories. Excluding models also participating in the IMCP, of the Stanford project, MARKAL, IMAGE and AMIGA incorporate ETC. As in the IMCP, a wide range of baseline emissions trajectories technology pathways are projected when uniform stabilization targets are imposed across participating models. Weyant attributes these variations to the uncertainty in long term projections of energy systems. Central conclusions derived from the comparative study can be summarized as follows: stabilization will require significant development and deployment of new energy technologies and implementation implies considerable expenditures over many years. Costs can be moderated significantly if options are pursued in parallel, and new technologies phased in gradually, and if policies to induce changes start earlier rather than later.

One fundamental reason for the wide range of results is the wide range of modeling implementations of ETC. In principle, the approaches could be judged by their ability to reproduce empirical data, but there are significant weaknesses in the empirical grounding of the models, so it is not feasible to select between the different approaches. As has been shown in section 2 above, the experience curve literature has provided evidence for the parameterization of increasing returns to scale arising from capital investment. However, these estimates have weaknesses, because they aggregate several learning processes and do not enable a clear distinction between cause and effect. The empirical basis for the knowledge capital models is also heavily contested, a major difficulty being the lack of methods to measure knowledge and spillovers.

The IMCP is a first attempt to systematically compare approaches to the incorporation of ETC into climate-economy models. The Synthesis Report of this issue (Edenhofer et al, 2006a) gives an overview of the range of methodologies and ideas in use. Their Table 1 provides a useful taxonomy and summarizes the features of IMCP models. Individual modeling papers in this issue report for details of ETC features. As noted, two main approaches to ETC can be identified – knowledge capital and experience curves – reflecting the endogenous growth and experience curve literatures. A consequence of new literatures discussed above and represented in the range of ETC modeling techniques of the IMCP, the incorporation of increasing returns to scale due to spillovers and learning is the major innovation in the climate economy literature; increasing returns and the implied imperfect competition allows the possibility of second best outcomes, even in dynamic optimizing models. The long-term and global models selected for this study provide insights into climate policy and economics of climate stabilization. Models include specific representations of the energy sector, generation, end-use or both, with differing levels of detail and abstraction. Most models include one or more backstop or low carbon technologies. Some models also consider energy use in the transport sector e.g. IMACLIM-R (Crassous et al, 2006) and E3MG (Barker et al, 2006). Several models include all the main GHGs. All models report results in terms of CO_2 emissions trajectories and Gross World Product or energy system costs.

The IMCP models cover the main theoretical approaches in the climate economy literature. DEMETER-1CCS (Gerlagh, 2006) is a dynamic general equilibrium model, IMACLIM-R is a dynamic recursive growth model and FEEM-RICE (Bosetti et al. 2006), ENTICE-BR (Popp, 2006) and now AIM/Dynamic-Global (Masui et al., 2006) are endogenous growth IAMs. DNE21+ (Sano et al, 2006) and GET-LFL (Hedenus et al, 2006) are energy system models. There are several hybrid models, where features of macroeconomic models and energy system models are combined. These are MIND (Edenhofer et al, 2006b), MESSAGE-MACRO (Rao et al, 2006) and E3MG.

3.1 Production Structures and Vintages

With the exception of FEEM-RICE and AIM/ Dynamic-Global models, the macroeconomic models and integrated assessment models have a number of different sectors for each region allowing for heterogeneity between sectors' use of energy. Multi-sectoral models offer the possibility of distinguishing technological progress in different areas of the economy as well as across different geographical regions. Technical change is then specified either through R&D expenditures determining improvements in energy intensity or through experience curves.

The crucial distinction in approaches to sectoral representation is whether or not models allow for substitution between carbon and non-carbon supplies. This has qualitative consequences from both theoretical and applied standpoints. Grubb and Ulph (2002) find that environmental constraints do not necessarily increase environmental innovation. This holds when the sector is represented as a single process that can be more or less emissions-intensive depending on the level of R&D. The impact of constraints on product sales on incentives to innovate is ambiguous. However, if alternative production options exist, markets for goods produced via lower-emitting processes grow in absolute terms. In such cases, the incentive to increase innovation is unambiguous and also opens the possibility of reorienting R&D from the higher to the lower emitting process within the sector. Obvious examples would include some reorientation of R&D from thermal to renewables technologies in power generation, or from heavy oils to biofuels technologies in the fuels sector. The modeling results in the IMCP appear to confirm the link between model specifications that allow for this possibility for reorientation, and possibilities for large impacts of endogenous change.

Installed capital vintages vary among models with ETC, and indeed among models without ETC. Total factor productivity is generally exogenous in CGE models. Technological progress implies that a model with ETC (or, indeed, exogenous technological change) has different installed capital vintages. The common approach to this problem is to specify an average productivity and then specify how the average productivity improves with ETC. This gets around the requirement for explicit representation of different vintages. Models with a production function that allows substitution in all time periods have a putty-putty vintage structure. DEMETER-1CCS, IMACLIM-R and E3MG have explicit putty-clay vintage capital structures. In IMACLIM-R, vintages in electricity production and end use are modeled through changes in mean input-output coefficients determined by investment. MIND has a clay-clay vintage capital structure for renewables and CCS technologies. The putty-clay and clay-clay vintage structures mean that substitution between factors, to account for changes in relative prices from e.g. carbon taxes or technical change can only occur through new investment, as opposed to changing the use of the current capital stock.

3.2 Methods of Incorporating ETC

Cross-cutting the top-down and bottom-up models discussed above, five distinct methods of incorporating ETC can be identified:

1. Explicit representation of some energy technology – renewables or a backstop, CCS, energy efficiency or some combination of these.
2. Increases in knowledge capital through R&D expenditure
3. Experience curves
4. Spillovers, from knowledge capital or in experience curves
5. Crowding out

Energy Technologies and Backstops

In climate-economy models, it is necessary to distinguish between energy related technical change and overall productivity increase. Many climate-economy models have a specific representation of technical change in the energy sector, while keeping total factor productivity improvements exogenous. As explained by the Kaya identity (CO_2 emissions = output * energy intensity of output * carbon intensity of energy), changes in emissions may take place through reduction of output, carbon intensity of energy production and/or energy intensity in general production.

The role of backstop technologies in climate energy models is often crucial. A backstop technology is a source of energy for which there is infinite supply above a given price level, such that the price of energy is capped at the backstop price; however, the backstop price may vary through technical change. Renewables (e.g. wind, solar, tidal and geothermal resources) serve as backstop technologies whereas nuclear fission is generally do not, because it is potentially subject to limitations in uranium supply and have different cost properties to renewables. While non-renewable fuels become increasingly subject to scarcity costs reflecting Hotelling's principle, renewable energy sources face no such costs. No attempts have yet been made to specify property rights on these natural processes, in contrast to underground resources. Although renewable backstop technologies may face higher costs than fossil fuel technologies at present, whether this remains the case in the long term horizon depends on the relative rate of learning. If their learning rates for renewables are higher and correct incentives are put into place for their investment, then the switch to low-carbon technologies will eventually be permanent.

All the IMCP models with a macroeconomic component allow for a reduction in energy intensity in production. The MIND model incorporates 'learning by doing' for both labor and energy productivity (with R&D and physical capital investments as decision variables). The CGE and endogenous growth models, including IMACLIM-R, allow for factor substitution through their production functions, subject to relative prices of fossil fuel and other resources compared to labor, capital and sometimes materials. This enables ITC to be modeled through policies to change relative factor prices, typically taxes on energy use (directly related to carbon emissions) or indirectly with GHG permit trading, if this increases the relative price of energy inputs to production. In the E3MG model, the sectoral energy demand is a function of energy prices among other variables, allowing the possibility of climate policies such as carbon taxes and permit trading schemes to be incorporated. It also includes indicators of technological progress in the form of accumulated investment and R&D, such that extra investment in new technologies induces energy saving. Such model feature considerations are irrelevant for energy sector models without a macroeconomic component do not include general industrial production. Several models also include R&D in energy saving technologies as an endogenous decision variable. Some models use experience curves for energy efficiency technologies e.g. GET-LFL has a experience curve for energy conversion and FEEM-RICE has ETC in abatement. AIM/Dynamic-Global, FEEM-RICE and ENTICE-BR all have some form of reduction in energy intensity through human capital and/or knowledge stocks, endogenized through an R&D variable.

There is a wide range in the level of detail of energy technologies in the different models. Typical for energy systems models, the GET-LFL and MESSAGE-MACRO models have considerable technological detail with learning applied to clusters covering all technologies. Although detailed to a lesser extent, the hybrid model E3MG also has technological detail with experience curves for each technology. In contrast, the DNE21+ energy system model has many technologies, but applies learning to three low carbon technologies to a limited degree.

In contrast to energy system models, technological representations in macroeconomic models are more aggregated. The FEEM-RICE and ENTICE-BR models have learning by searching applied to aggregate variables for technical progress in energy inputs. MIND includes fossil fuel availability, dependent on the ratio of current to initial resource extraction, as well as increasing marginal costs from resource scarcity. Carbon sequestration and storage (CCS) is included in the DEMETER-1CCS, DNE21+, GET-LFL, MIND, MESSAGE-MACRO and E3MG models. DEMETER-1CCS uses an effort variable for reductions in emissions from CCS to determine investment and maintenance costs, combined with a knowledge stock for CCS technological progress. The knowledge stock is derived from cumulated emissions reductions. This approach is similar to FEEM-RICE, which has a technological change index dependent on cumulated abatement. MIND has a detailed representation of CCS, with 6 steps and 4 different capital stocks for CCS, together with a choice of technologies for each step. Fossil fuel availability is subject to learning by doing in resource extraction, dependent on the ratio of current to initial resource extraction, as well as increasing marginal costs from resource scarcity. DEMETER-1CCS includes generic fossil and non-fossil energy technologies, with CCS for fossil energy.

This variation in the level of technological detail has at least two implications. Firstly, there are clear limitations to the direct comparison of results derived from the wide ranging models, hence conclusions must be drawn with care particularly with respect to its implications to technology specific policies. Secondly, it illustrates that a consensus is yet to be reached in the climate economy literature, about the features of energy technologies necessary in a model in order to draw conclusions about the economics of climate stabilization and insights for policy making.

Knowledge Capital and R&D

Various climate-economy models use a knowledge variable to calculate cost reductions and efficiency improvements in energy technologies. These variables are usually calculated in the same way as capital stocks, but based on R&D expenditures in addition to investment. They are equivalent to an experience curve, because they parameterize productivity increases from R&D (learning by searching in a two factor experience curve) and investment in capital (learning by doing in a two factor experience curve). However, they do not necessarily use the same learning rate formulation. The treatment as a stock variable introduces the 'learning rate' implicitly through the parameterization of knowledge accumulation and the use of the knowledge variable in reducing costs or improving efficiency. Such knowledge variables are often called 'human capital' in the endogenous growth literature. This suggests incorporating considerations of factors such as health, education (discussed in Temple, 1999), although no attempt has been made to date.

Most top-down models have R&D variables and a knowledge capital stock. AIM/Dynamic-Global has energy saving capital. In FEEM-RICE, a stock of cumulated abatement is combined with a generalized stock of 'energy knowledge' to generate an index of technical change, leading to increased carbon energy efficiency. R&D spending on energy adds to the energy knowledge stock. ENTICE-BR has knowledge accumulation from R&D in energy efficiency and the backstop technology. In E3MG, the sectoral energy and export demand equations include indicators of technological progress in the form of accumulated investment and R&D. This illustrates again, the diversity of approaches in the current literature.

Experience Curves

This is the most common approach to incorporating ETC. All the IMCP models have some form of cost reduction or productivity increase from cumulated investment. Since experience curves are the most common feature of ETC in climate energy modeling, it is also useful to clarify its meaning. As indicated, there is a difference between learning by searching or researching, and learning by doing. Several energy sector models, including MESSAGE-MACRO, have 2 factor experience curves where production costs reductions are dependent on both R&D expenditures and physical capital or installation expenditures. There is a further distinction between learning from cumulated investment (stock) and learning by producing/using (flow). Similarly in the FEEM-RICE model, a stock of cumulated abatement is combined with a generalized stock of 'energy knowledge' to generate an index of technical change that lead to increased energy efficiency. R&D spending on energy adds to the energy knowledge stock.

As noted, an important assumption in an experience curve regards floor costs. The conventional experience curve is a declining exponential, hence in order to prevent costs from tending to zero in the long run, many models have to specify a 'floor cost' for each curve. In the long run, the process of switching to new technologies will tend to a set of stable values for technology shares. These relative shares is determined by the relative floor price assumptions (as well as availability for non-backstop technologies), independent of learning rates. Thus, in the long run, a static equilibrium solution may emerge, even in these non-linear dynamic models.

Several limitations of experience curves can be readily identified, as discussed in Section 2 above. Because different components may display very different learning rates, there is a need to disaggregate experience curves into engineering elements. For example for wind turbines, different blade size, gearboxes, mast/installation, and connections to grid exhibit different learning rates. Of the IMCP models, this is only undertaken in GET-LFL and to a certain extent, MESSAGE-MACRO.

Spillovers

Whether explicit or implicit, all of the models include spillovers of some form. With models incorporating experience curves, the curve may be dependent on investment cumulated over different regions. Regional spillovers are then likely to be included. Several models have 'global' learning, where the sum of all regions' investments is incorporated in a single experience curve for a particular technology. The GET-LFL and MESSAGE-MACRO models have spillovers within clusters of technologies. If spillovers are included in the technical change specification, the positive externality will mean that ITC from policy has an increased aggregate impact. However, also implied is that the level of technical change induced will be sub-optimal (unless the government intervenes to correct market failures for knowledge).

Crowding Out

One important difference stemming from the assumptions by which learning is modeled is the importance of crowding out. Because R&D inputs are specialized, their supply is inelastic (see, for example, Goolsbee, 1998). Moreover, because investments in R&D in general have relatively high social rates of return (four times greater according to many empirical studies), the loss of R&D investment is more detrimental to the economy compared with other types of investments of the same value. Popp (2004) argues assumptions about the magnitude of crowding out have significant effects on the potential welfare gains from ITC. For example, because most learning by doing in models are single factor (do not consider R&D), they do not consider crowding out. Hence R&D is an important topic, and it matters whether it is R&D or other types of investment that is crowded out.

The endogenous growth IAMs make explicit assumptions about crowding out of R&D in the general economy from R&D in the energy sector. MIND models the tradeoff between two types of R&D, by including a second type of R&D. ENTICE-BR uses variations in the cost of R&D to capture the effect of crowding out, but does not explicitly model changes among types of R&D. FEEM-RICE uses the ENTICE-BR assumptions, where new energy R&D crowds out 50% of other R&D. More generally, macroeconomic models with investment decisions between different sectors will generate crowding out effects, although these will not be as strong as crowding out effects from lost R&D. Given ETC in the investment sectors, this will have an ongoing impact, generating path dependency in the economy, as is described in Crassous et al. (2006) for IMACLIM-R.

What Remains Exogenous?

The CGEs and the dynamic GE models include general technical change through improvements in total factor productivity (TPF), assumed as an exogenous improvement rate. MIND, however, has a fixed TFP. In energy system models, energy demand and GDP are exogenous (while including technical change in energy efficiency and end use technologies). Some models have an AEEI for various energy technologies – AIM/Dynamic-Global, DNE21+. MIND and MESSAGE-MACRO are the only models to include a resource extraction sector with technological change. Some models combine ETC in some energy technologies with an exogenous element of technical progress e.g. ENTICE-BR, AIM/ Dynamic-Global. Finally, a critical behavioral variable – discount rates or the pure rate of time preference are exogenous; rates vary widely, from 0 in E3MG (but 7% for investment decisions for energy capital), 1% in MIND, to 5% in GET-LFL.

Summary

Crosscutting IMCP is a common theme: technical change, progress and diffusion is driven by the development of knowledge capital and its particular economic characteristics of being partly non-rival and partly non-excludable. This leads to increasing returns from spillovers, with market failures due to oligopolistic competition and R&D expenditures less than the social optimum. There are two main formulations modelers use to capture this common idea: experience curves and knowledge capital. A two factor experience curve has cost reductions from R&D (learning by searching) and cost reductions from installed capacity (learning by doing). The knowledge capital formulations are equivalent to learning curves, because they describe productivity increases from R&D expenditures or capital investment. There is a tendency in the top-down models towards becoming hybrid models, because in order to incorporate ETC, they have to represent some detail in the relevant sectors, usually energy but also transport in some models. The top down literature is diverse in its theoretical treatment; the IMCP top down models have various representations of knowledge increase and also conventional learning curves. The bottom-up literature is quite cohesive – it has adopted one factor learning curves and is now moving to two factor learning curves.

4. SUCCESSES AND WEAKNESSES OF THE NEW MODELS

This section assesses the strengths and weaknesses of the various approaches when applied to ETC in climate mitigation economics. Have the models been able to incorporate the theoretical features of ETC and what is their empirical base? There are other important considerations that apply particularly to all models in a model comparison project. To make the results comparable, a common policy target and a common specification of the baseline should be adopted as far as possible. Another significant area of variation is the assumed decision making process. The baseline and representation of decision processes are discussed in the Synthesis paper. There is also the question of calibration/estimation of model parameters. To what extent is there an empirical basis for the key parameters that govern the extent of ETC; do the models use common data – for example, the rate of return to given R&D investments, or the extent of spillovers in a given industry, or the rate of learning by doing and ? These issues are discussed below.

Success!

The recent literatures surveyed above are reflected thoroughly by the scope of models of the IMCP; they all incorporate a learning process that has increasing returns and falling long run costs. Spillovers are taken into account, usually through assumptions of common learning across the different regions. However, there is a wide range of implementations: whilst some models have broadly specified ETC that is fundamental to the model structure, others have very restricted applications. We consider IMCP models, grouped by model types, then turn to some 'practical' modeling issues that illuminated by this comparative analysis.

Optimal Growth Models

The strength of optimal growth lies in its incorporation of knowledge capital, this group of models adopt theoretical structures used in the endogenous growth literature. Issues surrounding imperfect competition and increasing returns to scale is discussed extensively in the literature, and are addressed by the IMCP models. The major weakness of optimal growth models lies in their empirical base. Models are all calibrated to data, but their functional forms and parameterizations do not have a strong econometric evidence base, partly stemming from limitations identified in the more general literature relating to problems of measurement of knowledge, as discussed above in Section 2. These issues are discussed further below. The resulting variation in functional implementations and modeling outcomes are both an asset and limitation to the comparison project. In addition, energy sector specifications included in models cover a wide range – models start from an aggregated model then expand detail in some aspects of the energy sector with respect to level and method of including learning curves as well as knowledge and human capital.

Energy Sector Models

In contrast to the growth models, there is a common approach in the bottom up models. The learning curve literature comes from microeconomic observation, so the empirical work to estimate learning rates for the energy sector is a direct extension of this literature. The strength of energy sector models is the extensive technological detail. This enables the wealth of empirical information to be represented in the model structure. However, problems arise because models usually calculate a dynamic optimum – i.e. the minimum total cost of the energy sector over the time frame of the model – using linear programming methods. The non-convexities of knowledge spillovers and learning curves can lead to local maxima and potentially multiple global equilibria. However, if firms face non-decreasing marginal costs at a constant level of technology, there appears to be no problem of multiple equilibria.

The most sophisticated method used to solve such problems in this literature is the Mixed Integer Programming method adopted for the MESSAGE-MACRO model. In the MERGE-ETL model (Bahn and Kypreos, 2003), the boundary conditions are carefully chosen to restrict the model to a stable parameter space. The terminal conditions are defined in such a way as to avoid local optima. The DNE21+ model addresses the problem of multiple optima by limiting the implementation of learning. It has learning by doing for three specific technologies only, while having eight energy sources and four energy carriers in 77 world regions. Therefore, the impact of the new technologies on the overall energy system is restricted with significant impact on costs reductions. DNE21+ solves the optimization problem iteratively. Initial estimates are used for the learning variables and time series values. These are then input into the next iteration until differences between subsequent runs become small. This method is less computationally intensive than MIP used in MESSAGE-MACRO. This issue is discussed further in the context of CGEs below.

Computable General Equilibrium Models

The experience of the IMCP has shown that CGEs face considerable difficulties in incorporating ETC. Linear programming methods, as frequently used in CGE models, are best suited to solving problems with a single maximum. This is usually guaranteed by the adoption of constant or decreasing returns to scale in production functions. The introduction of increasing returns to scale for a part of the model may generate local minima and maxima and has been found in some cases to destabilize the model, such that finding a solution depends critically on the parameter values used. If the model is "tuned" to give plausible results, then the question of how these values relate to data becomes crucial. Another typical impact of increasing returns to scale is to generate instability, as the maximum may be a corner solution. If there are multiple corner solutions, then the model may flip between these solutions, generating implausible major changes between successive iterations or time periods.

One response is to limit the implementation of increasing returns. Of the recursive dynamic CGEs in the general literature, the WIAGEM model (Kemfert, 2005) uses a restricted implementation. The AIM/ Dynamic-Global model has been modified in the IMCP from a CGE to an optimal growth model and incorporates only energy efficiency i.e. productivity improving capital, along with an AEEI. The model optimizes allowing for (previously exogenous) productivity improvements over time, but the theoretical structure is not changed to include detailed dynamic functions. DEMETER-1CCS and IMACLIM-R take the latter approach, which involves considerable theoretical development.

Dynamic Simulation Models

The E3MG macroeconometric model represents the non-optimizing dynamic simulation approach. Since it is based on time series estimations, it has the advantage of having strong connection to historical data. At the same time, this historic bias is a limitation given the long timescales of climate economy models that anticipate considerable changes in future production structures. Such changes are incorporated, but cannot be estimated. Also, the econometric methodology implies backward looking investment functions as dependent on previous demand

and investment trends. This is inconsistent with forward looking, cost minimizing decision implemented for energy generation. As with other top down models, the model is implemented as a hybrid model, where the treatment of the energy sector is expanded compared to the other sectors.

Calibration/Estimation of Model Parameters

The calibration of long term dynamic models presents particular problems. Most CGE and endogenous growth models are calibrated on the most recent data, generating the dynamics from the model structure. An alternative school of thought uses time series econometrics. Both approaches encounter problems from the long run perspective, where economic structures are expected to change significantly. Therefore, as well as calibration/estimation using historical data, climate-economy models have to make explicit assumptions about future changes in structure. The calibration of learning curves often has the same problem. Econometric estimation of learning curves is not possible for new technologies where no historical data exists. Engineering estimates of performance of new technologies help to a limited degree (Anderson and Winne, 2004). As discussed in Section 2, there is still a limited empirical basis for the key parameters that govern the extent of ETC. Returns to R&D, the extent of spillovers, and knowledge (human) capital variables pose significant problems of estimation. Knowledge capital, like utility, is an abstract concept that has to be inferred through proxy variables – usually R&D expenditures and patent applications numbers in the technology and economics literatures. The limitations of these approaches also mean that the extent of spillovers in different industries is has not been clearly identified. The methods used for estimating rates of learning by doing mean that the estimates are not robust and the most important features of different technologies in determining learning rates are not clear.

What is Still Missing?

The innovation literature discussed in Section 2 above identifies the following theoretical features of technical change (see also Clarke and Weyant, 2002):

- Economic mechanisms by which technical change and technology diffusion takes place.
- Spillovers – public/private, inter-sectoral, inter-regional and the difference between private and social returns to R&D activity.
- Technological heterogeneity.
- Uncertainties in outcomes of innovation activity and decision processes in innovation, taking into account the risks and long timescales of many investments.

For climate economy models, there are two further important features:

- Following the Kaya identity, decarbonization of economic activity vs. decarbonization of energy production.

- Inertia and path dependence in technological systems such as energy, transportation, buildings.

What issues are yet to be addressed in climate modeling and ETC? Although the progress in modeling techniques has been impressive, some important limitations can be noted: the lack of uncertainty analysis; the limited representation of the diffusion of technology; the homogeneous nature of agents in the models.

Uncertainty

The models compared in the IMCP are all deterministic. This is a critical limitation, because non-linear, dynamic systems with heterogeneous agents where responses are essentially stochastic have fundamentally different properties to models that take aggregate averages or expected values. For example, the adoption of new technologies may initially happen in a niche market. The expansion of such a niche is known to be one way in which the diffusion process starts, but cannot be represented in a model with aggregate markets and a representative firm. A critical variation is firms' attitude to uncertainty in R&D outcomes and risky innovation. This is a major determinant of R&D and investment decisions, which also cannot be considered in a deterministic model. The differing optimal responses of society and private firms to uncertainty also cannot be considered. There is little in the literature that attempts to address this issue. Grübler, Nakićenović and Victor (1999b) is one of the few stochastic analyses using an energy sector model, while Bosetti and Douet (2005) is one of the first stochastic analyses with an optimal growth model. The only stochastic IAM in the literature is the PAGE2002 model, which has not yet fully incorporated ETC in its structure (Hope, forthcoming). Although the models report sensitivity analyses, these are very limited in comparison to the overall parameter spaces that these models occupy, given the large numbers of variables. The use of multiple scenarios to explore the overall range of possibilities generated by such models is also very limited, given the very wide ranges of futures that all these models can generate. Incorporating uncertainty will be a major challenge for the current generation of climate-economy models. Grübler, Nakićenović and Victor (1999b) and also Bosetti and Douet (2005) have demonstrated its feasibility with both bottom-up and top-down models incorporating ETC in the energy sector, but it will require fundamental changes in direction for most climate economy models. As discussed in Section 2, Aghion and Howitt (1998) provide an example using an endogenous growth model of Schumpeterian technical change.

Technology Diffusion

Technical change is a process of diffusion: from initial discoveries, inventions, new technologies usually develop in niche markets where there is a demand for a specific performance improvement, even with the higher costs of the new technology. If the technology is to be widely adopted, there is a gradual process of diffusion as new products and new markets are created and the price of the technology drops through learning processes. Thus models that differentiate between alternative technologies assume that new technologies are adopted on a small scale, even though they are more expensive. This opens the possibility of increasing market shares, given policy support. There is, however, little treatment of the barriers to the adoption and diffusion of new energy technologies observed in practice.

The models are also limited in their representation of inter-regional spillovers and imperfect global markets. As Keller (2004) demonstrates, technology transfer is a significant and complex aspect of technical change. Interregional spillovers are a critical part of the process: trade and FDI are an increasingly important part of the climate policy debate. A limitation of all the IMCP models is that they have restricted representations of the processes of knowledge transfer. Typically, models assume some spillovers, through the application of common learning (through R&D) to more than one region, but incorporate limited detail on the scope of spillover (e.g. how it relates with trade/FDI or capacity, education/academic activity, local R&D of receiving countries). Therefore, it is not possible for these models to examine questions of under what conditions knowledge development and transfer will take place, or what factors enable successful technology diffusion.

Heterogeneous Agents

R&D activities are introduced using aggregate data. Hence, the insights given by allowing for heterogeneous agents e.g. firms choosing to specialize in niche markets, or consumers who are technology leaders are not captured. This is, of course, partly inevitable in any large scale long-term modeling including climate change models. However, the problem is that this heterogeneity, when combined with non-linear dynamics, can give rise to very different model behaviors compared to a representative agent CGE with decreasing returns to scale.

Summary

The IMCP models provide a representative cross-section of the state of the art in climate economy modeling. They have adopted the two main approaches to modeling technical change in the broader literature – knowledge capital in endogenous growth models and learning curves. The degree to which climate economy models have managed to incorporate increasing returns and imperfect competition through knowledge spillovers is mixed. Recursive CGE models based on linear programming solutions face particular difficulties, because they may become unstable when they incorporate increasing returns. Dynamic CGEs with a changed theoretical structure have incorporated ETC, consistent with the bottom-up literature. The optimal growth models are able to incorporate widely accepted formulations of knowledge capital, because they adopt the theory of the new endogenous growth literature. Dynamic simulation models that already incorporate increasing returns and do not optimize are able to incorporate learning curves and increases in productivity from R&D. The bottom-up models, which are based on cost minimization, face similar problems to CGEs in including increasing returns, but have found various ways of overcoming the difficulties.

While the Synthesis Report considers the IMCP results in depth, we comment briefly here. Whereas the wide range of results from top-down models and the limited model specification detail poses limits to drawing clear-cut conclusions from these macroeconomic models, the bottom-up studies, in contrast, have some common findings, which are applicable to learning by doing in general. All of these models include learning curves as a mechanism for technical progress, so that the energy technology portfolio changes in favor of those technologies with the highest learning rates. Abatement costs estimates decline significantly with the incorporation of ITC. The IMCP analysis has clarified some points about the impact of ETC and ITC. In some models ITC makes a relatively small difference, but in the context of costs that are already relatively modest. In these cases, ITC does not necessarily lower costs much if major technological advances are already projected for the base case. In other models, ITC makes a large difference. In general, this appears to be associated with models that have enough technological detail necessary to allow for substitution of higher by lower carbon options in supply; responsiveness to the economic signals that enables the lower carbon supplies to "break through" in markets at large scale; outcomes with structurally different energy systems with various economies of scale applied to low carbon systems. Without accounting for these processes, ETC has limited impact on lowering stabilization costs.

5. METHODOLOGICAL ADVANCES: AN OVERALL EVALUATION

Following the new endogenous growth literature and the application of learning curves to the energy sector, there has been a transition in the climate energy literature, such that endogenous technical change is now a feature of most leading models, through representations of knowledge capital and learning curves. There is a common intuition underlying these models: technical change, both technical progress and the diffusion of new technologies, is driven by the development of knowledge capital and its particular economic characteristics of being partly non-rival and partly non-excludable. The models represent a second best world with imperfect competition from knowledge spillovers, opening the possibility of improved economic performance from well designed climate policy. This means that there are two market failures that should be considered in climate economy models with ETC: environmental externalities and R&D market failures. The new models with ETC have sometimes led to very different conclusions, compared to climate economy models with exogenous technical change. Overall costs of mitigation may be lower and given the market failures in technological development, it has shed renewed light on technology policies to initiate a transition to low carbon economies, although the optimal design of such policies and conditions for their success are still unclear.

There is a wide range of detailed implementations, with some models having broadly specified ETC that is fundamental to the model structure and others having very restricted applications. Recursive CGE models face particular difficulties and the IMCP was not able to report ETC results from a 'typical' recursive CGE. Dynamic CGEs with a changed theoretical structure have been more successful in incorporating the insights of the technical change literatures. The optimal growth models are able to incorporate ETC, because they adopt the theory of the new endogenous growth literature. Dynamic simulation models that already incorporate increasing returns and do not optimize are also successful, in that they can easily incorporate knowledge capital and learning curves. The bottom-up models which are based on cost minimization face similar problems to CGEs in including increasing returns, but have found various ways of overcoming the difficulties.

The main limitations of current models are: the lack of uncertainty analysis; the limited representation of the diffusion of technology; the homogeneous nature of agents in the models, including the lack of representation of institutional structures in the innovation process. Several possibilities for further work can be identified. There is a pressing need to disaggregate learning curves into engineering elements, tackle the problems of causality and the explanations for the learning curve phenomenon. Technology diffusion, within and across sectors, together with the role of FDI and trade is still poorly represented in the climate economy literature. As emphasized by work in the Schumpeterian tradition of disruptive new technologies, whether and how to incorporate uncertainty, as well as addressing heterogeneous agents are issues requiring further conceptual and empirical work.

With the wide ranging models (hence lack of consensus in climate change modeling), there is significant scope for comparative exercises so far led by the Stanford EMF and now the IMCP. Agreeing common assumptions such as discount rates, learning rates or stabilization targets would help reduce variability in the results, and inform discussions about the model structures. Comparative exercises also help policy analysis by mapping out the range of possible outcomes from the models that also relate to variations in economic and institutional processes.

Finally, what can the climate economy literature contribute to the rest of the literatures on technical change and growth? It has been pointed out that the endogenous growth models do not consider changes in the structure of demand,[2] yet, reduction in energy demand through efficiency measures is a common feature of the energy literature and is represented in several of the IMCP models. While endogenous growth models assume Say's Law holds in the long-run, the dynamics of a transition to a low carbon economy is central to climate policy analysis i.e. it is the transition pathways and policies to induce these pathways rather than the very long term equilibrium that matters. Demand led models such as the E3MG model are designed around such analyses, but all models have room to incorporate demand-side responses to efficiency measures (or productivity improvements) as

2. We thank Jean-Charles Hourcade for this idea.

a consequence of ETC and ITC relating to energy end uses and associated dynamics such as rebound effects. More generally, the wide range of representations of technical change in the wider theoretical and empirical literatures raises a challenge: how do the many insights into processes of technical change relate to one another? Might it be fruitful to adopt the hybrid – combined top-down/bottom-up – models that are becoming more common in the climate economy literature?

ACKNOWLEDGEMENTS

We thank all modeling teams of the IMCP for their cooperation with this project. We would also like to thank three referees for their many valuable comments.

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Induced Technological Change: Exploring its Implications for the Economics of Atmospheric Stabilization:

Synthesis Report from the Innovation Modeling Comparison Project

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This paper summarizes results from ten global economy-energy-environment models implementing mechanisms of endogenous technological change (ETC). Climate policy goals represented as different CO_2 stabilization levels are imposed, and the contribution of induced technological change (ITC) to meeting the goals is assessed. Findings indicate that climate policy induces additional technological change, in some models substantially. Its effect is a reduction of abatement costs in all participating models. The majority of models calculate abatement costs below 1 percent of present value aggregate gross world product for the period 2000-2100. The models predict different dynamics for rising carbon costs, with some showing a decline in carbon costs towards the end of the century. There are a number of reasons for differences in results between models; however four major drivers of differences are identified. First, the extent of the necessary CO_2 reduction which depends mainly on predicted baseline emissions, determines how much a model is challenged to comply with climate policy. Second, when climate policy can offset market distortions, some models show that not costs but benefits accrue from climate policy. Third, assumptions about long-term investment behavior, e.g. foresight of actors and number of available investment options, exert a major influence. Finally, whether and how options for carbon-free energy are implemented (backstop and end-of-the-pipe technologies) strongly affects both the mitigation strategy and the abatement costs.

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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1. INTRODUCTION

The Innovation Modeling Comparison Project (IMCP) aims to look at the impact of induced technological change (ITC) on the economics of stabilizing carbon dioxide emissions at different levels. The IMCP is motivated by the conviction that endogenous technological change[1] (ETC) is vital in modeling economic dynamics over the lengthy time scales required in climate policy analysis. Despite considerable progress in ETC research, significant discrepancies among models as well as uncertainties of model results still remain. The IMCP advances the understanding of ETC by assessing these discrepancies and analyzing their potential causes. This paper summarizes a quantitative model comparison experiment using a broad range of relevant models.

Two types of uncertainties contribute to the discrepancy of the results from different models. First, there is *parameter uncertainty*, referring to a lack of empirical knowledge to calibrate the parameters of a model to their "true" values. Parameter uncertainty implies an uncertainty of the predictions of any one model and discrepancies may result even in case of otherwise very similar models. Parameter uncertainty is addressed in model specific uncertainty analyses including sensitivity analysis and parameter studies, and modeling teams in the IMCP were encouraged to explore parameter uncertainty in the individual papers collected in this special issue. Second, there is structural uncertainty or *model uncertainty*, defined as the uncertainty arising from having more than one plausible model structure (Morgan and Henrion 1990, p. 67). In this paper, we address model uncertainty.

In general, model uncertainty may be reduced by eliminating possible model structures from the set of plausible models. One way of doing so is validating models against empirical evidence to discriminate "better" models and consequently discard "bad" models. However, even "perfect validation" provides no proof that a model best explains reality. Alternatively, "Ockham's razor" proposes that if another model explains the same empirical phenomena using less specific or more intuitive assumptions and parameters, then it can be deemed preferable. Yet to this date, the theoretical and empirical foundation of technological change within economics remains insufficient to allow for a sound evaluation of models according to Ockham's razor. In other words, the uncertainties about the appropriate model structure remain.

Our approach to model uncertainty involves identifying discrepancies in results of different models running the same scenarios, and investigating their origins. The analysis follows four steps: First, we classify the models according to their structure. Second, we assess discrepancies in a central model output, namely the impact of climate policy on the economy, or the "costs" of climate policy.

1. We distinguish between *endogenous* and *induced* technological change: Technological change is *endogenous* (ETC) if its course is an outcome of economic activity within the model. Given an endogenous description, technological change in policy scenarios may exceed (or fall short of) its extent in the baseline, i.e. policies *induce* additional technological change which we refer to as ITC.

Third, we analyze the different model dynamics leading to the discrepancies using aggregated indicators of model behavior and drawing on structural information about the models. We measure the impact of technological change on these quantitative indicators, *ceteris paribus*. Finally, we take a close look at the energy system as a major contributor to possible climate change.

The objective of this comparison is improved understanding of how and whether technological change matters. Technological change is a hotly debated issue because its impact on mitigation costs and mitigation strategies has political consequences. Recently, some models have been developed incorporating endogenous technological change. Examples of the papers which compare these models in a qualitative way are Sijm (2004), Clarke and Weyant (2002), Löschel (2002), Weyant and Olavson (1999), Grubb, Köhler and Anderson (2002), and Köhler et al. (2006), the latter includes an up to date survey of ETC in the literature.

The next section briefly summarizes the literature on modeling comparison; in the third section, the participating models are characterized and a taxonomy of models is provided. Section 4 outlines the method of comparison used in the IMCP. In Section 5, we analyze the impact of ITC on mitigation costs, mitigation strategies, and energy mix. Section 6 offers some conclusions.

2. MODEL COMPARISONS IN THE LITERATURE

There is a broad literature on estimating the economic impact of climate change mitigation policies using models of various types. The Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC) provide a comprehensive overview (IPCC 1996, 2001). Moreover, the Second and Third Assessment Reports (SAR and TAR) draw conclusions from comparative evaluations of these modeling studies. Among the original studies of model comparison, those of the Stanford Energy Modeling Forum (EMF) are particularly worth mentioning. This section briefly summarizes some of the key findings of previous model comparisons.

The SAR differentiates top-down (economic) and bottom-up (engineering) models, further distinguishing *Computable General Equilibrium* models (CGE), *optimizing* models, and econometric *macroeconomic* models among the top-down approaches. Top-down and bottom-up models have been known to differ greatly in their estimates of the costs of mitigation policies. The authors of SAR note that this classification is increasingly misleading as efforts are being made to combine features from macro and CGE models, and to incorporate bottom-up technological features in top-down models. Furthermore, they conclude that different assumptions about the economic reality represented in the models, e.g. about the nature of market barriers, have a far greater impact on the results than the type of the model. In their extended discussion of results from SAR, Hourcade and Robinson (1996) conclude that *"there is no* a-priori *reason that the two modeling approaches will give different results. Whether they* [bottom-up and top-down models] *do or not depends largely on their respective input assumptions"*.

Two Economics Reports of the PEW Center on Global Climate Change summarize the economics of climate change policy and the role of technology (see Weyant 2000, Edmonds et al. 2000). Both studies review why model results differ. Weyant (2000) attributes the differences to variations mainly in the baseline emission scenarios, different flexibilities regarding where, when, and which GHG emissions are reduced, and whether or not benefits from avoided climate change are taken into account. Once the effects of these differences are separated, the residual differences can be traced to substitution and technological change. Edmonds et al. (2000) emphasize Hourcade and Robinson's (1996) finding of the importance of assumptions underlying model design. Concerning the role of technological change, they note that technological change mitigates costs and occurs over long time horizons. They stress that technological change can be induced by policies, and that including induced technological change is important, however difficult.

On discussions about why studies differ, TAR revisits the top-down versus bottom-up controversy. Top-down models are distinguished into CGE and time-series-based econometric models, and TAR points out that the former type is arguably more suitable for describing long-run steady-state behavior, while the latter models are more suitable for forecasting in the short-run. TAR also notes that efforts are being made to eliminate these shortcomings (IPCC 2001, pp. 591).

EMF 19 (2004) set out to understand how models being used for global climate change policy analyses represent current and potential future energy technologies, and technological change. Weyant (2004) summarizes three main insights from the study: developing and implementing new energy technology is necessary for stabilizing atmospheric CO_2 concentration; the required transition will be costly to implement, and implementation will take many decades; but costs may be moderated if it is possible to pursue many options, to phase in new technologies gradually, and if supporting policies start soon.

In an extensive survey of the recent literature, Sijm (2004) focuses on models that exhibit features of endogenous technological change.[2] He separates bottom-up and top-down studies and finds major similarities in the outcomes of models in the former category, e.g. costs decline, the energy mix changes towards fast learners, and total abatement costs decline. Modeling studies in the latter category, however, show a wide diversity in outcomes with regard to the impact of induced technological change. He identifies variations in the following model features as possible explanations: ITC channels; optimization criteria; model functions; calibration; spillovers; and also aggregation; number and type of policy instruments; and the time horizon.

These modeling comparison exercises illuminate and outline reasons why models differ in their cost estimates. Several studies list induced technological change as a good candidate for explaining some of these differences. However, the extent of its impact and the precise reasons as to how and why technological change matters remain unclear in many cases. Focusing on the effects of ITC, all

2. For a recent collection of models incorporating ETC, see Vollebergh and Kemfert (2005).

participating modeling teams of the IMCP deliver scenarios in which technological change processes have been 'switched off' and 'switched on'. A comparison between these scenarios allows on the one hand, a quantitative assessment of technological change and on the other hand, a further explanation of the underlying economic mechanisms that explain different model outputs.

3. MODEL CLASSIFICATION

The models considered in this comparative study have two common aspects: they incorporate technological change in innovative ways and allow an assessment of costs of global carbon dioxide mitigation. At the same time, a wide range of model types is represented in this project. Understanding the conceptions underlying the designs of different model types is necessary when comparing models within and across model types. In this section we give a summary of the concepts on which we base our discussion. We start with a general classification, which serves as a guideline for the brief introduction of the models that follows. As the major motivation for the design of many models as well as a key question in this study, we draw focus on the determination of the economic impact of climate policies in terms of social costs, and recapitulate different concepts of costs which are prominent in different model types.

3.1 Model Types in IMCP

In Table 1, we differentiate four models types, mainly characterized by their calculus, i.e. the mathematical paradigm underlying the computation.

1. *Optimal growth models* – maximize social welfare intertemporally.
2. *Energy system models* – minimize costs in the energy sector.
3. *Simulation models* – solve initial value or boundary condition problems (this includes econometric models, i.e. models which base a subset of their relationships on historical time series).
4. *General equilibrium market models* – balance demand and supply among multiple actors.

Many models in this study transcend the outlined categories. Whilst the modeling paradigm that underlies a model is useful for understanding its dynamics, we urge the reader to consult the individual papers for an in-depth discussion of the models.

These papers also include discussions of the model calibration and sensitivity analysis of crucial parameters. Model calibration is important to gauge the parameter uncertainties going into the models, and sensitivity analysis assesses the effect of these uncertainties. Model calibration includes equations of the basic model and the equations specifying how technological change behaves. That is the basic model describing macroeconomic variables (such as gross world product, energy demand, etc.) on the one hand, and how technological change affects the dynamics of these main variables and is affected by them on the other hand. For this analysis,

Table 1. Classification of Models in the IMCP

	Technological detail	
Calculus	*Top Down*	*Bottom Up*
Welfare maximization	Optimal growth models ENTICE-BR FEEM-RICE DEMETER-1CCS AIM/Dynamic-Global MIND 1.1	
Cost minimization		Energy system models MESSAGE-MACRO GET-LFL DNE21+
Initial value problems	Simulation models E3MG	
Static equilibrium + recursive dynamics	Computational general equilibrium models (CGE) IMACLIM-R	

all models are calibrated such that the main variables show similar behavior during the first twenty years of the projected time. Again, we refer the reader to the individual model papers for details.

Model uncertainty, in particular structural differences in the description of ETC is assessed in this report. For the purpose of model comparison, the diversity of assumptions underlying the models (Table 2) becomes an asset to this project as it allows for robust conclusions to be drawn.

3.1.1 Optimal Growth Models

Economic growth is a major driver for GHG emissions. Optimal growth models are aimed at understanding growth dynamics over long term horizons. The key property of neoclassical growth models is their social welfare maximizing behavior. Early growth models determined optimal capital accumulation. Endogenous growth theory extends this framework to include economic forces that explain technological change. Among the growth models represented in this study a varying degree of technological change is endogenous. In AIM/Dynamic-Global, growth accrues from autonomous energy efficiency improvements in addition to capital accumulation (the later is of course present in all models). DEMETER-1CCS, ENTICE-BR and FEEM-RICE use exogenous total factor productivity (Table 2, last column) hence ETC implemented in these models also contributes to economic growth. In MIND, growth is fully endogenous. These models derive a first-best or a second-best social optimum and may be used as intertemporal social cost benefit analysis of mitigation strategies. *First best models* like MIND implicitly assume perfect markets and the implementation of optimal policy tools. In *second best mod-*

Table 2. Endogenous Technological Change (ETC) in the Participating Models

	ETC related to energy intensity	ETC related to carbon intensity	Other ETC	Exogenous TC
AIM/Dynamic-Global	• Factor substitution in CES production • Investments in energy conservation capital raises energy efficiency for coal, oil, gas, and electricity	• Carbon-free energy from backstop technology (nuclear/renewables)		• AEEI for energy from coal, oil, gas, and for electricity
DEMETER-1CCS	• Factor substitution in CES production	• Carbon-free energy from renewables and CCS • Learning-by-Doing for both	• Learning-by-Doing for fossil fuels	• Overall productivity
DNE21+	• Energy savings in end-use sectors modeled using the long-term price elasticity.	• Carbon-free energy from backstop technologies (renewables/nuclear) and CCS • Learning curves for energy technologies (wind, photovoltaic and fuel cell vehicle)		• Technological progress energy technologies (other than wind, photovoltaics, fuel cell vehicle)
E3MG	• Cumulative investments and R&D spending determine energy demand via a technology index	• Learning curves for energy technologies (electricity generation)	• Cumulative investments and R&D spending determine exports via a technology index • Investments beyond baseline levels trigger a Keynesian multiplier effect	
ENTICE-BR	• Factor substitution in Cobb-Douglas production • R&D investments in energy efficiency knowledge stock	• Carbon-free energy from generic backstop technology • R&D investments lower price of energy from backstop technology		• Total factor productivity • Decarbonization accounting for e.g. changing fuel mix

CONTINUED

Table 2. Endogenous Technological Change (ETC) in the Participating Models (continued)

	ETC related to energy intensity	ETC related to carbon intensity	Other ETC	Exogenous TC
FEEM-RICE	• Factor substitution in Cobb-Douglas production • Energy technological change index (ETCI) increases elasticity of substitution • Learning-by-Doing in abatement raises ETCI • R&D investments raise ETCI	• ETCI explicitly decreases carbon intensity (see ETCI in the energy intensity column)		• Total factor productivity • Decarbonization accounting for e.g. changing fuel mix
GET-LFL	• Learning-by-Doing in energy conversion	• Carbon-free energy from backstop technologies (renewables) and CCS • Learning curves for investment costs • Spillovers in technology clusters		
IMACLIM-R	• Cumulative investments drive energy efficiency • Fuel prices drive energy efficiency in transportation and residential sector	• Learning curves for energy technologies (electricity generation)	• Endogenous labor productivity, capital deepening	
MESSAGE-MACRO	• Factor substitution in CES production in MACRO	• Carbon-free energy from backstop technologies (renewables, carbon scrubbing and sequestration) • Learning curves for energy technologies (electricity generation, renewable hydrogen production)		• Declining costs in extraction, production
MIND	• R&D investments improve energy efficiency • Factor substitution in CES production	• Carbon-free energy from backstop technologies (renewables) and CCS • Learning-by-Doing for renewable energy	• R&D investments in labor productivity • Learning-by-Doing in resource extraction	• Technological progress in resource extraction

Note: This table provides an overview of the diverse implementations of ETC in this study. Features of ETC were loosely grouped according to their presumed impact, relating them either to energy intensity reductions or carbon intensity reductions. Naturally, the exact effects of ETC in a complex model cannot be known ex ante with certainty.

els like FEEM-RICE market imperfections or sub-optimal policy tools are not removable or modifiable. Policy of non-reproducible input factors instruments would be necessary. In other words, they may take so called no-regret options into account. In this case, the opportunity costs of climate protection can be lower or sometimes even negative compared to the baseline, dependent on the design of climate policy.

In AIM/Dynamic-Global, ETC concerns energy efficiency (Masui et al. 2006). In addition to autonomous energy efficiency improvements, investments in energy conservation capital raise macroeconomic[3] energy efficiency in the manufacturing sector, i.e. ETC affects the energy efficiency parameters in the production function which increases if the energy conservation capital stock increases faster than the output in the manufacturing sector. AIM/Dynamic-Global divides the world into six regions and describes regions with nine sectors which are mostly energy related.

FEEM-RICE (Bosetti et al. 2006) is modeled after Nordhaus' regionalized integrated assessment model, RICE 99 (Nordhaus and Boyer 2000). It differentiates eight world regions and computes the global solution by solving a non-cooperative Nash game. ETC in FEEM-RICE is represented by an energy technological change index (ETCI) which is increased through R&D investments as well as by learning-by-doing in carbon abatement. Its impact is twofold: ETCI affects the partial substitution coefficients in a Cobb-Douglas production function, shifting income shares from energy to capital. Secondly, ETCI decreases the macroeconomic carbon intensity. FEEM-RICE is presented in two parameterizations, FAST and SLOW, reflecting different assumptions about the speed of technological progress, its effectiveness and the crowding out effects between different types of investments.

ENTICE-BR (Popp 2006) is based on Nordhaus' DICE model (Nordhaus and Boyer 2000), hence it does not resolve regions. Among other modifications, Popp incorporates in his model, an R&D sector with two knowledge stocks. They are built up endogenously by R&D investments, one affecting macroeconomic energy efficiency and the other lowering the price of a generic backstop technology[4]. Energy is produced either by this backstop technology, or from fossil fuels in a corresponding sector. Both ENTICE-BR and FEEM-RICE derive a second-best social optimum by simulating market behavior in an intertemporal optimization framework.

The model MIND (Edenhofer et al. 2006) is an intertemporal optimization model with a macroeconomic sector and four different energy sectors: resource extraction, fossil-fuel based energy generation, a renewable energy source, and carbon-capturing and sequestration (CCS). The growth engine in the macroeconomic sector is fueled by R&D investments in labor productivity and energy efficiency. There is no autonomous total factor productivity improvement. The investments in the different energy sectors are determined according to an intertemporal optimal investment time path. MIND derives a first-best social optimum

3. Here, we use the term *macroeconomic* to indicate an effect or process described at the macro level, e.g. described by one parameter for the economy.

4. Backstop technologies provide carbon-free energy and are not subject to any scarcities.

and therefore calculates the potential of ITC for reducing the costs of climate protection if market failures and social traps at the international level are resolved by appropriate policy measures.

DEMETER-1CCS models a dynamic economic system which is intertemporally optimal for the representative household. The firms solve a per-period dynamic optimization problem, treating learning effects as external to the production decision level (Gerlagh 2006). Moreover, it comprises a composite good sector and different energy sectors for renewable energy sources (playing the role of a backstop-technology) and for fossil fuels. In the energy sector the costs are reduced through learning-by-doing.

3.1.2 Energy System Models

Energy system models usually derive a cost-minimum sequence of energy technologies for an exogenously given energy demand using linear programming. In more advanced versions, the energy technologies are improved by learning-by-doing. The main advantages of this approach are the detailed depiction of the energy sector and the possibility of basing technological change on an engineering assessment of different technologies. Three energy system models are participating: DNE21+, GET-LFL, and MESSAGE-MACRO.

DNE21+ differentiates eight primary energy sources in 77 world regions (Sano et al. 2006). Technological change has an endogenous description for wind power, photovoltaics, and fuel-cell vehicles; exogenous assumptions about technological change are made for other energy technologies. Energy demand in the end-use sectors is modeled using long-term price elasticities; gross world product (GWP) is exogenous to the model.

GET-LFL is a globally aggregated model differentiating eight primary energy sources (Hedenus et al. 2006). It includes a carbon capturing and sequestration (CCS) option which is used with different fossil fuels as well as with biomass. GET-LFL implements cost minimization with limited foresight in a partial equilibrium (energy market), implying an elastic energy demand. ETC in GET-LFL is implemented in learning curves for investment costs of carbon-free technologies as well as energy conversion technologies, and spillovers in technology clusters.

MESSAGE-MACRO. The MESSAGE model describes the entire energy system from resource extraction, through imports and exports, to conversion, transportation and end-use (Rao et al. 2006). Learning-by-doing is implemented for energy technologies. MESSAGE is solved in an iterative process with the economy model MACRO, allowing for some feedbacks between energy system and the macroeconomic environment, such as an impact on GWP.

3.1.3 Simulation and Econometric Models

We use the term simulation model to refer to models that start at a given state of the economy; then continue to calculate the next time step. In mathematical terms, they solve initial value problems or boundary value problems given as systems of differential equations. Econometric simulation models are additionally based on time series data, i.e. the equations are estimated from data.

Econometric models are represented by the Tyndall Centre's E3MG model (Barker et al. 2006). It is based on a post-Keynesian disequilibrium macroeconomic structure with two sets of econometric equations (describing energy demand and export demand) estimated using Engle-Granger cointegration. E3MG differentiates 20 world regions modeled with input-output structures, 41 industrial sectors, 27 consumption categories, twelve fuels, and 19 fuel users.

3.1.4 General Equilibrium Models

General equilibrium models compute demand/supply equilibria in an economy modeled in distinct, interdependent sectors. Implicitly, households and firms within these sectors try independently to optimize their welfare and their profits, respectively. Computable General Equilibrium models (CGE) are prominent examples of this type. CGE models calculate static equilibria at each point in time prescribing some growth dynamic in between time steps, i.e. they are recursive dynamic. This guarantees not only that all markets are cleared but also that a Pareto-optimum is achieved. Sectoral resolution and the dynamics of relative prices are the main strengths of CGE models.

IMACLIM-R is solved recursively but includes an endogenous growth engine that differs from standard CGE approaches (Crassous et al. 2006). The world is disaggregated into five regions, each made up by ten economic sectors. Cumulative investments drive both the energy efficiency and the labor efficiency at the same time. IMACLIM-R represents formation of mobility needs through infrastructures and technical progress in vehicles. Three transportation sectors (air, sea, and terrestrial) are differentiated in which energy efficiency is driven by fuel prices. Additionally, energy technologies in electricity generation improve via learning-by-doing.

3.1.5 A Comment on Model Types

Different modeling frameworks were created for different problems, with each model design tailored to address a specific set of questions. The characteristics of the modeling framework as well as the primary questions that guided its designs must be kept in mind when comparing the model results. Repetto and Austin (1997) note that macro and CGE models complement each other in predicting short-term and long-term responses to a climate policy. Making models to predict century long economic behavior poses a great challenge in modeling frameworks that rely on past data or the present structure of the economy. Growth models using an optimizing framework allow endogenous savings and investment decisions with unlimited foresight while many recursive dynamic CGE models restrict optimizing behavior of its agents to a sequence of static equilibria. Hence, the time path of emissions and investments derived by most CGEs are not intertemporally cost-effective. This lack of optimality is not a shortcoming of these models as they try to replicate the outcome of decentralized markets in which market imperfections are inherent. In contrast to recursive CGE models, an optimal economic growth model allows an understanding of transition paths and an assessment of what decentralized markets could achieve if appropriate policy instruments were applied. On the other hand, most intertemporal economic growth models lack economic detail and offer only limited insights into sectoral dynamics. Energy system models focus on sectoral dynamics providing very detailed predictions. When restricted to the energy sector, they neglect feedbacks with the macroeconomic environment, e.g. the revaluation of capital. The integration of energy system models with macroeconomic models is a topical subject under scrutiny and a feature of several models in this study.

Three models, MIND, MESSAGE-MACRO and E3MG, adopt a hybrid approach, i.e. they combine features from different model designs to address the gap between them. MIND integrates technological detail similar to energy system models in the framework of a growth model. MESSAGE-MACRO adds an economic environment to an energy system model by iterating the models MESSAGE and MACRO. E3MG includes a cost minimizing energy system sector within a Keynesian econometric model.

Finally, we note on the scope of the models. While all models are well calibrated, some models make very specific assumptions to explore special scenarios. Three models in particular are explorative in character. First, IMACLIM-R adopts a pessimistic view of technological change by assuming strong inertia and by neglecting carbon-free energy sources from backstop technologies. Second, AIM/Dynamic-Global focuses on the investment in energy-saving capital as a mitigation option, and largely neglects other options. As a consequence, economic growth cannot be decoupled from emissions. Third, FEEM-RICE is presented in a FAST version where especially optimistic assumptions are made about learning and the level of crowding-out.

4. METHODS OF MODEL COMPARISON

The following section outlines the IMCP approach of quantitative model comparison, specifically which scenarios were run, and which model outputs were reported. The effects of climate policies may be explored by comparing scenarios of climate protection with a business-as-usual scenario (baseline). In accordance with Article 2 of the UNFCCC which postulates stabilizing greenhouse gas concentrations, we investigate climate policy scenarios with the goal of stabilized CO_2 concentration. We focus on carbon dioxide as the most influential GHG, defining three policy scenarios stabilizing CO_2 concentrations at levels of 450ppm, 500ppm, and 550ppm, respectively. Where possible we also report results for a stabilization level of 400ppm. For this stabilization level the probability to meet the 2°C target is substantially increased (Hare and Meinshausen 2004). The 2°C target is perceived by some scientists and influential politicians, CEOs (like Lord Browne) and governmental bodies (like the EU Commission) as an interpretation of Article 2 of the UNFCCC. The concentration levels selected are somewhat arbitrary and serve to explore model responses to increasingly ambitious policies. As we prescribe a policy goal rather than a policy, model results represent a way of conforming to the policy goal and may guide the design of actual climate policy measures.

To assess the model response to climate policies and in particular the role of ITC, scenarios should ideally harmonize all other assumptions and also model calibration in order to isolate the effects of different implementations of ITC. It is known that the business-as-usual scenario has strong impact when evaluating the consequences of climate policies: assuming lower economic growth and therefore lower CO_2 emissions implies that climate protection poses a lesser challenge to the economy. Where models prescribe gross world product (GWP) and/or emissions exogenously, data from the Common POLES/IMAGE baseline (CPI) was used (Vuuren et al. 2003). However, harmonizing economic output and emissions in models which determine these numbers endogenously proves to be difficult if not impossible. Here, modeling teams have made an effort to calibrate their models to the CPI baseline, but there remain differences that must be taken in account when interpreting results.

Carbon dioxide concentration caps could not be imposed in models that do not include a carbon cycle submodel to translate emissions into concentrations. Such models either prescribe CO_2 emission paths corresponding to the selected concentration levels exogenously, or constrain the overall centennial carbon budget. Differences in the implementation of carbon cycle models may imply that the same concentration level requires more stringent emission paths. Care was taken that the carbon cycle models showed good agreement.

4.1 Scenario Definitions With and Without ITC

To assess the impact of ETC model output, stabilization scenarios were run with and without induced technological change. The baseline scenarios in IMCP comprise all components of endogenous technological change potentially incorporated in the considered model. A policy scenario ‘with’ induced technological change refers to a scenario in which additional endogenous technological change is induced by climate policy. In contrast to this, a policy scenario ‘without’ induced technological change means that climate policy cannot induce endogenous technological change beyond the baseline scenario. Therefore, in a policy scenario without ITC, technological change simply follows the time path of the baseline scenario as if it was given exogenously.[5] A comparison between ‘with’ and ‘without’ induced technological change measures the extent to which climate policy induces technological change in addition to baseline ETC. Table 3 summarizes these scenario definitions.

5. The time paths of ETC related variables in the baseline simulation are stored and then prescribed as exogenous, fixed time series in this scenario.

Table 3. Summary of IMCP Scenario Definitions

The *baseline* is a business-as-usual scenario. Technological change is determined endogenously.
Policy scenarios with ITC impose a policy goal of CO_2 stabilization at three different levels (450, 500, 550ppm CO_2) or comparable
*Policy scenarios without IT*C impose the same policy goal but restrict technological change to the extent found in the baseline scenario

4.2 Model Output and Indicators

The broad range of models is a key asset of this comparison, naturally comparable model outputs that are available in all models are of an aggregate nature. More specific outputs might allow deeper insights into some models but would exclude others. The selected model outputs (e.g. GWP, emissions, incremental costs of carbon, energy use, and the fuel mix) and the derived indicators (e.g. macroeconomic costs and sector costs, energy- and carbon intensity) reflect this trade off.

Despite the effort to harmonize assumptions and scenarios among models, it remains a challenging task to determine why model results differ, i.e. to disentangle the role of ITC from other assumptions. In addition to the analysis offered in this paper, modelers were asked to elaborate on the calibration of their model and its sensitivities in their paper contributions to this special issue, thus providing a starting point to assess the assumptions underlying the model calibration and their implications.

4.3 Concepts of Mitigation Costs

The SAR distinguishes four types of mitigation costs (IPCC 1996, p. 269). This taxonomy of costs provides a useful guide for the interpretation of results and is therefore recapitulated in the following:

1. *Direct engineering costs of specific technical measures:* These numbers provide some information about the costs of a mitigation measure or a specific technology. The cost estimates are mainly derived from engineering process-based studies of specific technologies. Examples include the costs of switching from coal to gas. In this model comparison, they are presupposed in all models.
2. *Economic costs for a specific sector* are computed in sector-specific models, which allow the integration of a multitude of mitigation measures, often in a partial equilibrium framework. For example, energy system models assess the sectoral costs of the energy sector.[6]
3. *Macroeconomic costs* reflect the impact of a given mitigation strategy on the level of the gross domestic product (GDP) and its components. At this level of analysis, feedbacks between sectors and

6. Note that MESSAGE-MACRO goes beyond this by linking with the MACRO model.

the macroeconomic environment are accounted for. Such "general equilibrium effects" can be calculated by models which encompass either the whole economy, or coupled models of specific sectors and macro-economy. Thus, macroeconomic costs include the effects of engineering costs and sector-specific costs.

4. *Welfare costs*: The GDP variations, underlying the assessment of macroeconomic costs, do not provide an adequate measure of human welfare because the ultimate goal of economic activities is not producing GDP but allowing consumption of private and/or public goods and leisure. Mitigation policies, however, may increase investments and thus GDP while at the same time reducing consumption. Therefore, GDP is not a reasonable indicator for human welfare. However, per capita consumption is also a flawed indicator for welfare because human welfare is not always a linear function of per capita consumption. Therefore, most intertemporal optimization models assume in accordance with some empirical evidence that the utility index is an increasing function of per capita consumption, and marginal utility is decreasing with consumption. This implies that costs measured in per capita consumption are exaggerated or underestimated depending on the per capita consumption level. Moreover, the utility index depends also on the distributional issues and non-market traded goods and bads. Economists who rely on welfare theory may argue that the utility index could be modified according to fairness criteria and public goods. Therefore, this index could be used as a reliable indicator for human welfare.

Within IMCP, we analyze the impact of mitigation strategies on the second and third types of costs. Welfare implications along the lines of item 4 are not assessed explicitly because the models participating in IMCP do not share a common measure of welfare.

It seems worthwhile to note that all these cost concepts leave room for interpretation and may fuel a debate about the explanatory power of mitigation cost estimations. When GWP losses and consumption losses per capita are reported in absolute numbers, these are naturally large and may create the impression that mitigation is a costly option. Put into perspective as relative percentage of the net present value of the GWP in the business-as-usual scenario, mitigation may be seen as only postponing economic growth for several months. A simple thought experiment illustrates this point: Assume that GWP growth of 2% per year in the business-as-usual scenario. If mitigation policy lowered growth to 1.97%, GWP losses over the whole century discounted by 5 % would amount to 1%. In consequence, the annual GWP that would have been achieved in 2100 is now reached in 2101 (see Azar and Schneider 2002 for a similar argument). Does this imply that mitigation costs nearly nothing for humankind? One could argue that with these trillions of dollars the lives of millions of poor people could be rescued, e.g. by investing in clean water facilities. On the other hand, damages caused by non-action may destroy the rural habitats of millions of people elsewhere which also rarely count in terms of GWP. There is need for further investigation of the extent to which rapid climate change affects the welfare of people. Whilst acknowledging that different social outcomes can be hidden behind an aggregated number like GWP and the limitations of this approach, some useful insights about the impact of ITC can be drawn using GWP. Clearly, a situation where GWP is increased because of ITC is preferable to a situation where climate policy reduces the opportunities to invest in other desirable global projects.

In the context of IMCP we report GWP losses and consumption losses in terms of relative net present value which means that we measure the net present value losses between the business-as-usual scenario and the policy scenario and relate them to the net present value of GDP in the business-as-usual scenario. This allows a comparison of the cost estimations of different models.

When interpreting mitigation costs, it is necessary to recall that in the IMCP we compare mitigation costs at given stabilization levels. Some models, e.g. ENTICE-BR and FEEM-RICE estimate climate change impacts caused by specific stabilization levels. Therefore, the benefits of avoiding such impacts are reflected in the GWP losses in these models. In the IMCP, we inform the reader only about the mitigation costs of achieving a certain stabilization level irrespective how much damages can be avoided by the predefined stabilization levels. In the cases of ENTICE-BR and FEEM-RICE the mitigation costs are reduced further by the damages caused at the specific stabilization level. Therefore, these GWP losses can be interpreted as net mitigation costs. In the following section we discuss the impact of technological change on these mitigation costs.

5. RESULTS AND DISCUSSION

This section presents the collected data as follows: First we outline and analyze the costs of achieving specific stabilization targets. Second, we analyze the necessary emission reductions in the different models in terms of their effect on carbon intensity, energy intensity, and gross world product. Third, the transformation of the energy system which is a key challenge to meet the climate protection targets is described and evaluated.

5.1 Mitigation Costs within Different Model Types

In this section we refer simultaneously to two different representations of mitigation costs. In both representations – Figure 1 and in Figure 2 – we show the mitigation costs as a loss of gross world product (GWP). Figure 1a shows mitigation costs from different models relative to the respective baseline GWP in the case when technological change is switched on (cf. scenario definitions in Table 3). In Figure 1b the cost estimations are reported when technological change is switched off, Figure

1c indicates the additional mitigation costs for the scenarios without technological change, i.e. the differences between Figure 1a and Figure 1b. Figure 1c shows the potential to induce technological change in the different models: the larger the cost increase when ITC is switched off, the lower the potential of endogenous technological change incorporated in the implementation in that model. If a models incorporated no endogenous technological change, Figure 1c would indicate no additional costs because costs with ITC would be the same as costs without ITC.

In Figure 2 the mitigation costs are shown as a function of the cumulative CO_2 reduction. The plotted data points correspond to the 550, 500 and 450 ppm stabilization scenario. The main purpose of Figure 2 is to relate costs to the mitigation gap which has to be overcome by the different models. In some models the costs are relatively low because of a small mitigation gap and not because of a strong impact of ITC on the costs. In all but two models, mitigation costs are computed as the difference in cumulated GWP (2000 to 2100) between baseline and policy scenarios, discounted at a rate of 5% and relative to (discounted) baseline GWP of the same time span.[7] As there is no endogenous GWP in DNE21+ and GET-LFL, they present instead energy system costs and producer/consumer surplus in the energy sector, respectively.[8]

By plotting the costs at different stabilization levels against the corresponding cumulative CO_2 reductions (also 2000 to 2100), the costs are put into perspective of the mitigation challenge that each model is confronted with in the policy scenarios.

The severity of the challenge is determined by the ‘mitigation gap‘, i.e. the difference between predicted business-as-usual emissions and admissible emissions in the policy scenario. Models tend to agree on the latter, which is a property of the carbon cycle modules in the models, but advocate various predictions of business-as-usual GWP growth and CO_2 emissions. Consequently, so called baseline effects have a strong influence on the results. Figure 2a depicts results from scenarios with ITC; for the scenarios in Figure 2b, ITC was disabled.

With one exception (E3MG), the models agree about the trend of costs: lower concentration targets imply larger costs. Also, costs rise disproportionately with CO_2 reductions.

In Figure 1a and Figure 2a, two models (E3MG and FEEM-RICE-FAST) show negative costs, i.e. gains from implementing climate policies. In the case of E3MG, this originates from the Keynesian treatment of demand-side long-term

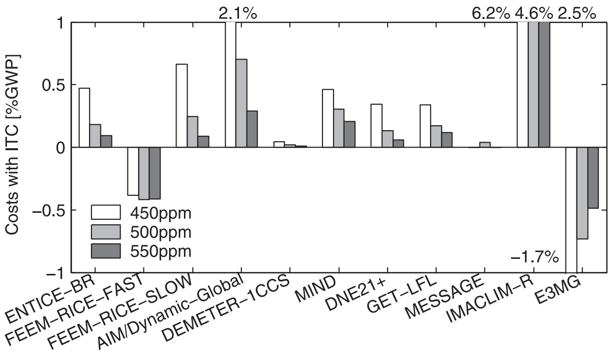
7. We use a 5% rate to discount GWP reductions from all models to make numbers comparable among models and to other studies in the literature. The rates of pure time preference used in models that anticipate future development vary: ENTICE-BR and FEEM-RICE use a 3% rate initially which declines over the course of the century; AIM/Dynamic-Global applies a 4% discount rate; the rates of pure time preference are 3% and 1% in DEMETER-1CCS and MIND, respectively; the energy system models (DNE21+, GET-LFL, and MESSAGE-MACRO) use a 5% discount rate. There is no (macroeconomic) discounting in E3MG (except in the electricity sector) and IMACLIM-R.

8. Surplus and energy system costs are converted to the same metric as the GWP losses, i.e. their difference between baseline and policy scenarios is presented relative to the present value of baseline GWP.

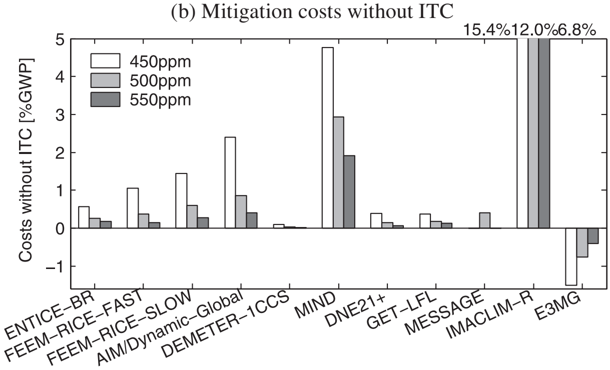
Figure 1. Mitigation Costs

Figure 1a shows loss of gross world product, except for DNE21+, which reports the increase in energy system costs relative to the baseline, and GET-LFL, which reports the difference in producer and consumer surplus. Figure 1b displays the corresponding data from the scenarios without ITC. Figure 1c shows the difference between Figure 1a and Figure 1b.

(a) Mitigation costs with ITC



(b) Mitigation costs without ITC



c) Difference of mitigation costs with ITC and without ITC

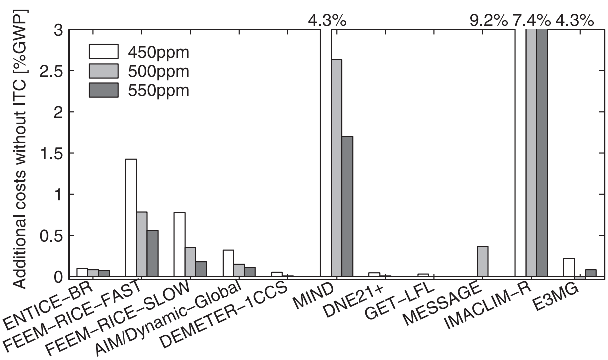
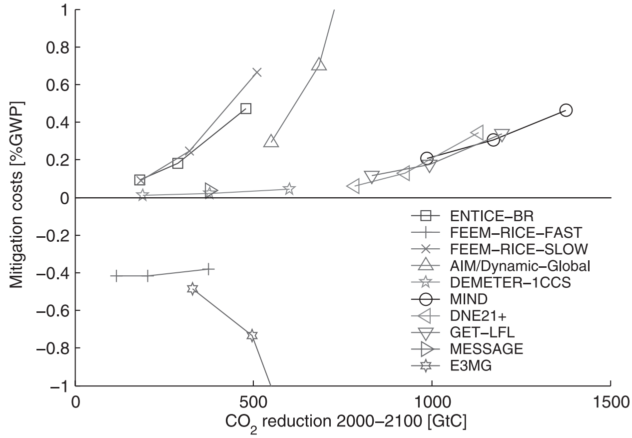


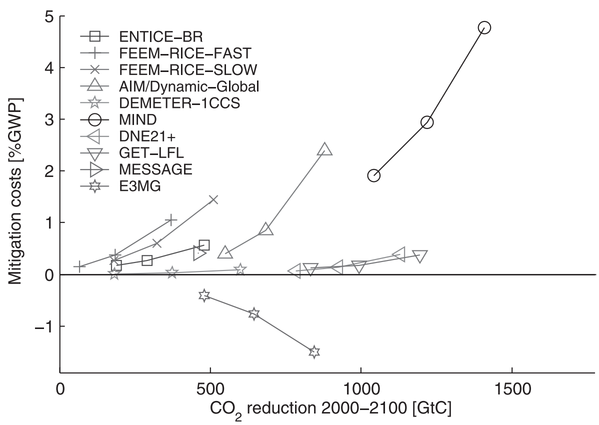
Figure 2. Mitigation Costs as a Function of Cumulative CO_2 Reduction

All models report loss of gross world product except the DNE21+ which reports the increase in energy system costs relative to the baseline, and GET-LFL which reports the difference in producer and consumer surplus. The plotted data points correspond to the 550, 500, and 450ppm stabilization scenarios (with increasing CO_2 reductions). In case of MESSAGE-MACRO, the presented scenario is 500ppm stabilization. Not shown for scaling reasons are GWP losses from IMACLIM-R which range from 2.5-6.2% in scenarios with ITC and 6.8-15.4% in scenarios without ITC.

(a) Mitigation costs with ITC relative to corresponding CO_2 reductions



(b) Mitigation costs without ITC relative to corresponding CO_2 reductions



growth that assume increasing returns to production and under-employment of labor resources in the global economy. In E3MG, policy-driven increases in carbon prices lead to more investment and output. In the case of FEEM-RICE-FAST the negative costs are the consequence of the optimistic assumptions on the effects of R&D investments and of the role that stabilization targets have in inducing more R&D investments. This reduces the inefficiencies in the global R&D market that are calibrated in their second-best baseline scenario.

We now discuss these results in more detail by model design and by individual model. We start with cost estimates of energy system models, which are relatively low, partially due to neglected general equilibrium effects. In a second part we consider the results of general equilibrium market models and simulation models which calculated relatively high mitigation costs because they are focused on price effects and neglect intertemporal investment dynamics. Finally, the optimal growth models within IMCP are discussed.

5.1.1 Energy System Models

Mitigation costs in the energy system models DNE21+, GET-LFL (Figure 1 and Figure 2) differ from those reported by other models in this exercise, which measure the loss of GWP (or welfare). The opportunity costs of climate protection are measured as the increase in energy system costs compared to the baseline in DNE21+, and measured in terms of producer/consumer surplus relative to the baseline in the case of GET-LFL. We emphasize that using alternative metrics in our comparisons is problematic. In fact, while macroeconomic models are less adept to account for the system engineering costs in the energy sector, some system engineering models do not report on the aggregated implications of mitigation for total GWP. Thus, as the energy sector accounts for the partial equilibrium effects, the mitigation costs appear relatively low in Figure 1 and Figure 2. MESSAGE-MACRO adopts a hybrid approach, combining a systems engineering and macroeconomic model, and thus calculates energy system costs as well as GWP losses. However, it remains open to debate whether all intertemporal equilibrium conditions hold in this framework and thus all relevant components of macro-economic mitigation costs are taken into account. For the sake of consistency with the macroeconomic models, Figure 1 and Figure 2 reports loss in terms of % GWP.

The main advantage of energy system models is their higher resolution with respect to technology representation, emphasizing internal plausibility and consistency of structural change in the energy system. They are hence better at accounting for costs related to barriers of technology diffusion and adoption than macroeconomic models, where technology is traditionally represented in a more stylized and generic way. The downside of using purely systems engineering approaches is that the reported energy system costs do not provide a comprehensive account of potential welfare losses outside the energy sector. As discussed above, costs of DNE21+ and GET-LFL presented in Figure 2 are thus relatively small compared to the majority of the macroeconomic models. The costs of mitigation depicted by MESSAGE-MACRO are seen to be relatively low as well, but mainly because of the small CO_2 reductions required to meet the 500-ppm stabilization target.

From a methodological point of view, the three systems engineering frameworks differ in particular with respect to representation of energy demand. In DNE21+ demand is price inelastic, i.e. feedbacks from changes within and outside the energy sector are not considered. GET-LFL takes into account price-elastic energy demand and therefore considers rebound effects in a partial equilibrium of the energy market. In partial equilibrium models, producer and consumer rents may be diminished by climate policy. Therefore, consumer and producer surpluses present a better estimate of the mitigation costs than energy system costs in this model. Both these estimates of energy system costs are relevant measures of the costs imposed by climate policy, because the transformation of the energy system is one of the greatest challenges posed by constraining CO_2 emissions. In MESSAGE-MACRO the price response of energy demand is estimated via its macroeconomic module (MACRO), where the economy is viewed as a Ramsey-Solow model of optimal long-term economic growth. In particular, feedbacks between energy and non-energy sectors are determined by relative prices of the main production factors capital stock, available labor, and energy inputs, subject to optimization.

Figure 1c compares the mitigation costs from Figure 1a (with ITC) and Figure 1b (without ITC). It is apparent from the results of DNE21+ and GET-LFL that ITC effects within the energy system are relatively small compared to those given by macroeconomic models, which account also for GWP changes outside the energy sector. Again, this might not come as a surprise because these energy system models calculate only partial equilibrium effects. Another reason may be that for the DNE21+ model, learning-by-doing to only selected technologies (wind, photovoltaic, and fuel cell vehicle). GET-LFL, however extensively incorporates learning-by-doing. In this case, climate policy does not induce significant progress for two reasons: floor costs for carbon capturing and sequestration and biomass are already nearly realized in the baseline scenario mainly because of spillover effects in technology clusters. Additionally, abundant resources of natural gas help to close the mitigation gap without further resorting to the carbon-free energy technologies which lack learning potential in the scenario without ITC. Results of the latter model in particular illustrates that technological detail is needed to understand possible compensation mechanisms that might limit inducement effects of climate policies in the energy sector.

Figure 1 includes the GWP losses from MESSAGE-MACRO (for the 500ppm scenario only). In the scenario without ITC, mitigation costs are much higher. However, comparability to the results from other models is limited, since MESSAGE-MACRO ran a fixed cost "without ITC" scenario. In other words, the structure of the energy system changes towards today's best practice technologies (given specific resource and environmental constraints). In contrast, the other models have defined exogenous technological enhancements in the scenarios without ITC. The effect of ITC in these and other macroeconomic models are discussed next.

5.1.2 General Equilibrium Models

CGE models are represented in the IMCP by IMACLIM-R. CGE models have been known to predict high costs and indeed, IMACLIM-R estimates GWP losses for 550, 500, and 450ppm stabilization targets at 2.5, 4.6, and 6.2% (Figure 1). As expected, these numbers are the highest cost estimates in this and there are reasons inherent to the model structure that explain this tendency.

Models like IMACLIM-R calculate a general equilibrium taking into account the relative price effects not only in the energy sectors but in all sectors. This way, climate policy not only induces a transformation of the energy system but also a revaluation of all capital stocks in the energy sectors and in turn in energy demand sectors. It follows that resources within the economy need to be reallocated according to the changed equilibrium. Hence in a general equilibrium model, climate policy has the potential to trigger a greater transformation than that of the energy system alone. Pitted against the need for change throughout the economy are potentially larger – economy wide – flexibilities to react to the restrictions of climate policy. However, recursive dynamic CGE models lack foresight as well as the flexibility of endogenous, sector specific investment decisions.

In particular, the IMACLIM-R model assumes that investments in the composite good sector simultaneously enhance labor productivity and energy productivity, i.e. investments in physical capital exhibit an externality. Additionally, labor productivity is improved by learning-by-doing. Climate policy induces increases and reallocations of investment in the energy sectors including the corresponding learning-by-doing. Due to learning-by-doing energy prices decrease and cause an additional energy demand – a rebound effect. These investments in the energy and transport sectors crowd out investments in the composite good sector and reduce economic growth. The reduction of investments in the composite good sector also lowers the growth rate in labor productivity, which reduces economic growth further. The double dividend of increasing investments becomes a double burden if investments have to shrink. Among other things, the crowding out effect and this double burden increase the opportunity costs of climate protection – an effect which is very pronounced in IMACLIM-R. Moreover, the interplay between inertia in the transport sector, imperfect foresight and non-optimal carbon tax profile induced further welfare losses. These welfare losses can be considerably lowered by efficiency gains and technology diffusion.

Without induced technological change, costs increase further in IMACLIM-R, demonstrating that the implementations of ETC endow the models with additional flexibility (Figure 1c). In IMACLIM-R, mitigation costs for the 550, 500, and 450ppm scenarios climb to 6.8, 12.0, and 15.4%, respectively.

5.1.3 Simulation Models

In E3MG, CO_2 permits and taxes are imposed on the economy in order to achieve the required stabilization targets. In contrast to other long-term studies but consistent with many shorter-term studies (e.g. IPCC 2001, p. 516), climate policy induces GWP gains. This result can be understood in comparison with the second-best solutions of optimizing models. These try to reproduce the market behavior which in general exhibits all sorts of market imperfections – like unemployment, postponed price adjustments, etc. – by relaxing assumptions about perfect market clearing. A crucial feature in E3MG is that although product markets clear, labor and other markets may not clear. Part of the effect of including ITC in the model is to raise growth by more labor transfer from traditional to modern sectors in the world economy.

This effect of taxation in E3MG is due to the fact that investors are limited in their foresight. In a perfect foresight model we would expect that investors adjust their portfolio of investment according to long-term price and taxation expectations.

5.1.4 Optimal Growth Models

Four of the models in the IMCP are implemented in the framework of growth models subject to intertemporal welfare maximization (MIND, ENTICE-BR, AIM/Dynamic-Global, DEMETER-1CCS, and FEEM-RICE, the latter in FAST and SLOW parameterizations). The large differences in CO_2 reductions necessary for stabilization between these models are caused by different baseline projections of GWP and the corresponding emissions. These different projections are a direct result of implementing ETC within these economy models. Whereas optimal growth models without ETC make an assumption about GWP growth, these models make assumptions about ETC which then contribute to overall GWP growth. This makes GWP growth a result of how ETC is modeled rather than an assumption. In most optimal growth models in the IMCP overall technological change is determined by an exogenous total factor productivity in addition to an implementation of ETC. MIND differs in this respect, describing technological change fully endogenously. All models share a common starting point in 2000. However, large differences result over the course of the century.

With the exception of AIM/Dynamic-Global, the cost predictions of the growth models in Figure 2 are low (below 1% GWP up to the 450ppm scenario). We have argued above that general equilibrium effects tend to raise the opportunity costs of climate policy, but these models are endowed with perfect foresight. In conjunction with endogenous investment possibilities this allows models to act flexibly thus avoiding large mitigation costs.

AIM/Dynamic-Global incorporates perfect foresight but studies only a single endogenous mitigation option. Energy efficiency depends on a stock of energy conservation capital. Investment in energy conservation capital improves energy efficiency and is a decision variable of the optimization. AIM/Dynamic-Global also includes carbon-free energy from renewables and nuclear power, but investments in these options cannot be induced by climate policy – only investments in energy conservation are a control variable. This demonstrates the impact of flexibility on mitigation costs and how the exclusion of mitigation options increases the costs substantially.

In contrast, MIND includes investment decisions into capital stocks of energy technologies, including the backstop technology in particular. We attribute the low cost estimates of these models to this flexibility.

ENTICE-BR and FEEM-RICE-SLOW compute slightly higher costs compared to MIND. ENTICE-BR incorporates a backstop technology which improves through R&D investments. However, this effect is overcompensated by the built-in crowding out effects caused by investments in the energy sector. In addition, the backstop technology displays most of its effects in the baseline scenario, independent of stabilization targets. In FEEM-RICE-SLOW costs are low because of the combined effect of learning-by-doing and R&D investments. An increase in R&D investments induced by a stabilization target enhances learning-by-doing as well. This makes R&D investments more profitable by oncreasing benefits from climate change reductions. ENTICE-BR and FEEM-RICE GWP numbers include benefits of climate policy, and that the gross numbers would be slightly higher.

In FEEM-RICE-FAST, there are negative mitigation costs, i.e. gains from mitigating carbon. The FEEM-RICE model is a second-best model in the sense that market imperfections occur in the baseline due to externalities in the R&D investments. Regions invest too little in R&D because of their non-cooperative behavior. If faced with climate policy, they are induced to increase their R&D investments, which get closer to cooperative levels. That is, an improvement of R&D investment is a by-product of climate policy. Therefore, climate policy has a clear net benefit. However, this net benefit changes to net costs if the learning-rate is slow and the crowding out effect between different types of investments is large.

The DEMETER-1CCS model also computes a second-best solution of the world economy accounting for independent actions of firms and households. DEMETER-1CCS's cost estimates are among the lowest in this study, for a number of reasons. In DEMETER-1CCS households are endowed with perfect foresight, hence even though firms show a static profit maximizing behavior, the model is at an advantage in averting mitigation costs. Moreover, the model makes optimistic assumptions about substitution possibilities between fossil fuels and carbon-free energy, and backstop technologies. The latter are assumed to exhibit high learning rates (20% for renewables and 10% in case of CCS), and the share of energy from these sources is not restricted, e.g. there is no sharp increase in costs when the energy supply has to rise as it does in many energy system models. Moreover, CO_2 emissions are low in the baseline scenario, so that complying with policy scenarios poses a smaller challenge than in other models.

If technological change is switched off (Figure 2b), costs increase. The comparison of Figure 1a and Figure 1b in Figure 1c shows that the cost reduction potential of ITC varies between different models: In FEEM-RICE-FAST as well as in FEEM-RICE-SLOW, ITC shows a large potential for reducing the mitigation costs when low stabilization scenarios should be achieved. Both versions of FEEM-RICE show remarkably similar behavior without ITC, in particular, GWP gains in FEEM-RICE-FAST have turned into losses, hence the observed effect can be attributed to "fast" technological change.

In AIM/Dynamic-Global disabling energy conservation investments has some influence on mitigation costs. The option of energy conservation investments is shown to have significant influence, but in comparison with options in other models, this option is less important.

In MIND, mitigation costs increase sharply when ITC is switched off. MIND demonstrates that removing backstop technologies when switching ITC off has a significant impact.[9] In scenarios without ITC, the MIND model exhibits mitigation costs comparable to costs in CGE models.

In ENTICE-BR the net effect of ITC is small because of two effects: first, investments in the energy sector are less productive than investments in the rest of the economy. Therefore, less technological progress is induced in the policy scenario. Second, the exogenously determined total factor productivity further reduces the impact of endogenous technological change on the model output.

5.1.5 Stricter Climate Policy (400ppm Stabilization)

Table 4 shows that a few models achieve a feasible solution when faced with a stabilization target of 400ppm (DEMETER-1CCS, MIND, FEEM-RICE, and GET-LFL). In general, the reason why many models cannot derive a feasible solution can be found in the inflexibility of the energy system to manage the required cumulative emission reductions. The inflexibility comprises phenomena like boundaries for the diffusion of backstop technologies, limited sets of mitigation options or myopic investment behavior.

Table 4. Mitigation Costs for 400ppm Stabilization

	Mitigation costs [%GWP]	
Model Name	**With ITC**	**Without ITC**
DEMETER-1CCS	0.07	0.17
FEEM-RICE-FAST	0.01	3.1
FEEM-RICE-SLOW	2.0	3.7
MIND	0.76	8.9
GET-LFL	0.62	0.67

5.1.6 Robust cost estimate

The IMCP set out not only to learn from the differences in model results, but also to identify robust findings. Is it possible to identify a robust estimate of

9. In MIND, the availability of renewable energy sources and carbon capturing and sequestration is considered an option of ETC because its use depends on the costs of carbon, consequently, in the scenarios without ITC, the extent of renewables and CCS is restricted to the baseline. In all other models, the availability of technologies is not considered as "ETC", e.g. in DEMETER-1CCS's scenarios without ITC, renewables and CCS may be used; however there is no learning-by-doing for these technologies in this scenario. Therefore, if endogenous technological change is switched off, MIND can only reduce energy consumption and GWP.

climate protection costs across models in the IMCP?

One might be hesitant to see robustness in the broad range of costs e.g. in the case of 450ppm stabilization, ranging from benefits to costs greater than 6% of aggregate GWP 2000-2100 (at present value). However, the range is reduced considerably when we recognize that three models are of a predominantly exploratory nature, i.e. their intent is not to give a best estimate but to explore an extreme scenario. These are: IMACLIM-R, which explores the role of the transportation sector under the assumption that energy sector and transportation sector are inflexible and externalities of investments in physical capital are biased against energy efficiency; AIM/Dynamic-Global limiting mitigation options to investments in energy conservation capital, hence emissions cannot be decoupled from economic growth in the long-run (these two models arrive at the highest costs in this study); FEEM-RICE-FAST exploring the possibility of "fast" technological change, which then results in benefits of climate protection rather than climate protection costs.

If we furthermore consider E3MG separately, because it is fundamentally different with its Keynesian rather than neoclassical point of view, we are thus left with a set of seven models and cost estimates that range from 0.04% to 0.66% for 450ppm stabilization. Average climate protection costs among these remaining models are 0.39, 0.16, and 0.1%, for 450ppm, 500ppm, and 550ppm stabilization, respectively. Here, the MESSAGE-MACRO model is only included in the 500ppm average because it did not run the other scenarios. If we exclude the two energy system models that do not report costs in terms of GWP, the numbers only slightly change to 0.41, 0.16, and 0.1 percent, for 450ppm, 500ppm, and 550ppm stabilization, respectively. These last numbers average over 4, 5, and 4 models, respectively. Table 5 summarizes these values along with average costs at alternative discount rates, illustrating the influence of the discount rate on the cost estimate.

In view of this and with the considerable uncertainties about model structure and other assumptions in mind, it seems a robust conclusion from the presented energy system models and optimal growth models to expect climate protection costs of up to one percent.

5.2 Mitigation Strategies for Different Stabilization Scenarios

In this section we identify the contributions of different carbon mitigation options towards achieving an overall mitigation target, and we assess the role of technological change in the mitigation effort. Kaya's identity[10] provides a set of indicators that pinpoint the different ways taken by models to meet a given target, namely the attribution of total carbon dioxide emissions to global economic output, energy intensity of GWP, and carbon intensity of the energy:

$$CO_2 = \frac{CO_2}{PE} \times \frac{PE}{GWP} \times GWP \tag{1}$$

10. Kaya's identity originally also differentiates between income effect (GWP per capita) and a population effect. As an exogenous population scenario is used in this study, we can neglect this factor.

Table 5. Average Discounted Abatement Costs

Concentration level [ppm CO2]	5% [%GWP]	Declining discount rate[a] [%GWP]	2% [%GWP]	1% [%GWP]	undiscounted [%GWP]
450 ppm	0.41	0.64	0.71	0.83	0.95
500 ppm	0.16	0.25	0.28	0.32	0.37
550 ppm	0.10	0.14	0.16	0.18	0.19

a. Declining discounting rates were adopted from the Green Book (HM Treasury 2003) starting at 3.5% for the first 30 years, then dropping to 3.0% until year 75, and 2.0 until year 125.

Table 5 shows abatement costs averaged over central models, i.e. we exclude models with a predominant explorative nature and we restrict the average to GWP losses only ignoring the different metrics from GET-LFL and DNE21+. That is, the above averages include ENTICE-BR. FEEM-RICE-SLOW, DEMETER-1CCS, MIND, and MESSAGE.

$$PE \qquad GWP$$

Here, CO_2 denotes emissions, PE primary energy, and GWP is gross world product. To facilitate interpretation and to help track down the features underlying these aggregate effects in the models, we summarize endogenous and exogenous technological change in the individual models in Table 2 and attribute the features of technological change to their likely effects in terms of either energy intensity or carbon intensity. Of course, the complex nature of the models does not allow a definite classification. Still, these preliminary classifications may serve to structure features of technological change and guide interpretation, for comprehensive model descriptions we refer to the literature references in Section 3.

5.3 Decomposition Analysis

The indicators output, energy intensity and carbon intensity are chosen because they provide information about fundamental differences in the mitigation strategies pursued by the individual models. Yet because of their highly aggregate nature, they abstract from the technological and implementational details in the models, thus allowing quantitative comparison across models.

Reduction of carbon intensity makes it possible to maintain a high level of energy use, putting relatively little stress on the economy as a whole (the climate issue is ‘solved’ in the energy sector). If this solution is not feasible (this depends largely on availability of carbon-free technologies), energy intensity must be decreased (implying a reduction of energy) to comply with the climate policy. Forcing the economy to use drastically less energy can amount to ‘choking’ it, i.e. it may lead to a reduction in output (gross world product). The decomposition analysis allows quantification of the contribution of carbon intensity, energy intensity and output reduction to the required effort of emission reduction. For the purpose of this modeling comparison we use the refined Laspeyres index method (Sun 1998, Sun and Ang 2000). We apply the decomposition analysis to the differences of cumulative values between baseline and policy scenario. Figure 3 displays the decomposition of the centennial CO_2 reductions along Kaya's identity for different models.

5.3.1 Mitigation Strategies to Comply with 550ppm Stabilization

The stacked bars in Figure 3 show the CO_2 savings in the 550ppm policy scenario from the baseline cumulated over the century. Additionally, shading indicate how much reductions in carbon intensity, energy intensity, and output (GWP) contribute to these savings.

The necessary carbon dioxide reductions differ widely between models. The cumulative reductions necessary to comply with a 550ppm concentration cap range from ~116GtC to ~987GtC (in FEEM-RICE and MIND, respectively), with correspondingly great differences in the challenge that these reduction pose for an economy.[11] We stress that models tend to agree on the maximum cumulative CO_2 emissions for a given stabilization scenario: averages among models for cumulative CO_2 emissions are 589, 783, and 931 GtC for 450, 500, 550 ppm stabilization scenarios, respectively. The corresponding standard deviations are 72, 77, and 92 GtC. The differences in Figure 3 stem mainly from different CO_2 emission paths in the baseline: cumulative CO_2 emissions in the baseline range from 980 to 2000 GtC, mean 1430, with a standard deviation of 323 GtC. To account for such baseline effects, we will base our analyses on measures that are relative to this 'mitigation effort' as much as possible.

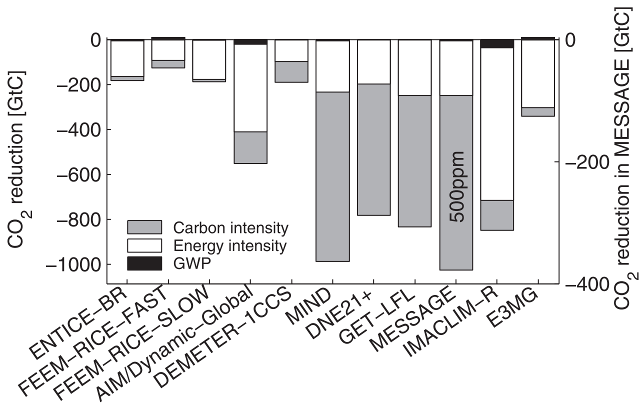
Note that baseline growth and CO_2 emissions seem unrelated to model types. This is not very surprising when growth and emissions are exogenous and therefore arbitrary. In other models, it is possible to calibrate growth and emissions, e.g. in recursive CGE models, by a variation of exogenous model parameters like the total factor productivity. In the optimal growth models, total factor productivity, efficiency of R&D investments, and elasticity of substitution can be adjusted to approximate a given baseline scenario. However, the baseline is not determined by exogenous parameters alone but also by the endogenous features of technological change. This implies that CO_2 emissions of such models cannot be fully harmonized. Nevertheless, there is no reason to assume that models with endogenous technological change exhibit an inherent trend to particularly high or low emission scenarios.

A group of models (IMACLIM-R and AIM/Dynamic-Global) share similar behavior. Here, the larger part of the CO_2 reductions can be attributed to lowered energy intensity and cut-backs in production. They also show the largest cut-backs in production of all models. A possible explanation is that an inability to provide enough carbon-free energy (which would show up as carbon intensity reduction) forces economies to reduce the energy input (evident in the reduced energy intensity) to an extent where it harms the economy (visible as GWP reduc-

11. An obvious corollary is that emission reductions are necessary to meet even the 550ppm policy goal despite the presence of ETC in the baseline.

Figure 3. Cumulative CO_2 Reduction for the 550ppm Stabilization Scenario

CO_2 reductions are attributed to reductions in carbon intensity, energy intensity, and gross world product using decomposition analysis. Note that the 550ppm scenarios are not available from MESSAGE-MACRO and we therefore display results from their 500ppm scenario using a separate scale on the second y-axis.



tions). IMACLIM-R resorts to decreasing energy intensity and reducing GWP because it does not incorporate a backstop technology. Here, the increasing energy price reduces energy demand and induces additional investments in the electricity- and transport sectors which crowd out the overall investments in the composite good sector which are needed to induce economic growth. An optimum, cost-effective tax profile would probably lower costs compared to the exogenous linearly increasing tax imposed in these scenarios.

The RICE/DICE models, FEEM-RICE and ENTICE-BR, show strikingly similar behavior but this differs substantially from the remaining growth models. Here, the predominant mitigation strategy is to increase the energy efficiency. FEEM-RICE does allow explicitly for carbon intensity reduction as well as for energy intensity reduction. However, both are driven by the same index of technological change. Hence the ratio of reductions in carbon- and energy intensities is implied by model structure and calibration, and it is not a degree of freedom in the model. Both FAST and SLOW versions of the FEEM-RICE rely more on energy intensity reduction than on carbon intensity reduction. The FAST version shifts the mitigation strategy towards carbon intensity reductions. ENTICE-BR explicitly includes a backstop technology so one might expect a bigger carbon intensity effect. However, carbon-free energy is already strongly represented in the baseline (the share of renewables rises from 4% in 2000 to 11% in 2100). The required CO_2 abatement is therefore small and can be met by energy efficiency improvements via R&D investment in a corresponding knowledge stock and factor substitution.

DEMETER-1CCS behaves differently. Here, energy intensity reductions and carbon intensity reductions make equally large contributions, while production cut-backs are kept at a minimum. A low emissions baseline and optimistic assumptions about substitution possibilities and carbon-free energy sources play a key part in this and were discussed in detail in the preceding section.

In energy system models, the mitigation strategy relies heavily on carbon intensity reduction, i.e. CO_2 emissions are mitigated largely by switching to low carbon energy sources. Indeed, all these models include options to build up a backstop technology providing carbon-free energy, and in each case learning curves are implemented for some backstop technologies. At the same time, a significant share of the CO_2 reductions is attributed to reductions in energy intensity implying some sort of energy conservation. In DNE21+, energy demand is exogenously given. However, energy savings in end-use sectors in climate policy scenarios are modeled using long-term price elasticities. GET-LFL implements learning-by-doing in energy conversion technologies as well as a price dependent energy demand in a partial equilibrium. In MESSAGE-MACRO runs, energy demand is determined in the MACRO economy model, which allows energy to be substituted by other factors.

Remembering that MIND includes a reduced form energy sector that borrows from bottom-up energy system models, the similar ratios of carbon and energy intensity in MIND and in the energy system models is no surprise. Rather, it indicates that energy system dynamics are successfully approximated by the reduced form model. Furthermore, MIND consistently describes the macroeconomic environment taking into account general equilibrium effects. Hybrid models like MIND therefore constitute an attempt to bridge the gap between top-down and bottom-up models in order to assess the importance of the investment dynamics.

In E3MG most of the necessary reductions are attributed to reduced energy intensity. There are three routes by which carbon intensity and energy intensity are affected: First, an increasing price of carbon induces a reduction in energy demand, and second, a switch to carbon-free technologies within the power and transport sectors. Finally, the share of fossil fuels in the overall energy mix is slightly decreased because the elasticity of substitution in the energy and transport sector is very low.

5.3.2 Effects of Enhanced Climate Policies

Figure 4 indicates the change of the portfolio of mitigation options, if instead of 550ppm CO_2 concentration, the more ambitious level of 450ppm has to be achieved. How and in which way do the mitigation strategies change when a more demanding climate protection goal is pursued? Bars in Figure 4 give the change of the mitigation portfolio in terms of the contributions to overall CO_2 reduction in Figure 3. They are symmetrical because an increased share of one option is always balanced by a corresponding decrease in one or more other options. For example, a 20% increase of the carbon intensity effect accompanied by the corresponding 20% decrease of the energy intensity effect in the case of DEMETER-1CCS implies that the contribution of carbon intensity rises from 50% to 70% whereas the contribution of energy intensity drops to 30%.

Figure 4. Change of the Mitigation Strategy with More Ambitious Climate Policy

The bars in this figure give the absolute differences between the percentages describing the contributions of the options in the 550ppm and the 450ppm scenarios. There is no result for MESSAGE-MACRO because only the 500ppm scenario was available.

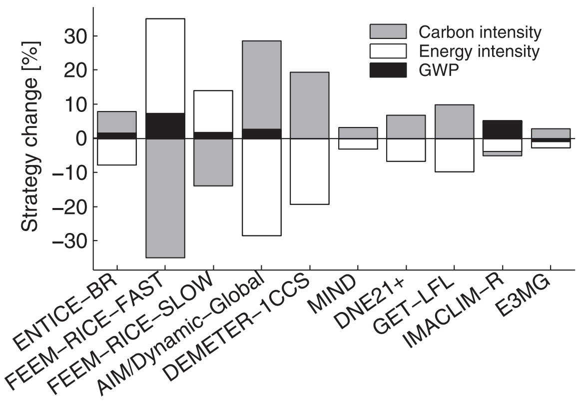


Figure 4 shows that lowering the stabilization level has different impacts on the portfolio of mitigation options in the models. Whilst several models show little change (e.g. MIND and E3MG), others show substantial changes. Large changes may indicate that favorable mitigation options which contribute to CO_2 abatement in laxer policy scenarios have been exhausted hence other options are increasingly deployed for more stringent climate policies. Small changes suggest that the greater challenge is addressed much the same way as the lesser challenge.

In DEMETER-1CCS, the contribution of carbon intensity reduction increases by nearly 20% to a share of 70%. In other words, carbon free energy from renewables and CCS now contribute to mitigation to a similar extent as they do in energy system models. The reason lies in the fact that the 550ppm scenario in DEMETER-1CCS is relatively close to the baseline, and a large share of the necessary emission reductions can be accomplished by energy savings. In contrast, the 450ppm concentration target requires a much more substantial departure from the baseline, and the option of factor substitution decreases in relative importance.

In many models (ENTICE-BR, AIM/Dynamic-Global, DEMETER-1CCS, MIND, DNE21+, GET-LFL, E3MG) we observe a similar pattern of change in the portfolio: to achieve 450ppm stabilization, a mitigation strategy is chosen that incorporates a larger share of carbon intensity reduction than in case of the 550ppm stabilization. In all of these cases, a carbon-free technology is implemented, and this change can be attributed to a heavier use of carbon-free energy in the energy mix. Exceptions to this pattern are FEEM-RICE and IMACLIM-R. FEEM-RICE and IMACLIM-R have in common, the feature that they do not model a carbon-free energy technology. This seems to limit their potential to reduce carbon intensity compared to models with a backstop technology. The difference is particularly striking when FEEM-RICE is compared to ENTICE-BR. The two models share the general model structure of Nordhaus' DICE/RICE models, yet only the latter incorporates a backstop technology with the consequence that it becomes possible to increase the contribution of the carbon intensity effect.

In IMACLIM-R, most of the additional CO_2 reductions are accomplished by reducing GWP. The limited potential of carbon- and energy intensity reduction is largely exhausted at the 550ppm stabilization concentration. The reduction potentials are limited due to capital inertia preventing the retirement of old capital. As before in the 550ppm scenario, a rebound effect in the transportation sector and crowding out of growth inducing investments in composite goods determine the GWP losses.

5.3.3 Mitigation Strategies With and Without ITC

Figure 5 shows how the portfolio of mitigation options changes when features of endogenous technological change are disabled, i.e. technological change is restricted to the extent computed in the baseline. The bars give the change in portfolio (cf. Figure 4). Large changes indicate that including the possibility for ITC has a big impact on the mitigation strategy.

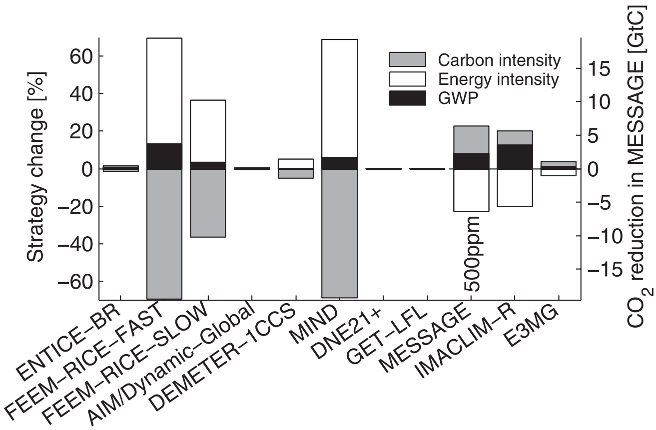
MIND, FEEM-RICE, and IMACLIM-R show relatively large changes. In MIND, the modelers' understanding of ITC plays an important part (see Footnote 9).[12] When the common definition of ITC is applied, changes in MIND are closest to the changes in DEMETER-1CCS, i.e. there are much smaller changes. Four models show little change (AIM/Dynamic-Global, DNE21+, GET-LFL, and ENTICE-BR) because model behavior with and without ITC is very similar.

In Figure 5, ENTICE-BR, FEEM-RICE, DEMETER-1CCS, and MIND share the same sign for the change in the contribution of carbon intensity reduction. In these models, the carbon intensity effect decreases implying that the *induced* technological change works more towards decarbonization rather than reducing energy intensity. Naturally, this mirrors the fact that these models implement features of endogenous technological change that are related to decarbonization, e.g. learning curves for backstop technologies. Two qualifications apply: MIND also includes endogenous energy efficiency reduction. In this case, Figure 5 shows that induced carbon intensity reductions outweigh induced energy intensity reductions. Secondly, in FEEM-RICE-SLOW the contribution of carbon intensity decreases from an 11% contribution to -23% contribution. Here, the average global carbon intensity is *higher* in the policy scenario without ITC than in the baseline because under climate policy, a larger share of global energy use is al-

12. A small carbon intensity effect remains, because the fixed amount of renewables represents a greater share of the (reduced) total energy in the policy scenario without ITC than in the baseline, which implies reduced carbon intensity for the energy mix.

Figure 5. Change in Mitigation Strategies when ITC is Disabled in the 550ppm Scenario

The bars in this figure give the absolute differences between the percentages describing the contributions of the options in the scenarios with ITC and without ITC. For message-macro, the 500ppm scenario is used instead.



located to countries with relatively high carbon intensity (U.S., Europe, and other high income countries), thus raising the global average relative to the baseline.

Conversely, in E3MG, MESSAGE-MACRO, and IMACLIM-R, the climate policy induces a larger contribution of energy intensity reduction, though for differing reasons. In IMACLIM-R, stabilization levels without technological change can only be achieved with a substantial reduction of GWP because of the sunk costs in the energy system, the constant rate of exogenous technical change and the absence of sequestration options. The carbon tax induces no additional change in the pace of technological change. The economy only adapts to the imposed carbon tax through a changed energy mix (see the increasing carbon intensity in Figure 5 if technological change is switched off). Therefore GWP has to be reduced in order to compensate decreasing energy intensity.

In E3MG the key feature of the model underpinning the ITC results is that GWP growth has been made endogenous, with technological change having a major influence (via export equations). However, endogenous technological change only has a small decarbonization effect on the global economy. Energy demand and supply is very small in relation to the rest of the economy, around 3-4% of value added, and technological change is led by improvements in the use of machinery and information technology and communications. These improvements allow long-term growth to proceed by decreasing energy-intensity if technological change is switched on. The growth itself ultimately comes from the demand by consumers for goods and services, promoted by technological and marketing innovations.

Disabling ITC possibilities increases the contribution of GWP reduction to mitigation in all cases. This comes as no surprise: Removing the flexibility of inducing further technological change from the model makes it more difficult for the models to reduce CO_2 emissions without cutbacks in production.

5.4 Timing of Mitigation Options

Figure 6 depicts the timing of the mitigation options (adopted from Gerlagh 2006). We show the reduced carbon intensity in the 450ppm policy scenario relative to the baseline versus the reduced energy intensity as a time trajectory, from 2000 until 2100 with bullets set every 20 years. A trajectory where both options contributed to the same extent would run along the bisector. Steeper or gentler slopes indicate a preference for carbon intensity reduction or energy intensity reduction, respectively.

Interestingly, in a majority of models, the trajectory bends to the left with time indicating that carbon intensity reduction becomes increasingly more important. A plausible explanation is the widespread use of carbon-free technologies that need to be built up gradually by investments, and often become increasingly more productive through learning-by-doing. The trajectory of IMACLIM-R illustrates well, how lack of a backstop technology prevents this change in the mitigation strategy: the model sticks to its mainly energy saving strategy over time. FEEM-RICE-SLOW shows similar behavior: the reduction of energy intensity dominates the reduction of carbon intensity (i.e. the slope of the trajectory is less than unity) because of a missing backstop technology.

Similar to the other models, FEEM-RICE initially increases the reduction of both energy intensity and carbon intensity. While FEEM-RICE-SLOW retains this mitigation strategy, FEEM-RICE-FAST decreases reductions of carbon intensity. As mentioned before, carbon intensity and the elasticity of substitution are driven by the same endogenous index of technological change in FEEM-RICE, and the relation of carbon intensity and energy intensity is therefore determined by model structure.

In GET-LFL energy demand is reduced by an increasing energy price, which in latter periods is compensated by a stronger reduction of carbon intensity.

5.5 Energy Mix

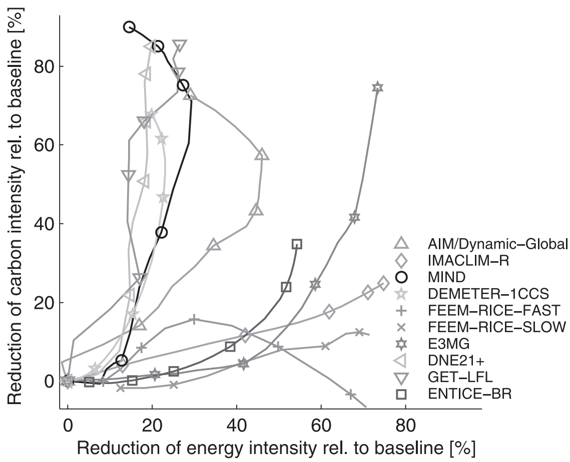
In the previous section, we showed that the dynamics in the energy sector, e.g. the development of a carbon-free technology, have a key impact on carbon abatement. In this section we take a close look at the projected development of the energy system and the role of ITC.

Figure 7 shows the development of the energy system characterized by the mix of energy sources at the beginning (2000), middle (2050) and end of the century (2100). Five energy sources are distinguished, namely three fossil energy sources (coal, gas, and oil) plus renewable energy sources, and nuclear fission. If additional energy sources were implemented in a model which could not be subsumed in these categories, or if a model does not differentiate between

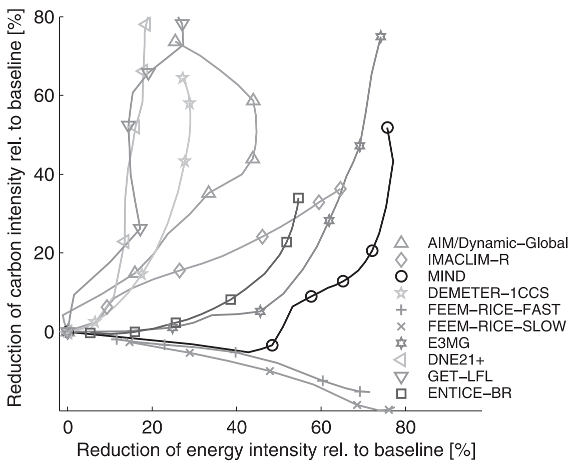
Figure 6. Trajectories in Energy Intensity/Carbon Intensity Space

Trajectories start at the origin and bullets are set 20 years apart. Figure 6a shows the 450ppm scenario with ITC, Figure 6b the same scenario without ITC.

(a) Strategy trajectory with ITC



(b) Strategy trajectory without ITC



the categories, the data is presented in the categories of "aggregate fossil" and "aggregate non-fossil" energy sources. Results are reported in three columns per model giving the baseline energy mix, the 450ppm policy scenario with ITC, and the 450ppm scenario without ITC.[13] In 2000, the three cases coincide. The models FEEM-RICE and ENTICE-BR are not shown as these models do not compute energy in Joules but incorporate "carbon services" to productions measured in carbon instead. In the case of MESSAGE-MACRO, results from the 500ppm scenarios are displayed instead of the unavailable 450ppm scenarios.

5.5.1 Different Formulations of the Backstop

We have seen that implementing a backstop technology can make a great difference in how models respond to climate policy goals. In accordance with the literature, we define a backstop technology as a carbon-free technology whose usage is not restricted by scarcity of non-reproducible production factors. What makes backstop technologies so important in carbon abatement?

In Figure 8, we sketch model behavior given two different assumptions about backstop technology. The price of energy from a fossil resource is indicated in black, and an exogenously set price for energy from the backstop technology is indicated in light gray. In contrast, the price of energy from a backstop technology is plotted in dark gray for an endogenously determined backstop price. Solid time paths indicate business as usual, and slashed curves are induced by a policy goal. We assume that imposing a policy goal brings down the price of energy from the backstop technology because larger investments in carbon-free energy sources need to be made and therefore more learning occurs. The price of energy from fossil resources rises due to the costs of the corresponding emissions, e.g. through carbon taxes or emission permits.

Under climate policy, the price of non-backstop-technologies (like exhaustible resources) is rising sharply and intersecting the exogenous backstop price, at which point the latter becomes economical and is used to an extent that keeps the energy price at this same level (intersection 1).

For the backstop technology that is explicitly modeled, i.e. capacity is being build up, and its price changes according to a learning curve, the backstop technology is competitive much earlier and at a lower price (intersection 2). The price of carbon-free energy declines from the beginning, indicating that investments are being made in anticipation of the later competitiveness. Intersection 3 illustrates that this may even be the case in the absence of a policy goal.

From these illustrations we conclude that the cost-decreasing potential of backstop technologies is strengthened when lowering prices endogenously is an option in the model, furthermore, if economic agents possess the foresight and the possibilities to make early investments in order to use this option.

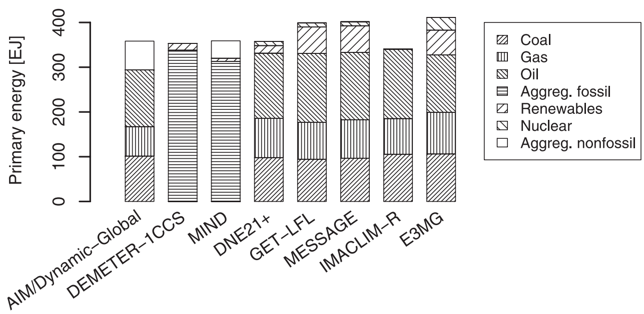
There are models in IMCP without a backstop technology (IMACLIM-R and FEEM-RICE). As we have seen, these models mainly reduce energy intensity

13. Alternatively, the laxer scenarios could have been used to arrive at much the same conclusions. We decided on the most stringent case because here the observed effects are more pronounced. The alternative figures were omitted due to limited space.

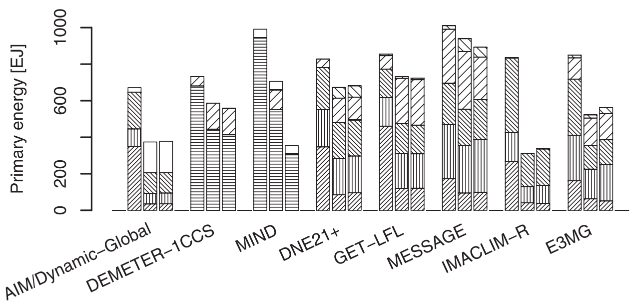
Figure 7. Energy System Represented by the Contributions of Different Energy Sources to the Overall Primary Energy Consumption

In 2050 and 2100, the three bars per model display the energy mix in the baseline scenario, 450ppm policy scenario, and 450ppm policy scenario without ITC. In 2000, these three cases coincide. We use darker shading for energy from fossil fuels and lighter shading for carbon free energy sources. Data from the 500ppm scenario is shown in case of MESSAGE-MACRO. Also in case of this model, the third bar represents a fixed costs scenario and not the usual scenario "without ITC."

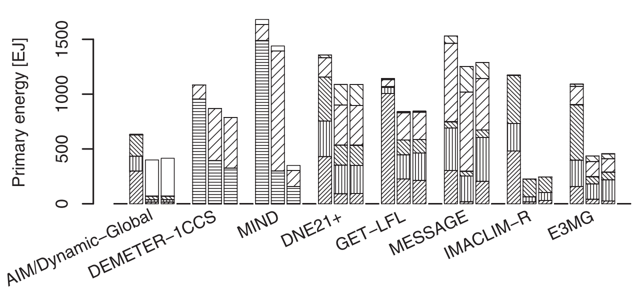
(a) Energy mix in 2000



(b) Energy mix in 2050



(c) Energy mix in 2100



to achieve climate protection goals.

Those models that incorporate carbon-free energy from backstop technologies (i.e. rather than prescribing an exogenous price, the backstop technology is endogenous to these model) are of the second type discussed above (ENTICE-BR, AIM/Dynamic-Global, DEMETER-1CCS, MIND, GET-LFL, DNE21+, MESSAGE-MACRO, and E3MG).

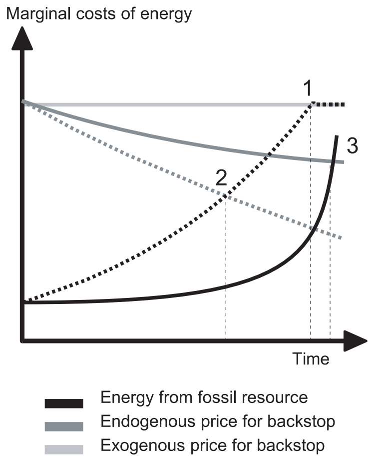
It is also interesting that especially in GET-LFL the investments in the backstop technology are undertaken long before the break-even-point is achieved. The reason is that intertemporal optimum decision-making anticipates the temporal spillover effects (learning-by-doing or accumulation of knowledge through R&D). The model GET-LFL is only a limited foresight model. Nevertheless, this feature implies that temporal spill-overs are partially internalized. In GET-LFL the impact of the backstop technology on the overall energy mix is very modest because in both cases the backstop technology has gained a substantial proportion of the energy mix in the business-as-usual scenario (Figure 7). In GET-LFL enough cost reduction potential has already been realized in the business-as-usual scenario. Moreover, the GET-LFL model assumes a high share of gas in the fossil fuel mix, so that a modest reduction in the energy demand makes it possible to achieve climate protection goals even without much ITC.

In DEMETER-1CCS, ITC has only a moderate impact on the energy mix for two reasons: First, the business-as-usual scenario already assumes some learning as the backstop technology is introduced as a technological option in 2025. Hence the cost reduction potential in the policy scenario is limited. Second, the business-as-usual scenario also assumes a decreasing fossil fuels price path, thus the marginal effect of learning-by-doing is limited and the break-even point is changed little.

Figure 8 also helps to understand the role of technological change in the resource extraction sector. Similar to technological change in the case with backstop technology, it could reduce the growth rate of the price of energy from fossil fuels by making more fossil resources available at lower costs. If learning-by-doing was assumed, the effect would be more pronounced in the baseline than in the policy scenario, which would widen the gap between the resource price with and without policy goal. Cost reductions of fossil fuels due to technological progress decreases the competitiveness of the backstop technology and therefore increases the opportunity costs of climate protection. Note, that sensitivity analysis in MIND supports this qualitative insight – technological progress in the extraction sector is one of the most sensitive parameters in determining the opportunity costs of climate protection (Edenhofer et. al. 2006). Thus, it would be interesting to see other model types including realistic representation of endogenous technological change in resource extraction and its effects on resource availability into their estimates of climate protection costs.

Another aspect is illustrated by Figure 7: as discussed above, some models will rather cut back on energy use relative to business-as-usual than provide carbon-free (or low carbon) energy. This is evident in Figure 7 when overall energy consumption in the policy scenarios is much lower than in the baseline; ex-

Figure 8. Different Formulations of Backstop and Resource Scarcity



amples are IMACLIM-R, and E3MG. Other models manage to make almost as much energy available as in the baseline by changing to low carbon or carbon-free energy sources, e.g. MIND, DEMETER-1CCS and the energy system models. This echoes the findings from the previous section, and is in fact one of the underlying factors influencing whether a model implements a mitigation strategy of carbon intensity reduction or energy intensity reduction.

5.5.2 Shadow Prices, Carbon Taxes and Path Dependency

The price of carbon plays a different role in different models (Figure 9 and Figure 10). First best models of the economy (e.g. MIND) make the implicit assumption that all market imperfections may be cured. Hence, the result of welfare maximization in these models is a Pareto-efficient solution without any further restrictions. In these models, the shadow price of carbon represents the social costs of carbon. Second best models, e.g. general equilibrium models, simulate market behavior, i.e. the model incorporates distortions that cannot be removed by policy instruments for institutional or political reasons. The carbon tax in DEMETER-1CCS represents a second-best optimum in the sense that it is imposed on the economy in order to guarantee the achievement of the stabilization level and a minimum of welfare losses subject to the market distortions that cannot be removed by policy instruments because of institutional or political inertia.

In the other models in Figure 9 (IMACLIM-R and E3MG) the imposed tax does not represent a second best optimum because the carbon tax only allows the achievement of a stabilization level irrespective of its welfare implications. The carbon tax profiles in IMACLIM-R and E3MG are prescribed exogenously, i.e. they are non-optimum.

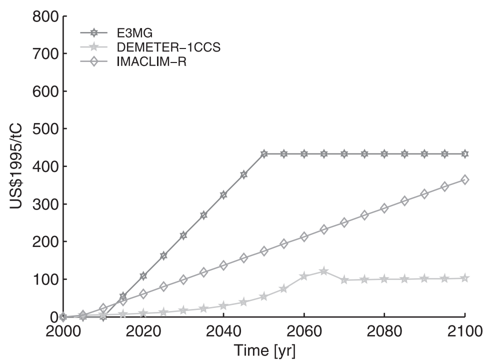
In the class of optimal growth models, the carbon price is a dual variable and represents the social costs of carbon (Figure 10). Moreover, the time path of carbon follows an optimum path which could be interpreted as an ideal market for carbon permits or as an imposed optimal carbon tax. In energy system models the carbon price is also a dual variable in an optimization framework. However, the carbon price does not necessarily represent the total social costs of carbon because of the omitted feedback loops between the energy sector and the macro-economic environment in that partial-equilibrium framework.

The carbon price also reflects the effect of ITC in some models. In nearly all models the carbon price is higher in the scenarios without technological change. However, in MIND the carbon price behaves differently: it increases exponentially

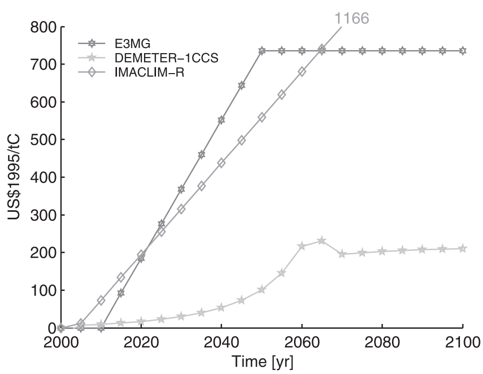
Figure 9. Carbon Tax

Figure 9 a shows the 450ppm CO2 stabilization scenario with ITC, Figure 9b shows the corresponding scenario without ITC. Values greater than $800 per ton of C were cut off; the corresponding maximum value is given.

(a) Carbon tax with ITC



(b) Carbon tax without ITC



in the case without ITC but it peaks and decreases if ITC is switched on.

There is an interesting pattern in carbon price development in some models: towards the end of the century, the shadow price reaches a maximum and begins to decline. This is true for all scenarios with ITC in MIND and in the 450ppm scenario for DEMETER-1CCS. If the price of the backstop technology decreases over time, even without an increasing shadow price of emissions (and fossil fuel price), the backstop technology remains competitive with fossil fuels. In contrast to a model with an exogenous price of the backstop technology, learning-by-doing of the backstop technology creates a path dependency because its price is determined endogenously by investments in learning-by-doing. There is no longer an incentive for investors to promote fossil fuels after the energy system is transformed because the price of the backstop technology also declines with the transformation of the energy system. The shadow price in most energy system models increases throughout the century indicating that the transformation of the energy system is not completed before 2100. This may be in part because renewables or nuclear power (as backstop technologies) are not able to substitute fossil fuels until the end of the century, due to bounds on market share for renewables, moderate price increases for fossil fuels that remain too low to trigger a transformation, and relatively optimistic assumptions about CCS. The remaining share of fossil fuels will turn carbon into a scarce factor in production with a positive price.

Path dependencies occur if the transformation to a carbon-free energy system is irreversible in that the carbon-free technologies become the least cost set of options.

5.5.3 The Specific Role of Carbon Capturing and Sequestration

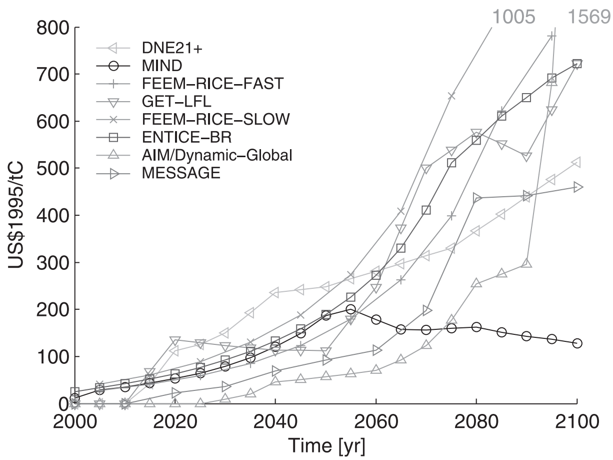
Among the participating models, five explicitly incorporate the option of capturing and storing CO_2 emissions from combustion (DEMETER-1CCS, MIND, DNE21+, GET-LFL, and MESSAGE-MACRO). Figure 11 shows how much CO_2 is captured in different scenarios, accumulated over the century. Figure 12 gives the corresponding time paths of carbon capturing and sequestration (CCS) for one exemplary scenario (500ppm CO_2 stabilization).

As one would expect, Figure 11 shows that the more challenging the climate policy target, the more CO_2 is captured and stored. There is no CCS in the baseline, as capture and storage of CO_2 is costly and hence only becomes economical in the presence of climate policy. DNE21+ is an exception, because the model includes an option to use CCS in the context of enhanced oil recovery which makes CCS economical in its own right. The contribution to overall abatement (the difference of cumulative emissions between baseline and policy scenarios) is substantial, in particular in MIND, DNE21+, and GET-LFL. However, nowhere is CCS the dominant mitigation option but rather, it is always predicted to be one among many (we conclude this from the fact that captured CO_2 is only a small proportion of the difference of emissions in baseline and policy scenario).

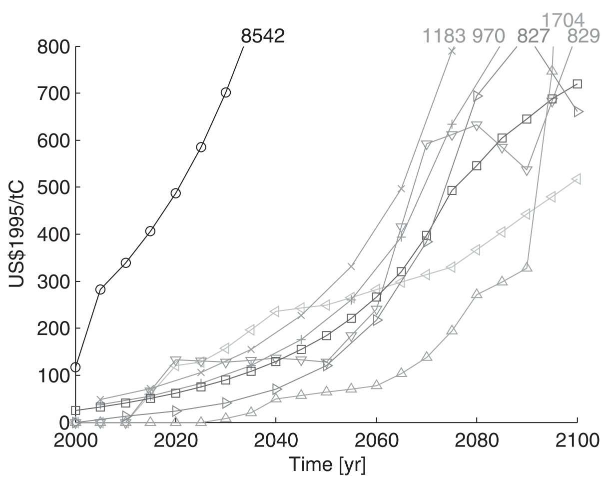
Figure 10. Shadow Price of Carbon

Figure 10a shows the 450ppm scenario with ITC, Figure 10b shows the corresponding scenario without ITC. In case of MESSAGE-MACRO, the figures show numbers from the 500ppm scenario instead of the 450ppm scenario. Values greater than $800 per ton of C were cut off; the corresponding maximum value is given.

(a) Shadow price with ITC



(b) Shadow price without ITC



As mentioned before, the models show agreement on the allowable carbon budget in the policy scenarios, yet they predict divergent cumulative emissions in the baseline. This affects the predicted extent of CCS. DEMETER-1CCS and MESSAGE-MACRO, on the one hand show fairly low baseline emissions and in turn low predictions for CCS. On the other hand the remaining three models are faced with a greater need to reduce emissions and resort to a stronger usage of the CCS option. Both groups, DEMETER-1CCS and MESSAGE-MACRO as well as MIND, DNE21+ and GET-LFL show good agreement in their predicted utilization of the CCS option.

Figure 12 shows the development of CCS over the course of the century. The five models show diverse behavior. In two of the linear-programming energy system models (DNE21+ and GET-LFL) the capacity of CCS increases almost linearly with time and is still rising at the end of the century. This suggests that the rapidity of increasing this capacity is restricted, but no (anticipated) constraints to the volume of CCS are effective yet. GET-LFL includes CCS in combination with energy production from biomass. Thus in GET-LFL CCS is indeed not constrained by fossil fuel scarcity.

In contrast, CCS in DEMETER-1CCS levels off towards the end of the century. Here, CCS activity has reached at least a temporary equilibrium. Possibly the low emission profiles in the baseline allow these models to reach a CCS capacity that is both sustainable and sufficient for the policy target.

MIND and MESSAGE-MACRO show yet another type of behavior. In MIND, capacities for CCS are built up even faster than in the energy system models, but after a peak around mid-century the usage of CCS declines. Similarly, in MESSAGE-MACRO CCS peaks in 2080 and declines. Both models respect the scarcity

Figure 11. Captured CO_2 and Total CO_2 Emissions

The figure summarizes usage of the CCS option in the baseline and two policy scenarios as a share of total amount of CO_2. CO_2 that is not captured is emitted.

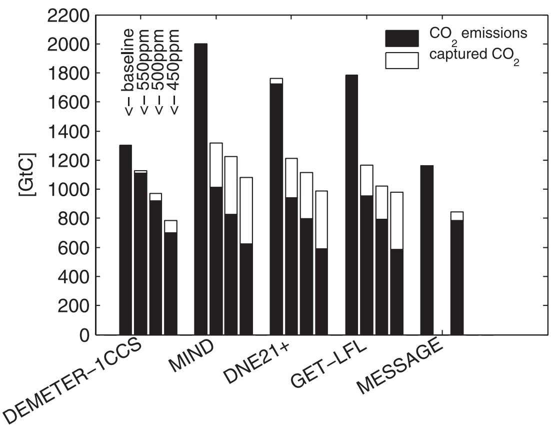
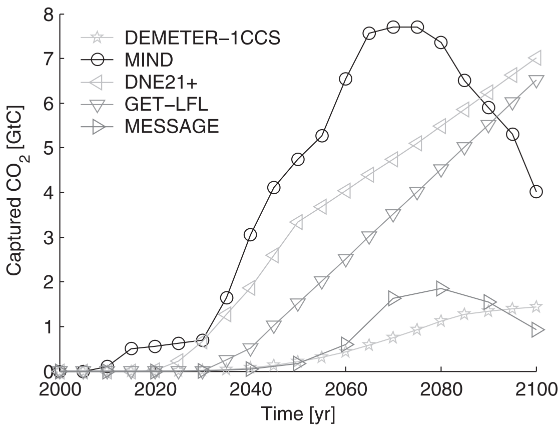


Figure 12. Carbon Capture and Sequestration Over the Course of the Century



of fossil fuel resources increasing costs on the utilization of CCS in the long-run. While CCS is at a competitive advantage over renewable energy technologies due to cheap fossil fuels early on in MIND and MESSAGE-MACRO, this advantage is lost as renewables become more economical due to learning-by-doing.

Two more features contribute to the temporary nature of CCS in MIND: readily available storage sites are subject to scarcity[14], and MIND includes leakage from storage sites at a fixed rate (i.e. the same percentage leaks from the storage site in each time period), implying that CCS does not prevent but only strongly delays emissions into the atmosphere. The leakage rate is highly uncertain, but it plays an important part in determining whether CCS constitutes a temporary rather than a permanent solution. It would therefore be instructive to see whether other models confirmed this result from MIND (Bauer et al. 2005), when leakage is included.

Carbon capturing and sequestration (CCS) is different from backstop technologies because it is dependent on non-reproducible inputs, e.g. fossil resources[15]. Furthermore its extent is limited by the availability of storage sites. If all relevant intertemporal social costs are taken into account, CCS is only a temporary solution until the backstop technology becomes competitive. CCS is an end-of-pipe technology allowing in the best case a welfare improving postponement of the diffusion of the backstop technology. In a theoretical analysis,

14. In MIND, the assumption is that with the rising utilization of CCS, increasingly long pipelines are needed to transport CO_2 to the storage site. In general, spatial aggregation within the models and limited knowledge about the location of suitable storage sites add to the uncertainties in modeling CCS.

15. GET-LFL also includes CCS in combination with energy production from biomass.

Edenhofer et al. (2005b) show that temporary welfare gains from CCS increase when (a) the discount rate is increased, (b) the energy penalty is decreased, (c) the operation and maintenance costs (O&M) are reduced, (c) the leakage rate of deposits are lowered, (d) the capacity of deposits is increased and (e) the costs of the fossil fuels are decreased. Gains are also higher when the price of the backstop technology is high and/or when its learning rate is low.

The CGE model within IMCP has not incorporated CCS so far. In general, CGE models could inform about the market potential of CCS under different policy scenarios. However, CGE models allowing only for a recursive dynamic are not appropriate for deriving realistic market behavior because they implicitly assume purely myopic investment behavior which is arguably an exaggerated or extreme behavior.

6. CONCLUSION

This model comparison aims to draw robust results on ETC by identifying both the differences between and the underlying mechanisms of the multitude of participating models. We find that the participating models describe a wide range of possible futures, with and without climate policy. Although there is no consensus on the potential role of induced technological change, we identify crucial economic mechanisms that drive ITC. This modeling comparison exercise demonstrates a large influence of the following determinants:

1. Baseline effects
2. First-best or second-best assumptions
3. Model structure
4. Long-term investment decisions
5. Backstop and end-of-the-pipe technologies

6.1 Baseline Effects

All models in the IMCP incorporate endogenous technological change in their baseline, sometimes in addition to exogenous technological change. In effect, baseline emissions are difficult to harmonize and vary widely. Both endogenous and exogenous components contribute to this mitigation gap. In some models optimistic assumptions about exogenous parameters result in relatively low costs which are then due not to induced technological change, but mainly to exogenous assumptions. In addition, if the baseline scenario already includes many positive effects of technological change related to energy and carbon savings, then the introduction of stabilization targets does not induce much addtional technological change. Consequently, the cost difference between scenarios with and without ITC is small.

6.2 First Best or Second Best Assumptions

It has important consequences whether a *first best or a second best* world is modeled: First best models implicitly assume perfect markets and the implementation of optimum policy tools. In other words, first best models preclude so called no-regret options. Therefore, they are inherently more pessimistic about the costs of climate protection because climate protection reallocates scarce resources which are utilized in an optimum way in the baseline to climate friendly investments. In contrast, second best models assume that climate policy can positively affect market imperfections as a side effect. Compared to first best models the opportunity costs of climate protection in second best models can be lower and even negative, depending on the design of policy.

6.3 Model Structure

Previous model comparison exercises have shown that CGE models tend to calculate higher mitigation costs than energy system models or economic growth models (Löschel 2002); we find that this result still holds. However, the underlying reason is not necessarily the model type, but rather in assumptions commonly made by "CGE modelers", "energy system modelers", and "economic growth modelers", e.g. about foresight and intertemporal behavior of the agents.

It turns out that energy system models calculate low mitigation costs because they only assess the impact of mitigation strategies on energy system costs. Yet partial equilibrium analysis explicitly omits general equilibrium effects - partial equilibrium models by definition exclude feedback loops between the energy sector and other sectors of the economy. In particular, energy system models implicitly assume that investments within the energy sector can be funded by the economy at a constant rate of interest. However, this assumption is not justified when an ambitious climate policy is imposed in the system. This would depreciate capital stocks in various sectors and therefore also change the return on investment in the energy sector. Consequently, the changed return on investment induces a reallocation of investments across sectors. This investment dynamic is a major determinant of macroeconomic costs of climate policy which is neglected in partial equilibrium analyses. Moreover, most energy system models neglect rebound effects and the crowding-out implications of investments. The impact of these general equilibrium effects emerge to be significant.

In contrast, CGE models demonstrate the quantitative impact of general equilibrium effects. However, recursive CGE models reduce the flexibility of long-term investment behavior remarkably. By assumption, investment shares for different sectors are fixed even if an ambitious stabilization level is imposed on the economy. Some CGE models include a backstop technology, however, its costs are independent of the timing of investments. Mitigation costs are overestimated because of the underlying assumptions that investors are myopic.

The econometric model in IMCP describe a second best world. Imperfections on the labor market and design of the carbon tax allow substantial welfare improvements from climate policy. The policy implication is clear. Policy makers can claim that climate policy is a free lunch. However, it should be emphasized that second best do not claim that climate policy is the only way or the best way to cure market failure. If better solutions exist, then climate policy is no longer a free lunch but has positive opportunity costs. It seems promising to calculate these opportunity costs based on the strength of both frameworks.

Optimal growth models allow greater flexibility. Some of the optimal growth models are already designed as multi-sectoral and intertemporal optimization models comprising a reduced form energy sector. These models demonstrate the effect of full temporal and sectoral flexibility. In contrast to energy system models they do not assume that the differences of the return on investments across sectors can be ignored. It turns out that an appropriate timing of investments has the potential to reduce the mitigation costs substantially. In particular, the optimum timing of backstop technologies (like renewables) and end-of-pipe technologies (like CCS) has a great potential for cost reduction.

6.4 Long-term Decision Making: Foresight and Flexibilities

Assumptions about *long-term investment decisions* exert a major influence: The number and flexibility of mitigation options has been shown to have an impact on mitigation costs (Edenhofer et al. 2005a). This observation is confirmed in this study.

Perfect foresight enables investors to anticipate necessary long-term changes and to control investment decisions accordingly, including possible externalities such as learning-by-doing. The multi-sector optimal growth models in this study demonstrate the potential of perfect foresight to reduce mitigation costs. Models allowing for flexible and long-term investment decisions achieve an equilibrium that can be characterized by low emissions and low macroeconomic costs. Naturally, assuming perfect foresight is normative rather than descriptive, i.e. its model results are motivation for policies rather than an exploration of its effects.

The assumption of intertemporal optimization may exaggerate the potential of ITC to reduce mitigation costs because the rationality and foresight of investors and entrepreneurs implicit in their intertemporal optimization behavior represents an optimistic assumption. The assumption of great foresight of the actors in such models becomes more realistic when a macroeconomic policy ensures credible expectations. Currently, the number of uncertainties for investors is large, including uncertainty about emission targets, well-designed international tradable permit schemes, subsidies for R&D investments, well-behaved capital markets allowing for long-term investments, and competition and globalization on the energy market. A stable macro-economic environment and clear long-term emission targets are crucial for the transformation of the energy system. Therefore, a focus for post-Kyoto discussions beyond 2012 should be the design of policy instruments allowing for long-term investments.

6.5 Backstop and End-of-the-pipe Technologies

Finally, the results depend on the design of *backstop and end-of-pipe technologies*: Whether and how a carbon-free energy source is implemented has an essential impact on mitigation costs as well as on the mix of mitigation options.

If a model allows for endogenous long-term investments in backstop technologies and/or end-of-pipe technologies, then mitigation costs are substantially reduced and the stabilization targets can be met without drastic declines in energy consumption. Moreover, available carbon-free energy sources shift the abatement strategy towards decarbonization rather than energy saving.

Nearly all models conclude that more ambitious climate protection goals increase the costs. It should be noted that this is not a trivial statement because due to learning-by-doing, mitigation costs could be decreased if less ambitious stabilization targets are imposed. However, modeling teams in IMCP assume that learning-by-doing has its clear limits because of floor costs, barriers of diffusion and other market imperfections like insufficient internalization of intertemporal or interregional spillovers.

Over the past decade the debate has been focused mainly on the learning-by-doing potential of backstop technologies. However, this study shows that this is only one aspect. Another key factor determining the competitiveness of the backstop is technological progress in the fossil fuel sector. Assumptions about the fossil fuel sector and its potential for technological change are crucial for determining costs and strategies. Therefore, further modeling efforts should also focus on a more realistic representation of technological progress within the fossil fuel sector.

Moreover, all models indicate carbon costs that rise with time in the early years, and most maintain this across the century. However, some models which incorporate backstop technologies and carbon capturing and sequestration show a "hump" in the time path of carbon permit prices, i.e. carbon costs peak and decline afterwards. This supports what some technical change analysts have supposed: experience from learning-by-doing or the reality of sunk costs introduce a path dependency scenario development, and thus the marginal costs of maintaining low emission levels decrease in the long term due to cumulative learning effects and the usage of a broad range of mitigation options like improvement of energy efficiency, the diffusion of backstop technologies and the temporary use of end-of-pipe technologies.

6.6 Hints for a Future Research Agenda

This modeling comparison exercise takes a first step in assessing the quantitative impacts of ITC on mitigation costs and mitigation strategies. We assess the impact of ITC is isolated by imposing ceteris paribus conditions, i.e. ITC is induced by climate stabilization targets in a setting where boundary conditions and parameters remain unchanged.

Beyond the IMCP, we recommend research expansion two ways. First, future model comparisons could refine the harmonization of the participating models to a baseline of central variables (capital stock, investments, direction of technological change) and parameters in order to minimize baseline effects. Second, more sophisticated ceteris paribus scenarios could be run, e.g. exploring the impact of single ITC options rather than enabling and disabling all ITC as it was done here.

Not all important aspects of ITC could be addressed in this study. They should be explored in future model comparisons, e.g. regional spillovers. Moreover, while this study restricted policy intervention to imposing stabilization levels (i.e. represents only the targets approach to policy), the effects of different policy instruments are neglected. An exercise comparing policy instruments across different model types could accelerate research on optimal climate policy design.

IMCP allows to set out a formulation of an agenda to improve modeling design. First, we have explored some reasons for the gaps between top-down and bottom-up models and discussed several models that begin to bridge this gap. These hybrid models seem a promising starting point from which to develop a coherent framework incorporating intertemporal, intersectoral and interregional effects of induced technological change. Second, as it has turned out in the IMCP, assumptions about long-term investment behavior have a strong impact on mitigation costs and strategies. Therefore, experiments with different assumptions about long-term expectations and long-term flexibility of investment behavior would be highly valuable. Third, the way carbon-free energy is made available has turned out to have a major influence on the response of the model to climate policy goals and therefore deserves attention. This is explored by many models implementing backstop- and/or end-of-the-pipe technologies. We argue that endogenous technological change in the extraction sector of fossil fuel is a complementary prerequisite for a comprehensive understanding of ITC. Many modeling teams within IMCP have incorporated learning-by-doing of the backstop technology. In contrast to this, endogenous technological change in the exploration and extraction sector of fossil fuels has not received as much attention. There is significant technological change (e.g. in the resource extraction sector) with a potentially strong influence on the opportunity costs of climate protection. A better understanding of the underlying dynamics may therefore both satisfy scientific curiosity and also provide a prerequisite for improving the design of climate policy.

ACKNOWLEDGEMENTS

We would like to thank all modeling teams for the productive cooperation in this project, especially for repeatedly checking the interpretations and conclusions we derived about their models. While we were writing this synthesis report we received many valuable comments and they are gratefully acknowledged here. Beyond the IMCP modeling teams, we would like to thank three anonymous referees. We also would like to thank Nico Bauer and Marian Leimbach for valuable comments and discussion. John Schellnhuber has supported our work in many ways. Kai Lessmann was funded by the Volkswagen Foundation, Project II/78470, which we gratefully acknowledge.

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Induced Technological Change in a Limited Foresight Optimization Model

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The threat of global warming calls for a major transformation of the energy system in the coming century. The treatment of technological change in energy system models is a critical challenge. Technological change may be treated as induced by climate policy or as exogenous. We investigate the importance of induced technological change (ITC) in GET-LFL, an iterative optimization model with Limited Foresight that incorporates Learning-by-doing. Scenarios for stabilization of atmospheric CO_2 concentrations at 400, 450, 500 and 550 ppm are studied. We find that the introduction of ITC reduces the total net present value of the abatement cost over this century by 3-9% compared to a case where technological learning is exogenous. Technology specific policies which force the introduction of fuel cell cars and solar PV in combination with ITC reduce the costs further by 4-7% and lead to significantly different technological solutions, primarily in the transport sector.

1. INTRODUCTION

Anthropogenic emissions of greenhouse gases have likely raised the annual average global surface temperatures (Houghton et al, 2001). The energy system is the single most important source of net carbon dioxide emissions. Thus, in order to prevent further anthropogenically induced climate change, the energy system needs to be transformed to a system with significantly lower carbon emissions. Energy systems models have been used to identify cost-effective carbon abatement strategies, as well as to estimate costs of stabilizing the atmospheric carbon concentration (Azar et al, 2003; Manne & Richels, 1997).

One crucial issue in energy systems modeling has been the question of how to deal with technological change. Traditionally, models have assumed

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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exogenous learning over time (Azar & Dowlatabadi, 1999). More recent models, however, use learning-curves in order to endogenize technological progress (Mattsson & Wene, 1997; Barreto, 2001; Seebregts et al, 2000). This is important, particularly for emerging technologies such as solar PV, fuel cell and wind. Under such modeling approaches, accumulative installed capacity rather than time itself drive down costs. Some models incorporated two-factor learning curves that also takes learning from R&D into account (Bahn and Kypreos, 2002). Endogenous learning in optimization models, however, causes computational problems because the optimization problem becomes non-convex. Faced with multiple optima it is not possible to guarantee that the solution obtained is a global optimum. Therefore Mixed Integer Programming (MIP) is often used, which amounts to a linear approximation of the model. This method guarantees global optimality, although at the expense of increased computation time (Bahn & Kypreos, 2002).

Most energy system models optimize under perfect foresight. Some recent models, however, elaborate with iterative limited foresight (Martinsen, et al 2004; Nyqvist, 2005). These models do not derive the optimal energy system from a social planner's perspective, but have the advantages of being better suited for simulating market behavior.

In this paper, we use a model called Global Energy Transition – Limited Foresight with Learning (GET-LFL) in which we combine an optimization approach based on limited foresight and learning-by-doing. This modeling approach allows the problem to remain convex, and it has a relatively short computation time.

The aim is to compare the effect of introducing induced technological change (ITC) in an energy system model. Several types of comparisons can be made in order to evaluate the implications of ITC to abatement costs. For example, an ITC model may be contrasted with a model with technology costs fixed at their year 2000 values. Such an approach would result in lower costs for a model with ITC. Another approach may compare a model with ITC with a model with exogenous learning, i.e. where the costs of various technologies drop over time. Under this approach it is unclear whether or not ITC would imply lower costs of meeting the climate change target – results depend on model specifications, for instance, the rate of exogenous learning assumed in the benchmark model.

This paper compares an ITC case with a case without ITC, in which the cost of different technologies are determined by the endogenous learning generated in a baseline scenario (without the carbon constraint).

The aim of the paper is to:

- Investigate the effect of the assumption of induced technological change on abatement strategies, carbon price and abatement costs for scenarios in which the atmospheric concentration of CO2 is stabilized at 400, 450, 500 and 550 ppm.

- Study the impact of technology specific policies, i.e., policies directed at developing a specific technology (e.g. a subsidy for solar PV).

The paper is structured as follows. In section 2 we describe the model, paying special focus on the details concerning the implementation of learning-by-doing and iterative limited foresight optimization. Section 3 presents and discuss results and section 4 draws conclusions.

2. MODEL DESCRIPTION

In this paper we use an extended version of the GET model (Azar et al, 2003; 2005). GET is a globally aggregated model that has three end-use sectors, electricity, transportation, and heat (which includes low and high temperature heat for the residential, service, agricultural, and industrial sectors). Primary energy supply sources include coal, oil, natural gas, nuclear power, hydro, biomass, wind- and solar energy (that can be converted into heat, electricity and hydrogen). Conversion plants may convert the primary energy supplies into secondary energy carriers (e.g. hydrogen, synthetic fuels, electricity, natural gas for vehicles and gasoline/diesel). The transportation sector is divided into aviation, ships, trains, cars and trucks and considers explicitly the costs for vehicles and fuel infrastructure.

Carbon capture and storage is an abatement technology in the model that can be used on both fossil fuels and biomass. There are energy efficiency losses as well as increased capital costs for carbon capture technologies, and additional costs for transport and storage of the captured CO_2. The cost of transporting and storing CO_2 from biomass is assumed to be twice as high due to smaller scale typically associated with carbon capture from biomass (Azar el al, 2005). The total storage capacity is assumed to be 600 Gton C. Nuclear power, another potential abatement technology, is constrained to the present electricity production in the scenarios presented here, due to the political controversy surrounding this technology.

In GET-LFL (Global Energy Transition, Limited Foresight with endogenous Learning) some new features are added to the original GET model. Notably the model is an iterative limited foresight model, rather than a perfect foresight model (this feature was introduced by Nyqvist, 2005). Furthermore learning-by-doing is introduced and end-use demand is elastic. The price elasticity of energy demand in the transportation sector and electricity sector is set to 0.3, whereas the elasticity in the heat sector is assumed to be 0.4 (see Atkinsson & Manning, 1995 for a survey). No end-use energy efficiency investments are explicitly modeled but these are considered to be reflected by the price elasticity. In the model, global GDP and energy demand is based on the CPI baseline (Vuuren et al, 2003) and fossil fuels reserves are based on Rogner (1997). A discount rate of 5% per year is used throughout the period.

2.1 Learning-by-doing

Learning-by-doing is introduced in the model for both the cost of energy capital and vehicles, and the efficiency of conversion technologies. The capital costs are reduced by the learning rate for every doubling of cumulative installed capacity (Arrow, 1962; Barreto, 2001). In the absence of investments, costs remain constant.

However, we have assumed an exogenous and exponential decline in the cost for fuel cell cars as well as for solar PV. By the year 2100, costs have declined by 60-70%. This development can be seen as a result of further research and development that we assume will take place regardless of whether there is any climate policy in place or not.

There are great uncertainties about future learning rates for technologies. Estimates used in this paper are based on learning rates from three references: Riahi, (2004); McDonald and Schrattenholzer, (2001) and Kram et al, (2000). We assume the learning rates to be around 5% for mature technologies, such as power production from fossil fuels, and between 10% and 15% for more immature technologies such as carbon capture, wind power, fuel cells and solar PV. Each technology is assumed to have an initial investment cost in the year 2000, and a floor investment cost below which the cost cannot drop. The ratio between the initial and floor investment costs differs between technologies. It is around 0.8 for semi-mature technologies such as combined heat and power plants, and around 0.2 for immature technologies such as solar PV.

Further, technological clusters are included in the model in order to model spillover of learning between different technologies, which may give rise to for instance, co-evolution of technologies. Five different clusters are included: gasification of biomass and coal (used for production of hydrogen, synthetic fuels as well as electricity); carbon capture technologies that may be used with fossil fuels and biomass in combination with electricity or hydrogen production; synthetic fuels production from biomass; coal and gas, hydrogen production from fossil fuels and biomass; and finally, combined heat and power production. Learning is assumed to partially diffuse between different technologies within the clusters. This is simulated through spillover factors, a factor of 0.5 means that investing 1 kW in say coal gasification leads to the same drop in the cost of biomass gasification (per kW) as investing 0.5 kW in biomass gasification. Spillover factors are set to 0.5 between different fuels (e.g. spill-over from coal gasification to biomass gasification), and 0.8 for the same cluster using the same fuel but for different kinds of production (e.g. carbon capture from hydrogen production to carbon capture from electricity production).

2.2 Limited Foresight

GET-LFL is based on iterative optimization with limited foresight (for details see Nyqvist, 2005). Each time period, t, the model maximises the sum of consumer and producer surpluses for the next thirty years. The costs for the different technologies are static, i.e. equal to the cost level in the beginning of the period. The decisions for the first period t are then saved. The next time period, t+1, a new optimization is made with the decision variables from time t as input data. In this period, the costs of different technologies may have dropped because of learning by doing in previous periods.

The model does not foresee potential cost reductions due to learning in the coming periods, neither are scarcity rents generated for the whole period, as they are in perfect foresight models. In GET-LFL, scarcity rents on fossil fuels only arise if the "planned" extraction pathway would lead to depletion of the resource over the next 30 years.

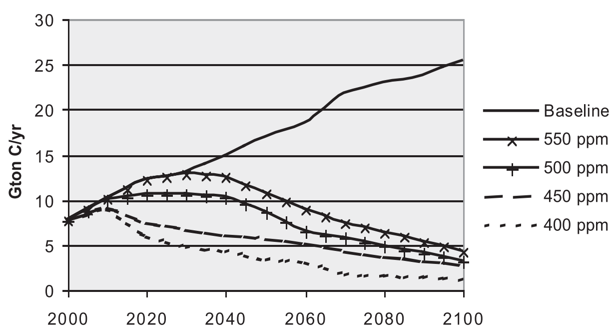
The model aims to simulate a market with complete spillover of know-how between companies and with an emission target set by policy makers. In this setting, companies would not invest in immature more expensive technologies, since in a perfect market (according to standard theory), investments are made according to the marginal costs of production. And since spillover of learning between companies implies that there is no private benefit of investing in a more expensive technology in order to reduce costs in the future. However, companies in the real world may foresee some cost reductions, and therefore invest in technologies even though they are not presently profitable. Thus, these interactions are much more complex than modeled here (see e.g. Grubler, 1999).

Furthermore, our model does not consider niche markets, which offer the potential for learning by doing. For example, PV may at present, be a cost-effective technology in certain off grid applications (pocket calculators, in space, far from the electricity grid, etc). There may thus be more learning in the real world than what our model suggests, even in the baseline scenario.

2.3 Scenarios and Cases With and Without ITC

For each stabilization scenario, the emissions are bound to a trajectory resulting in an atmospheric concentration of 400, 450, 500 and 550 ppm CO_2 by the year 2100. The emission trajectories, shown in Figure 1, do not allow overshoots, except for the 400 ppm scenario (where the atmospheric concentration peaks in

Figure 1. Exogenously Set Emissions Trajectories for Each Stabilization Scenario. The Baseline Trajectory is Generated in a Model Run Without Carbon Constraints



2060 at 415 ppm). The emissions due to land use changes are also exogenously set using a combination of data from the CPI baseline (Vuuren et al, 2003) and the B2 SRES scenario (Nakicenovic, 2000).

The baseline scenario, without any carbon constraint, is run with endogenous learning. Thereafter, all stabilization scenarios are run in two different ways, one with Induced Technological Change (ITC) and one without Induced Technological Change (no-ITC). The investment costs in the no-ITC case are fixed to follow the cost profiles generated in the baseline scenario. In the ITC case, the emission cap induces investments (in abatement technologies), which causes cost reductions through learning-by-doing.

3. RESULT

3.1 The Baseline Scenario vs. ITC Stabilization Scenarios

The main abatement option used in all stabilization scenarios are biomass, wind, oil and natural gas instead of coal, a reduction of the energy demand and carbon capture and storage from both coal and biomass (see Figure 2). In the baseline scenario (no carbon abatement), oil-based fuels are replaced by synthetic fuels produced from coal around 2050, whereas oil-based fuels are used in the transport sector during an even longer time period in the stabilization scenario. This latter, rather paradoxical result, can be explained by the fact that the costs of synthetic fuels from coal is lower than gasoline from non-conventional oil, whereas the opposite holds for a world with sufficiently high carbon taxes.

More stringent carbon constraints generate higher energy prices which reduce energy demand. The demand is reduced by 30-35% from 2060 and onwards in all scenarios. The reason for the small difference in energy use between the different scenarios is that the same abatement technology is most often used on the margin which determines energy price and thereby demand.

3.2 Comparing ITC and no-ITC Cases

Here, we compare the stabilization scenarios with ITC and without ITC (no-ITC). The deviation between the ITC and no-ITC cases for the primary energy supply mix in specific sector is typically less than 5% in all scenarios. However, larger deviations occur for short periods of time for certain energy sources, up to 15% in the 500 and 550 ppm scenarios, and up to 20% in the 400 and 450 ppm scenarios.

In the 400 and 450 ppm scenarios, the ITC case mainly affects the marginal costs of carbon abatement (henceforth also called the carbon price) after 2070. In the 450 ppm scenarios the difference between the carbon price in the ITC case and the no-ITC is around 100 USD/ton C, as seen in Figure 3, and around 200-300 USD/ton C for the 400 ppm scenario. The cut in the marginal cost curve in 2090 is due to the emission trajectory that levels off in 2090, and

Figure 2. The Primary Energy Supply

Figure 2a. Baseline Scenario

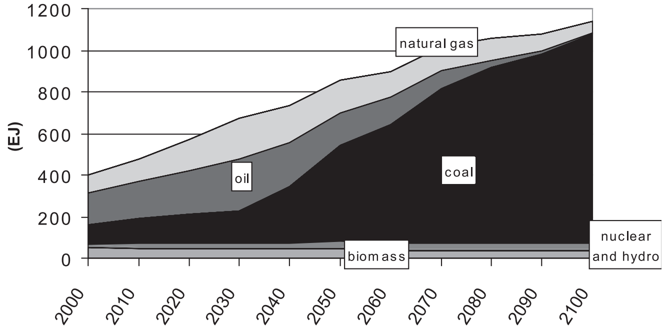


Figure 2b. 450ppm Stabilization Scenario With ITC

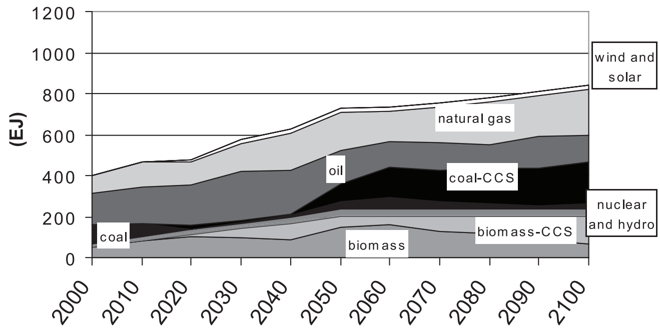
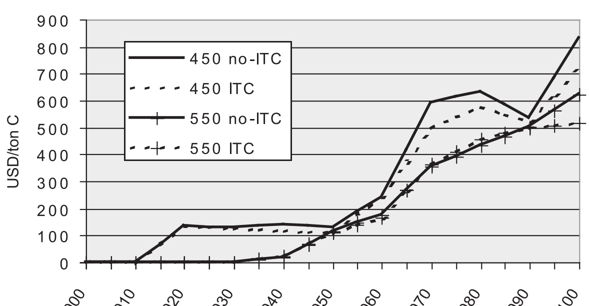


Figure 3. Carbon Price in the 450 and 550 ppm Scenario, With ITC and Without ITC



then becomes slightly steeper thereafter. The other discontinuities (in 2020 and 2050) are due to the fact the emission targets from 2020 to 2050 may be fulfilled by using more of the same abatement technology at the margin, therefore the carbon price does not increase. In 2050 the emissions target is set so low that a new more expensive technology must enter to fulfill the emission target, thus the carbon price increases. In the 500 and 550 ppm scenario, there carbon prices differs around 100 USD/ton between the ITC and no-ITC cases for both scenarios from 2080 and onwards.

The aggregated discounted welfare (sum of consumer and producer surplus) loss due to carbon abatement (henceforth also called the abatement cost) ranges from 10 TUSD (10^{12} USD) in the 400 ppm scenario to 2 TUSD in the 550 ppm scenario. The abatement cost is 3-9% lower in the ITC cases (depending on the scenario) than the no-ITC cases.

3.3 Explanation for the Low Impact of ITC

There are two main explanations for the small differences between the ITC and the no-ITC cases: (i) spill-over of knowledge between technologies and (ii) large potential of fossil fuel abatement technologies.

First, there is spillover within technological clusters. Therefore, investments in gasification of coal, for instance, leads to learning that is useful when biomass is gasified (a process that is also of importance for carbon capture). In the baseline scenario, fossil fuels dominate the energy supply. This leads to improvements of technologies that use fossil fuels, and as a result of spill-over of learning, there is also some improvement of biomass and fossil fuel with carbon capture and storage in the baseline scenario.

Second, in the mitigation scenarios, natural gas instead of coal, biomass and carbon capture and storage from fossil fuels and biomass dominate the changes in the energy supply. These technologies partially gain learning also in the baseline scenario. More advanced technologies such as fuel cell vehicles and hydrogen production from solar, which do not gain learning in the baseline scenario, are not even used in the 400 ppm stabilization scenario until after the year 2100. These two observations explain the modest impact of ITC on the welfare cost of carbon abatement (in our modeling approach in the base case runs).

3.4 ITC and Technology Specific Policies

In the previous experiment, an emission cap induced investments in the energy system and thereby, in learning. However, in the real world, investments in more advanced technologies are not only triggered by carbon abatement policies, but also by government policies that support specific technologies. For instance, few expect that private companies will make investments in grid-connected PV only as a result of expectations that there will be a stringent climate policy in place by the year 2030. Here, we study a case (ITC TP) where technological change is

Figure 4. Transportation Fuels

Figure 4a. 450 ppm Scenario in the Case With ITC and Technology Specific Policies (ITC TP)

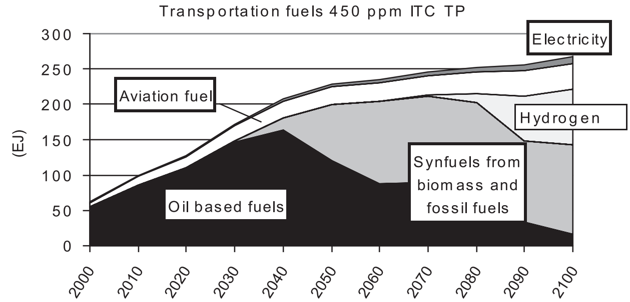
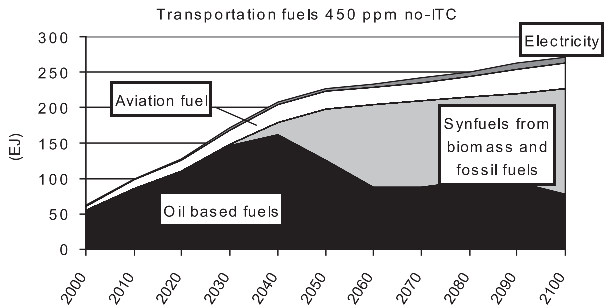


Figure 4b. 450 ppm Scenario in the Case Without ITC (no-ITC)

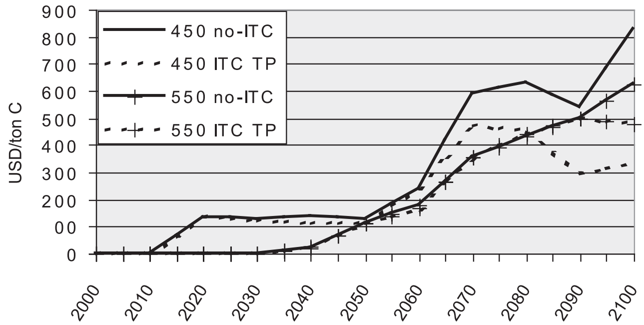


induced by the emission cap as well as technology specific policies. We define technology specific policies as those that are primarily aimed at supporting the commercialization of immature but promising technologies. Such policies include feed-in tariffs, green certification and directed subsidies.

We prescribe that at least 0.015% of the total car stock in 2040 (200,000 cars) consists of hydrogen fuel cell cars. We also prescribe that 0.2% of the global electricity demand (40 GWp installed capacity) is supplied by solar PV. After 2040, there is no prescribed level for any of these technologies.

By forcing the technologies to enter the market, the costs for these individual technologies are reduced by roughly 60% within only a decade. The impact of technology specific policies is largest in the transport sector, where hydrogen powered fuel cell cars take a significant market share from 2060 and onward in the 400 and 450 ppm scenarios, see Figure 4. Solar PV enters the market in all scenarios, but wind and solar PV combined does not exceed the limit of 30% of the electricity demand because the intermittent nature of solar

Figure 5. Carbon Price of Carbon in the 450 and 550 ppm Scenario, in the No-ITC and ITC TP Cases



and wind power. Hydrogen production from solar is not a cost-effective option in our scenarios until after the year 2100.

The marginal cost of carbon is reduced significantly in the technology specific policy case. The carbon price in the 400 ppm scenario ITC TP case is approximately 900 USD lower than in the no-ITC case in 2100 (a reduction by 80%). In the 450 ppm scenario the difference is 300-400 USD/ton C as seen in Figure 5, whereas 550 ppm scenarios remain fairly unaffected. It is worth noting that the difference in carbon prices is small until 2070, even though the policy is introduced in 2040. This stems from the fact that the advanced technologies are not cost-effective until around 2070 despite their rapid learning rates.

It is interesting to note that the marginal cost of carbon actually decrease in the 450 ITC TP case. The reason is that fuel cell vehicles are the abatement technology at the margin from 2070 and onwards and they therefore determine the carbon price. As investments are made in fuel cell vehicles, learning is gained and the cost for fuel cell vehicles decreases. This explains why the marginal price decline after having peaked at 500 USD/ton C in 2070.

Technology specific policies reduce the net present welfare loss due to carbon abatement compared to both the ITC and no-ITC cases in all scenarios. The reduction of welfare losses ranges from 6 to 16% depending on scenario (see Table 1). Since the changes between all cases mainly occur after 2070, the benefit in welfare is discounted to a large extent, which partly explains the fairly small differences in abatement costs.

This modeling exercise also demonstrates the risk of technology lock-in. In the real world, where perfect foresight is rare, market actors have the tendency to make invest decisions based on the static competitiveness of technologies without accounting for the different learning rates. For this reason, there is a risk of technology lock in. Our modeling effort simulates this risk.

Table 1. Net Present Welfare Loss Due to Abatement in the ITC and ITC with Technology Policy Relative to the Stabilization Scenario Without ITC

	Abatement cost no-ITC (TUSD)	Cost relative to no-ITC ITC (%)	ITC TP (%)
400 ppm	9.7	93	84
450 ppm	5.4	91	88
500 ppm	2.7	97	94
550 ppm	1.8	97	93

3.5 Sensitivity Analysis

The abatement technologies chosen in the stabilization scenarios as well as total abatement costs are dependent on various choices of parameters. However, for most parameters the relative difference between the ITC and no-ITC case remain fairly constant. In this section we elaborate with parameters that tend to increase the relative importance of ITC.

Assuming gas reserves are halved compared to the base case runs, availability of carbon storage sites is halved and disregarding spillover within technological clusters, ITC reduces the total abatement cost by around 15% compared to the no-ITC case for all stabilization scenarios. In this case, the stabilization scenario must rely more heavily on renewables. These technologies do not gain any learning in the baseline scenario due to the exclusion of spillovers, hence the importance of ITC increases in this case.

The floor costs set a limit on how much the costs for a specific technology may decrease due to learning. Therefore, even although there are more extensive investments in abatement technologies in the stabilization scenarios, there is a rather small difference in costs for many important abatement technologies between the ITC case and the baseline (and thereby the no-ITC case as well). Assuming that the costs of technologies may decrease below the floor costs therefore increase the effect of ITC. The total abatement cost is reduced by 15-20% in the ITC case compared to the no-ITC case for the 400 and 450 ppm scenarios. The difference is even larger for the 500 and 550 ppm scenarios, at around 30-35%.

4. CONCLUSION AND DISCUSSION

We have analyzed the impact of introducing induced technological change in an energy systems model called GET-LFL, which is an optimization model with limited foresight. Our main results may be summarized as follows:

- The introduction of induced technological change (ITC) leads to a reduction of the overall cost to meet the climate target by 3-9% compared to a case without ITC (no-ITC).
- The introduction of ITC does not lead to any major changes in the energy supply in our model compared to our case without ITC (in general the difference in the primary energy supply mix remain below 5%).
- ITC combined with technology specific policies leads to significant changes in the fuels used for transport in the 400 and 450 ppm scenarios after 2070. Further it reduces the total abatement cost by 12-16% compared to the no-ITC cases.

It is important to note that the cost reductions reported above depend heavily on assumptions that were made for the no ITC scenario. Therefore, interpreting results presented in this study as evidence to suggest that technological change is not particularly important to meeting stringent climate targets is erroneous. Clearly, a radical transformation of the energy system is needed to achieve perhaps a 90% reduction in emissions compared to baseline, by the end of the century.

The key reason why ITC does not emerge as playing an important role in reducing costs to meet the climate targets in this paper is that substantial learning is embodied in the base case, which thus leads to lower costs in the no-ITC case.

Defining technological development in this way the no-ITC case represents just one out of a number of potential cases. One alternative way is to make comparisons with scenarios without any technological development at all. Under such an assumption, ITC would emerge from the modeling exercise as very important. Depending on no-ITC case assumptions, it may not be feasible to reach a 450 ppm scenario with currently existing technologies. Alternatively, if exogenous rapid learning is used as a benchmark case, the ITC case is likely to emerge as more costly.

An important insight provided by our modeling approach is the implication of endogenous learning for understanding path dependent technology development. Such phenomena are difficult to obtain in models with perfect foresight. Introducing technology specific policies in the form of a forced introduction of fuel cells and solar PV quite radically alter the transport sector. The policy instrument induces cost reductions in fuel cells by shifting resources to this mandatory technology, making it the most cost-effective and dominant technology option in the transport sector. Without technology specific policies the energy system is locked into a cost ineffective state. This highlights the importance of technology specific policies, such as subsidies, green certificates and feed-in tariffs, as an important complement to higher carbon prices (Sandén and Azar, 2005).

ACKNOWLEDGMENT

We would like to thank Swedish Energy Agency (STEM), the Swedish Agency for Innovation Systems (Vinnova) and the Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS) for financial support. We would also like to thank Björn Nyqvist for implementing limited foresight into the GET model, and Tobias Persson, Maria Grahn, Martin Persson and Daniel Johansson for valuable information and suggestions.

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

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

1. INTRODUCTION

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

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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The authors wish to gratefully acknowledge the contributions of Arnulf Grübler at the International Institute of Applied Systems Analysis.

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

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

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

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

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

2. TECHNOLOGICAL CHANGE IN ENERGY SYSTEMS MODELS

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

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

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

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

3. SCENARIO DEVELOPMENT

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

We develop two variants of the B2 scenario:

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

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

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

1. The original SRES B2 scenario included exogenous technological change

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

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

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

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

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

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

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

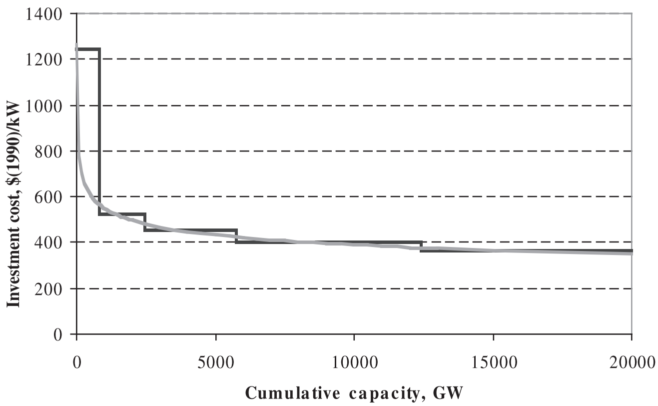
The learning process for technology improvements in our analysis is assumed to take place on a global scale. Although this might not necessarily be consistent with the existence of trade barriers, regional economic blocks or the importance of localized learning, we have retained this simplifying assumption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

4. METHODOLOGY

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

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

Figure 1. Example of Linear-Approximation of Learning Curve



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

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

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

5. RESULTS

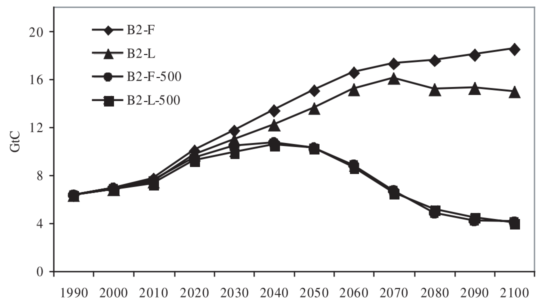
Assumptions on technological change lead to differences in baseline emissions. As Figure 2 shows, the B2-L scenario with endogenous learning leads to a somewhat lower carbon future as compared to the static costs B2-F case. However, the carbon reductions achieved due to technological learning are seen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

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

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

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

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



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

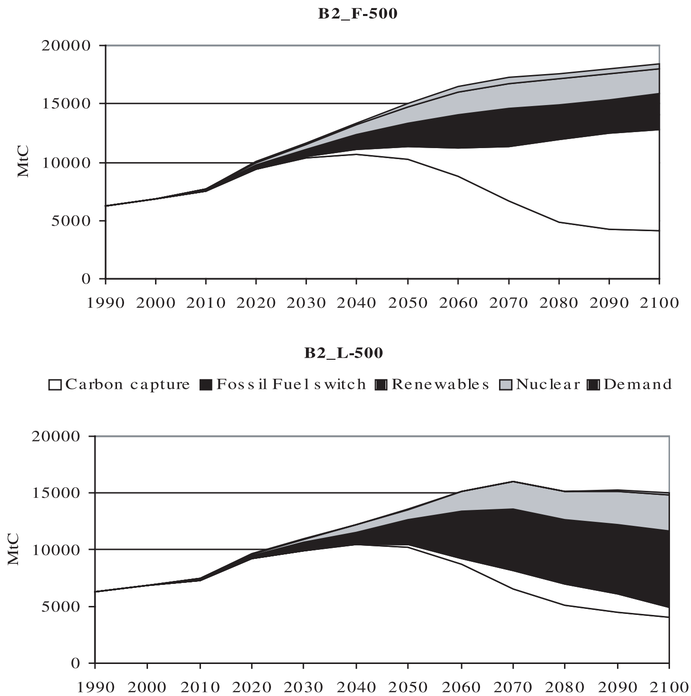
4. Note that in order to enhance comparability between the scenarios, results from Roehrl and Riahi (2000) were normalized using the same energy demand assumptions as for the scenarios presented in this paper.

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

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

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

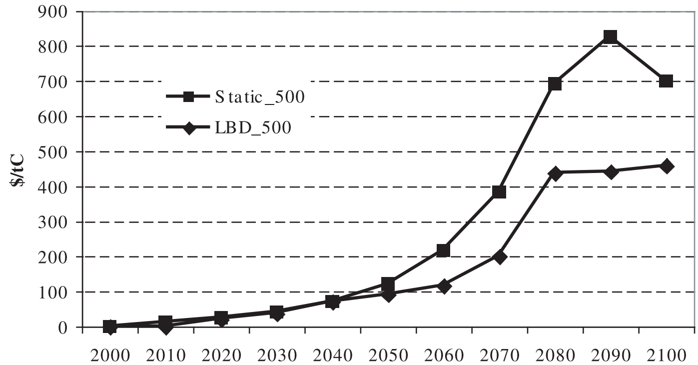
Figure 3. Sources of CO_2 Mitigation in B2-F-500 and B2-L-500 Scenarios



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

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

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



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

Table 2. Percentage Reductions in GDP and Energy Demand

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

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

7. We do not consider emission trading costs here

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

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

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

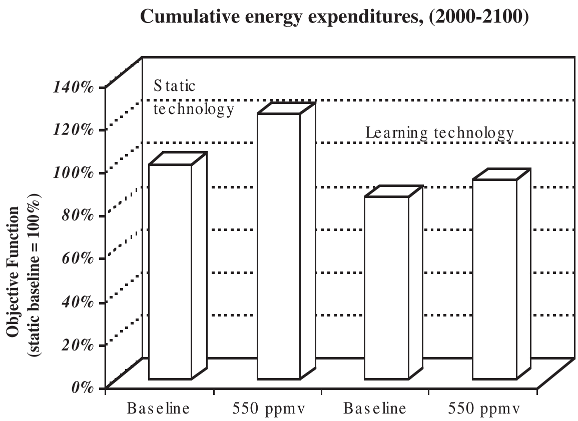


Figure 5b. Cumulative Investments in the Different Scenarios (2000-2030)

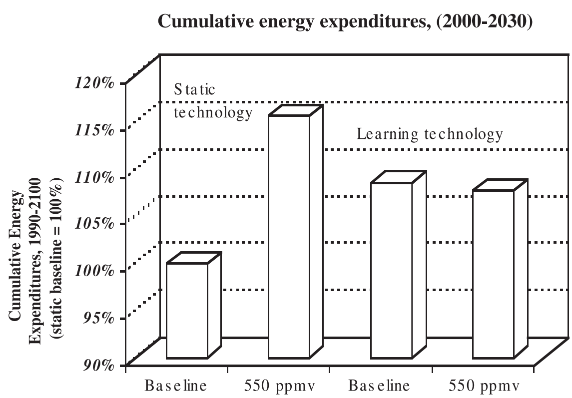


Figure 5b illustrates the changes in investment patterns in the learning cases compared to the static one. Both the B2-L and B2-L_500 indicate higher short term investments compared to the B2-F case. In the longer term, this trend is reversed with lower investments in both learning cases, a typical picture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

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

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

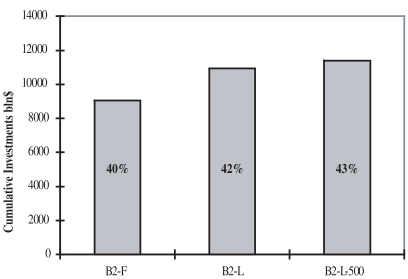


Figure 6b. Shares of Investments in Renewable Technologies in B2-L_500

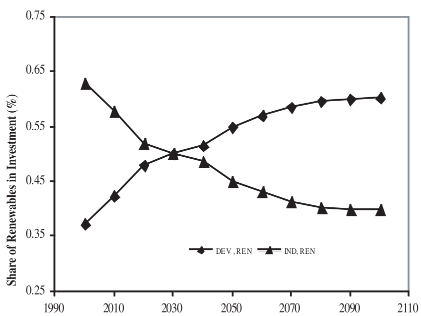


Figure 6a shows that in the B2-L learning scenario total cumulative investments by 2030 in developing countries[10] increase compared to the B2-F

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

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

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

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

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

6. CONCLUSION

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

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

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

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

7. ACKNOWLEDGEMENT

The research reported was supported by an institute-wide collaborative effort within IIASA's Greenhouse Gas Initiative (GGI) project. The interdisciplinary research effort within GGI links all major research programs of IIASA dealing with climate change related research areas including population, energy, technology, forestry, as well as land-use changes and agriculture. GGI's research includes both basic as well as applied, policy-relevant research, aiming to assess conditions, uncertainties, impacts as well as policy frameworks for addressing climate stabilization both from a near-term as well as long-term perspective.

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Analysis of Technological Portfolios for CO_2 Stabilizations and Effects of Technological Changes

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In this study, cost-effective technological options to stabilize CO_2 concentrations at 550, 500, and 450 ppmv are evaluated using a world energy systems model of linear programming with a high regional resolution. This model treats technological change endogenously for wind power, photovoltaics, and fuel-cell vehicles, which are technologies of mass production and are considered to follow the "learning by doing" process. Technological changes induced by climate policies are evaluated by maintaining the technological changes at the levels of the base case wherein there is no climate policy. The results achieved through model analyses ixnclude 1) cost-effective technological portfolios, including carbon capture and storage, marginal CO_2 reduction costs, and increases in energy system cost for three levels of stabilization and 2) the effect of the induced technological change on the above mentioned factors. A sensitivity analysis is conducted with respect to the learning rate.

1. INTRODUCTION

It is important to consider technological change endogenously when evaluating strategies for long-term global warming mitigation. This is because it is often observed that the practical application of new technologies in the initial stages usually involves very high costs; however, their adoption is accelerated once their costs decrease below certain thresholds on account of appropriate subsidies, etc. Optimization models that consider endogenous technological changes intrinsically have a nonconvex character. Multiple optima may exist because of that character and the conventional non-linear programming solvers cannot identify a global optimal solution. Therefore, endogenous technological changes cannot be easily evaluated using optimization models. In order to solve

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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optimization models of this type, Messner (1997) and Kypreos et al. (2000) used the mixed integer formulation; Manne and Barreto (2004) solved using the Baron algorithm. However, these approaches are not practical for large-scale models because huge amounts of computation are required.

We developed a world energy systems model—DNE21+ (Akimoto et al., 2004; 2005)—that considers the technological change endogenously for three technologies, namely, wind power, photovoltaics (PV), and fuel-cell vehicles (FCVs). These are technologies of mass production and are considered to follow the typical learning-by-doing which is a function of cumulative installation with a constant learning rate (Grubler et al, 2002); they should thus be treated endogenously. On the other hand, the technological changes in other large-scale technologies such as nuclear and carbon capture and storage (CCS) can not be represented only by the cumulative installation. They are affected rather by R&D investment. R&D investment costs cannot be treated explicitly in our model. Therefore, their technological changes are treated exogenously in this paper. The DNE21+ is a linear programming model that employs a bottom–up approach for the technologies at the energy supply side and minimizes the total cost of world energy systems. Its high regional resolution enables a detailed analysis of the relatively high cost of energy transportation, regional differences in energy systems, technology levels, and potential of renewable energies such as wind power. Our model size is huge and the above mentioned approaches for solving models with endogenous technological changes cannot be practically applied to our model. Therefore, model-run iteration, described in Section 3.4.1, is used to solve endogenous technological changes.

Model analyses were conducted for the base case (no climate policy) and three levels of CO_2 concentration stabilization. For each stabilization level, two cases—one with and the other without induced technological change (ITC)—were studied in order to quantitatively analyze the effect of ITC. In addition, a sensitivity study was conducted with respect to the learning rate.

2. THE MODEL

2.1 Model Framework

The DNE21+ model was originally developed for the analysis of the post Kyoto regimes which requires to treat major countries separately and was extended to be used also for the study of the ITC effect. It considers a time range that covers the entire 21st century with the representative time points of 2000, 2005, 2010, 2015, 2020, 2025, 2030, 2040, 2050, 2075 and 2100. The model disaggregates the whole world into 77 regions: US, Canada, UK, France, Japan, Australia, China, India, Russia, etc. To take intoconsidering consideration the transportations of energy and CO_2 in more detail, large countries, such as US, China, and Russia are further disaggregated into several regions. The model represents the energy supply sectors in the bottom-up fashion and the end-use energy sectors in the top-down fashion similar to DNE21 (Fujii and Yamaji, 1998) and LDNE21 (Yamaji et al., 2000) models, which are forerunners of this model. The further details of modeling are described in the next section. The total cost of energy systems between 2000 and 2100 is minimized.

2.2 Energy System Modeling

Primary energy sources of eight types are explicitly modeled: natural gas, oil, coal, biomass, hydro & geothermal, PV, wind and nuclear power. Coal, oil, natural gas, methanol, hydrogen and biomass fueled power plants, hydro & geothermal, wind, PV and nuclear power plants are explicitly taken into account for electricity generation, and integrated coal gasification combined cycle (IGCC) with CO_2 recovery is also formulated. In addition, various types of energy conversion technologies, such as oil refinery, liquefaction of natural gas, coal gasification, etc., are explicitly modeled as technological options. The model also has the historical vintages of these technology facilities. As for CO_2 recovery, both of chemical absorption from flue gas of thermal power plants and physical absorption from outlet gas of fossil fuel gasification plants are explicitly modeled. In connection with CO_2 recovery, two major CO_2 sequestration measures, ocean sequestration and underground sequestration, are explicitly formulated. Underground CO_2 sequestration is further divided into four types: injection into oil wells for enhanced oil recovery (EOR) operation, storage in depleted natural gas wells, injection into coal-beds for enhanced coal-bed methane recovery (ECBM) operation and sequestration in aquifers.

The end-use energy sector of the model is disaggregated into four types of secondary energy carriers: solid fuel, liquid fuel, gaseous fuel and electricity. The liquid fuel demand is further decomposed into three types of oil products: gasoline, light fuel oil and heavy fuel oil. Electricity demand is expressed by load duration curves having four kinds of time periods: instantaneous peak, peak, intermediate and off-peak periods. The future energy demand in case of no climate policy is exogenously provided by energy type, region and year. Energy savings in end-use sectors are modeled in the top-down fashion using the long-term price elasticity and transportation technologies in end-use sectors, for example, are not explicitly formulated. However, hydrogen energy economy is attracting great attention recently. Therefore, we tried a simplified modeling of FCVs as one of the greatest hydrogen consumers. For this evaluation, it is assumed that the gasoline demand is partly substituted for by hydrogen which is to be used for FCVs. While the production costs of both gasoline and hydrogen are endogenously determined inside the model, the direct comparison between their costs does not give the answer because of the cost difference in the two kinds of vehicles; we impose the cost penalty on the hydrogen due to the higher cost of FCVs. This modeling is the first step for the evaluation of FCVs and further extension, e.g., modeling of infrastructure for supply of hydrogen, will be required.

The world disaggregated regions in the model are linked to each other by interregional trading of eight items: coal, crude oil, synthetic oil, methane, methanol, hydrogen, electricity and CO_2. The way of transportation, e.g., tanker, pipeline, is selected under the criteria of the least cost inside the model.

3. MODEL ASSUMPTIONS

3.1 Primary Energy Potentials and Costs

The potentials and costs of the eight types of primary energy are assumed as follows. Most of the assumed potentials are based on geographic information systems (the GIS) data, which are easily processed to provide each region with its corresponding potential.

3.1.1 Fossil Fuel

Assumed potentials of conventional oil and natural gas are derived from USGS GIS data (USGS, 2000) and those of unconventional oil and gas by country are estimated using the data of Rogner (1997). The potential of coal is assumed using the country data of WEC (World Energy Council, 2001). Table 1 summarizes the assumed world fossil fuel potentials. The production costs of the fossil fuels are assumed based on the study mainly by Rogner.

Table 1. Assumed Fossil Fuel Potentials in the World

	Anthracite and Bituminous	**Sub-bituminous**		**Lignite**
Coal [Gtoe]	424	208		253
		Conventional		Unconventional
	Remaining Reserves	Undiscovered (Onshore)	Undiscovered (Offshore)	
Oil [Gtoe]	137	60	44	2,342
Natural gas [Gtoe]	132	59	52	19,594

3.1.2 Renewable Energy

The world potential of hydropower is derived from WEC (2001) and assumed to be 14,400 TWh/yr. The world potential of potential of wind power, PV and biomass is assumed to be about 12,000 TWh/yr, 1,271,000 TWh/yr and 3,960 Mtoe/yr respectively. These latter three types of energy potentials are estimated combining some GIS data, such as wind-speed, solar radiation power, land use, etc. The potentials of all the four kinds of renewables are classified into five cost grades. The costs by grade in the year 2000 are summarized in Table 2.

Table 2. Cost of Renewables by Grade in the Year 2000

Grade	Hydropower [$/MWh]	Wind power [$/MWh]	PV [$/MWh]	Biomass [$/toe]
1	20	56	209	171
2	30 / 60	60	272	185
3	120	71	352	227
4	150	87	487	454
5	180	118	720	1000

3.2 Assumptions about Technologies

The technologies that are considered in this model are almost identical to those in DNE21 (Fujii and Yamaji, 1998). This section explains the assumptions about main technologies and a location factor that is a parameter for considering regional differences in facility costs.

3.2.1 Power Generation

The assumed parameters of electricity generation such as unit facility costs and generation efficiencies are shown in Table 3 (OECD/IEA, 2000). With respect to conventional technologies such as fossil-fuel power generation, costs are assumed as being fixed over a century; however, the improvements in the generation efficiency are assumed to occur with time. Further, in the case of IGCC and biomass-fueled power generation that are relatively new technologies, both cost reductions and efficiency improvements with time are assumed. Here, the costs given in Table 3 are the standard costs considered in this study. The assumed regional cost at each time point is calculated based on these standard costs and the location factor that is explained in Section 3.2.3.

3.2.2 CO_2 Capture and Storage

Table 4 shows the assumed facility costs and energy requirements for CO_2-capture technologies. The cost reduction and energy efficiency improvement of CO_2-capture technologies are exogenously assumed to occur with time; this assumption is based on several sources (David et al., 2000; Fujii et al., 1998). In this model, the cost of electricity generation is endogenously determined based on the region, time point, and kind of time period within the model. Therefore, although the energy requirements are exogenous, the costs per ton of avoided CO_2 emissions are also determined within the model. Table 5 summarizes the assumptions about the potentials and costs of CO_2 sequestration. The details of the procedures used for estimation are presented in Akimoto et al. (2004).

Table 3. Assumed Facility Costs and Generation Efficiency for Electric Power Plants

		Facility costs [US$/kW]	Generation efficiency [LHV %]
Coal-fueled power	High	1,200	42.0–52.0
	Middle	900	36.0–46.0
	Low	700	22.0–27.0
Oil-fueled power	High	450	50.0–60.0
	Middle	300	37.0–47.0
	Low	200	20.0–25.0
N. gas-fueled power	High	450	52.0–62.0
	Middle	300	38.0–48.0
	Low	200	24.0–29.0
IGCC with CO_2 recovery		1,700–1,450	34.0–49.0
Biomass-fueled power	High	1,800–1,200	36.0–46.0
	Low	1,300–700	18.0–28.0
Nuclear power		1,900	
Methanol-fueled power		450	52.0–62.0
Hydrogen-fueled power		450	52.0–64.5

Note: Generation efficiency improvements are assumed to occur with time.

Table 4. Assumed Facility Costs and Required Energy for CO_2 Capture

	Facility cost [US$/(tC/day)]	Energy requirement [MWh/tC]
CO_2 chemical recovery from coal-fueled power	59,100–52,000	0.792–0.350
CO_2 chemical recovery from gas-fueled power	112,500–100,000	0.927–0.719
CO_2 physical recovery from gasification plants	14,500	0.902–0.496

Note: Cost reduction and energy efficiency improvement are assumed to occur with time.
Source: David et al. (2000); Fujii et al. (1998)

Table 5 . Globally Assumed CO_2 Sequestration Potentials and Costs

	Sequestration potential [GtC]	Sequestration cost† [$/tC]
Oil well (EOR)	30.7	81–118‡
Depleted gas well	40.2–241.5††	34–215
Coal bed (ECBM)	40.4	113–447‡‡
Aquifer	856.4*	18–143
Ocean	–	36**

† Costs of CO_2 capture are excluded.
‡ The proceeds from recovered oil are excluded.
†† 40.2 is the initial value in 2000, and the capacity increases with natural gas production.
‡‡ The proceeds from recovered gas are excluded.
* The potential is the "practical" one, which is 10% and 20% of the "ideal" potentials for onshore and offshore, respectively.
** The cost includes that of CO_2 liquefaction.

3.2.3 Location Factor

The facility cost can be divided into several components such as material and equipment costs, construction labor cost, etc. Regional differences in these components have been reported in several literatures (e.g., Saito, 2000). Based on these literatures, a location factor that is expressed by Eq. (1) is assumed for the construction labor cost. $LF_{r,y}$ denotes the location factor at region r and year y. Table 6 shows the location factor at each representative time point. The facility cost for each region and time point is adjusted by multiplying this factor by the construction labor cost. The shares of the construction cost in the facility cost are assumed to be 17.3 % for electric power plants, whereas they are 30.4 % for other plants. The material and equipment costs were assumed to be constant for all the regions.

$$LF_{r,y} = 0.151\mathrm{n}(GDP / capita) - 0.54 \qquad (1)$$

Table 6. Assumed Location Factor

	2000	2005	2010	2015	2020	2025	2030	2040	2050	2075	2100
$LF_{r,y}$	0.27–1.05	0.28–1.07	0.28–01.08	0.30–1.09	0.31–1.10	0.34–1.11	0.36–1.14	0.42–1.18	0.47–1.22	0.55–1.29	0.60–1.34

Note: The share of the construction cost in the facility cost: Electric power plants = 17.3%; Others = 30.4%

3.3 Population, GDP and Final Energy Demands

Future scenarios of population, reference GDP and reference final energy demands are derived from B2 Marker Scenario of IPCC SRES (Nakicenovic et al., 2000; TGCIA, 2000). We made, however, some modifications on the original scenario data so as to keep consistency with the historical data (IEA, 2002; World Bank, 2002; OECD/IEA, 2000) and with the region division of this model. Energy savings in end-use sectors are modeled using the long-term price elasticity. Based on several data (e.g., IEA, 1999), the elasticitiy of electricity and non-electricity is originally assumed to be –0.3 and –0.4, respectively. The model finds the least cost energy systems which meet the final energy demands in Reference case, and also does so in emission reduction cases assuming that energy saving takes place based on the price elasticity.

3.4 Endogenous Technology Learning

3.4.1 Methodology

The technological change is treated endogenously for wind power, PV and FCVs as described before. In this paper, the typical learning curve as expressed by Eq. (2) is assumed for these technologies. C_y, *FC*, *LR* and CI_y denote Cost at year *y*, Floor cost, Learning rate and cumulative installation at year *y*, respectively. The learning rate is the cost reduction ratio for doubling of the cumulative installation. *FC* and *LR* are exogenously provided and C_y and CI_y are endogenously determined according to Eq. (2).

$$C_y = (C_{2000} - FC)\,(1 - LR)^{\log(CI_y/CI_{2000})/\log 2} + FC \tag{2}$$

The determination of C_y and CI_y is carried out through iterative model runs. For the first model run, time series values of initial guess are used for C_y, and time series values of CI_y are obtained by the model run. New time series values of C_y are determined by Eq. (2) using the obtained time series values of CI_y. The new time series values determined for C_y in this way are used for the second model run. This operation is iterated until the variations of time series values of C_y between the two successive model runs become acceptably small (below 0.5 %) for all the three technologies. Although the required times of model-run iterations vary depending on the circumstances, a good convergence was achieved by conducting several times of iterations (five to ten times).

As mentioned above, optimization models addressing endogenous technological changes have a nonconvex character and multiple local optima may exist. Therefore, we attempted the calculation using another set of initial values which are the floor costs of the three technologies as an optimality check. The achieved total system cost was higher than that obtained with the original initial values. Although this check does not guarantee the solution with the original initial values to be global optimal, the obtained solution is considered acceptable; it can be attained in practical time.

3.4.2 Wind Power and PV

Wind power and PV have mature technology components whose cost portions are regarded to be fixed and only the remaining portions undergo the cost reduction according to learning rates. The assumed parameters are shown in Table 7. In this study, these technologies are regarded as products that are traded freely among the world and these parameters assumed to be common among the regions.

The initial values of time series costs for the first model-run were set based on the costs in the year 2000 shown in Table 2 and the annual cost reduction rates. The annual reduction rates were assumed to be 1.0 %/yr for wind power and 3.4 %/yr for PV, which were determined based on EPRI/DOE (1997). Figure 1 shows the convergence of the time series cost for the base case without CO_2 constraint.

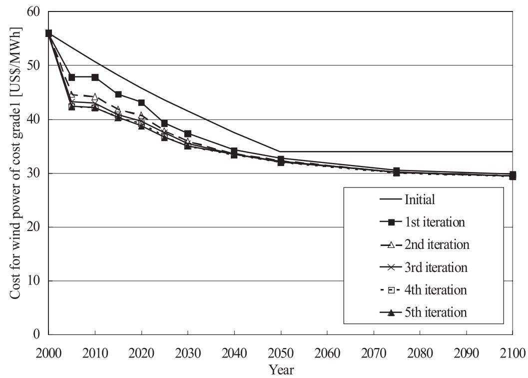
Table 7. Assumed Cost Reduction for Wind Power and PV

	Floor cost ratio in 2000 [%]	Ratio of cost for learning in 2000 [%]	Learning rate*** [% for doubling]
Wind power	36*	64	15
PV	13**	87	25

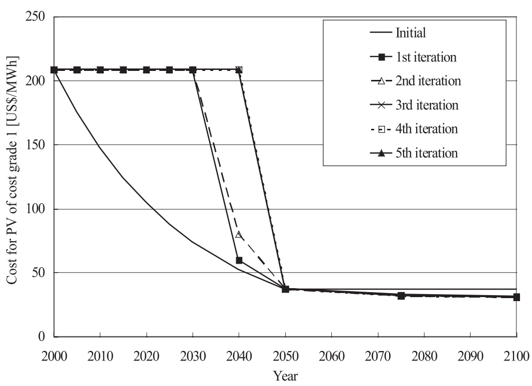
* Cost for construction, electric facilities, road for access, etc.
** Cost for power conditioner Source: Yamada and Komiyama (2002)
*** Source: A. Grubler et al (2002).

Figure 1. Convergence of Time Series Cost for Base Case

a. Wind power



b. PV



3.4.3 FCVs

The assumed cost reduction for FCVs is shown in Table 8. FCV technology was divided into four components. The initial values of cost for the first model-run were set based on the study of Tsuchiya (IAE/NEDO, 2003). The cost difference between FCV and gasoline vehicle is imposed as a cost penalty on the cost of hydrogen which substitutes for gasoline.

Table 8. Assumed Cost Reduction for FCVs

	Cost in the year 2000 [US$/vehicle]	Floor cost [US$/vehicle]	Learning rate [% for doubling]
Fuel cell	149,000	2,500	20
Hydrogen tank	3,300	420	10
Motor, battery controller	8,750	1,250	10

Note: Cost for gasoline vehicle and component common to that are 12,500 and 8,400 US$/vehicle, respectively.

The energy efficiency of FCVs at wheel is 3.1 times of that of gasoline vehicles.

4. MODEL ANALYSIS RESULTS

4.1 Simulation Cases

In this work, three CO_2 stabilization cases were studied with and without ITC besides Base case of no CO_2 constraint. The CO_2 emissions paths for stabilizations were determined based on TAR WGIII (IPCC, 2001) Chapter 2 diagrams. However, DNE21+ model is an energy system model and does not explicitly treat the land use change or CO_2-emitting industries like cement. Therefore, the emissions from land use and cement production were determined exogenously based on SRES B2 and they were subtracted from the above determined CO_2 emissions paths to obtain the path of CO_2 emissions only from energy systems. For the cases with ITC, the technological changes of wind power, PV and FCVs were treated endogenously in the same way as for Base case using the same parameters as shown in Table 7 and 8. However, we shall obtain different time series costs, that is, different cost reduction rates among the three constraint cases and Base case because the constraint cases demand more low-carbon technologies and consequently accelerate their cost reductions according to the learning curves, and the more stringent the constraint is, the faster the cost reduction proceeds. Thus, ITC is considered as the acceleration of "learning by doing process" in this study. On the other hand, for the cases without ITC, the time series costs of the three technologies that were obtained for Base case were kept fixed even for the emission constraint cases. A discount rate of 5 % was adopted throughout the study. The treatment of other technologies excepting the three endogenous technologies is fixed all through the cases.

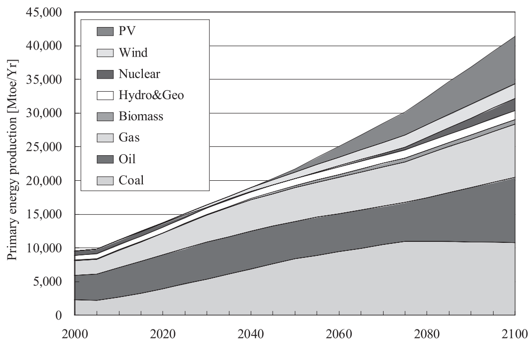
4.2 Model Results and Discussions

Figure 2 shows the world primary energy productions for Base case and ITC cases. Nuclear and renewables are expressed in primary equivalent by using a conversion factor of 0.33. The utilization of Non-fossil fuels, such as nuclear power, wind power, PV, biomass, increase in CO_2 concentration stabilization cases. Figure 3 shows the CO_2 emission and sequestration. Sequestration in aquifers and ocean sequestration play an important role for the stabilization of CO_2 concentration, and the lower stabilizations require the earlier utilization of CO_2 sequestration. Figure 4 shows the world final energy consumption. Gasoline is substituted for by hydrogen for FCV use and the trend is especially clear in 450 ppmv-ITC case.

Next discussed is the effects of ITC. Figure 5 shows the achieved time series costs for the three technologies with endogenous learning for Base case and cases with ITC. For wind power and PV, only the costs of grade 1 are shown. Although the cost for wind power for Base case is lower than that for 550 ppmv-ITC and 500 ppmv-ITC in some time points because of the competition among the technologies for mitigating global warming, the lower stabilization cases induce the early introduction of the three technologies, and as a result, the cost reductions in the early time period are observed. The differences in cost between Base case and cases with ITC are mainly observed during the short time period when substantial technology introduction is implemented, and they are small after a certain number of installations; this means that the effect of the ITC manifests

Figure 2. World Primary Energy Production for Base Case and ITC Cases

a. Base Case



b. Comparison

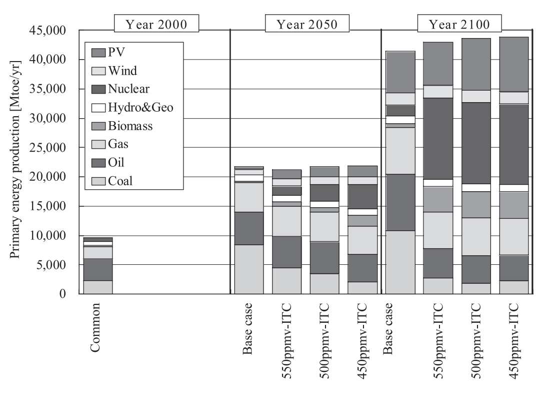
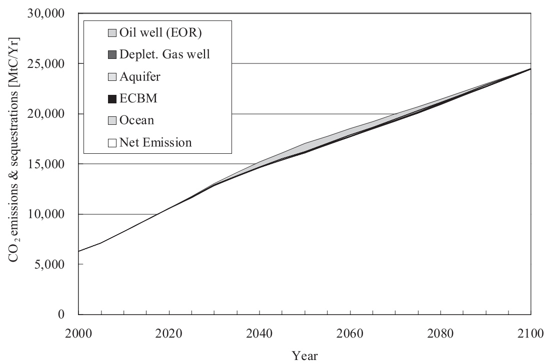
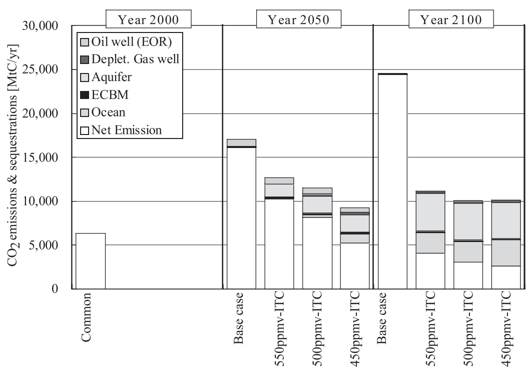


Figure 3. World CO_2 Emission and Sequestration for Base Case and ITC Cases

a. Base case



b. Comparison

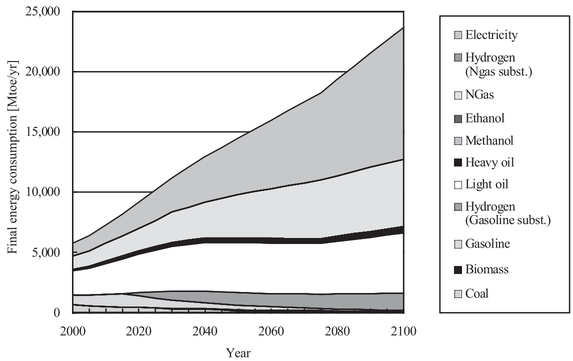


during a time period of a substantial initial introduction. For example, the largest difference in cost of PV between Base case and 450 ppmv-ITC case is observed in 2040. The costs in 2040 and the averaged annual cost reduction rates between 2000 and 2040 are 208 US$/MWh and 0 %/yr for Base case and 34 US$/MWh and 4.4 %/yr for 450 ppmv-ITC, respectively.

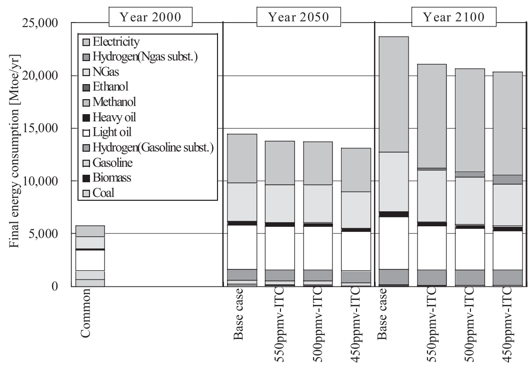
Figure 6 shows relative changes in primary energy production by source, in CO_2 sequestration and in hydrogen consumption for FCV use that substitutes for gasoline that are cumulatively caused during the 100 years by the ITC of the three technologies. In the figure, positive values mean increases for ITC cases as compared to without-ITC cases and negative values mean decreases for ITC cases. The CO_2 sequestration represents the sum of the five types as shown in Figure 3. The effects of the ITC on wind power and PV production are observed to increase when the stabilization level becomes lower. For 450 ppmv stabilization, the cumulative increases for the 100 years are 6.7 and 12.0 % for wind power and PV, respectively. For the hydrogen that substitutes for gasoline, the increase in consumption by the ITC is conspicuous for 450 ppmv but is small for 550 and 500

Figure 4. World Final Energy Consumption for Base Case and ITC Cases

a. Base case



b. Comparison



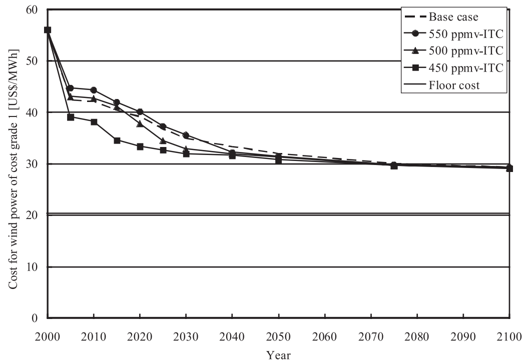
ppmv stabilization, because the hydrogen consumption in Base case is almost the same as that in 550 ppmv-ITC and 500 ppmv-ITC as shown in Figure 4.

Contrary to the acceleration of these three technology utilization, the other technologies of exogenous learning are less utilized by the ITC and the decrease ratios of nuclear energy production and CO_2 sequestration are relatively large among these technologies. It is considered that mainly the above two technologies are replaced by the technologies of endogenous learning due to the ITC.

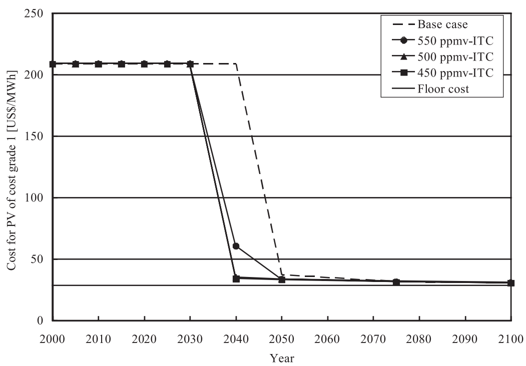
Figure 7 shows the changes caused by the ITC by time series. For the technologies of exogenous learning, nuclear energy production and CO_2 sequestration are shown as examples. The lower the stabilization level is, the earlier the effect of the ITC on wind power and PV production are observed. For 450 ppmv stabilization, the largest increases are approximately 240 (in the year 2025) and 1,400 (in the year 2040) Mtoe/yr for wind power and PV, respectively. For the hydrogen substituting for gasoline, the increase in consumption and the ratio of increase are largest in 2015 for 450 ppmv stabilization and they become smaller with time.

Figure 5. Time Series Costs for the Three Technologies With Endogenous Technology Learning

a. Wind power



b. PV



c. FCVs

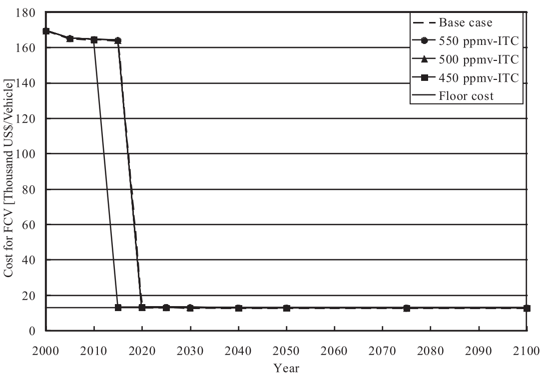
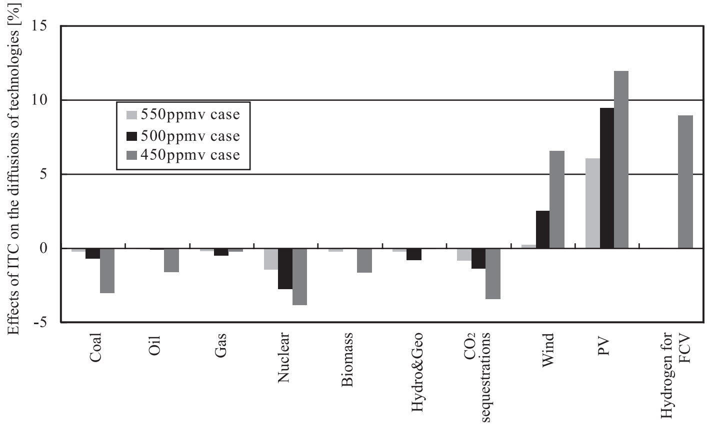


Figure 6. Effects of ITC on the Diffusions of Technologies Accumulated for the 100 years (Change for ITC Cases Relative to Without-ITC Cases for the Three CO_2 Stabilization Levels)



The utilizations of nuclear power and CO_2 sequestration decrease especially around the middle of the century according to the accelerated utilization of the three technologies with endogenous technological changes. The largest decrease of nuclear production and their ratio relative to that of without-ITC cases is approximately 150 Mtoe/yr (10%) in 2050 for 550 ppmv, 440 Mtoe/yr (48%) in 2040 for 500 ppmv, 540 Mtoe/yr (20%) in 2040 for 450 ppmv. For CO_2 sequestration, it is 160 MtC/yr (6%) in 2050 for 550 ppmv, 200 MtC/yr (11 %) in 2040 for 500 ppmv, 500 MtC/yr (14 %) in 2040 for 450 ppmv.

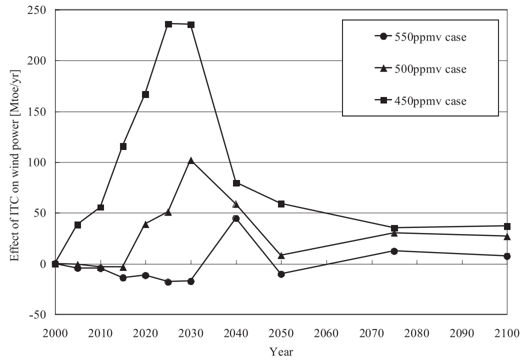
Figure 8 shows the marginal CO_2 reduction costs and the increases in discounted total system cost relative to that for Base case. The marginal reduction costs increase with the lower concentration level. On the other hand, the increases in marginal CO_2 reduction cost by the ITC suspension are much smaller than those by the CO_2 stabilization level difference. The increase in total system cost becomes larger non-linearly as the stabilization level lowers, and the increase by lowering the stabilization level is larger than that by the ITC suspension as shown in the right figure.

The above small effects of the ITC suspension on the marginal CO_2 reduction cost and total system cost are considered to be caused by the small portion of endogenously treated technologies in all the technologies considered in the model. If the technological change of new technologies such as CO_2 capture will be able to be treated endogenously, the effect of ITC will become more conspicuous even in the marginal cost and the total system cost.

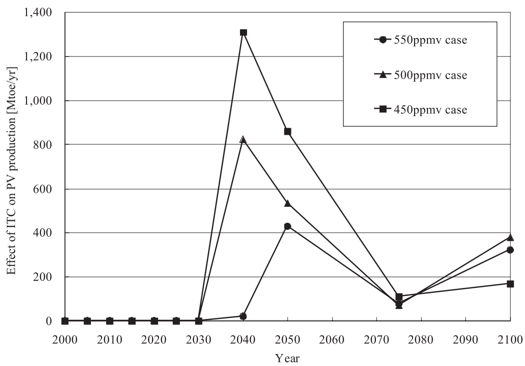
A sensitivity analysis with respect to the learning rate was conducted; the learning rates of the three technologies were changed by 5 percentage points at the same time for the three CO_2 stabilization cases. Figure 9 shows the obtained time series costs for the two sets of learning rates and for the three stabilization cases.

Figure 7. Effects of ITC by Time Series (Changes for ITC Cases Relative to Without-ITC Cases for the Three CO_2 Stabilization Levels)

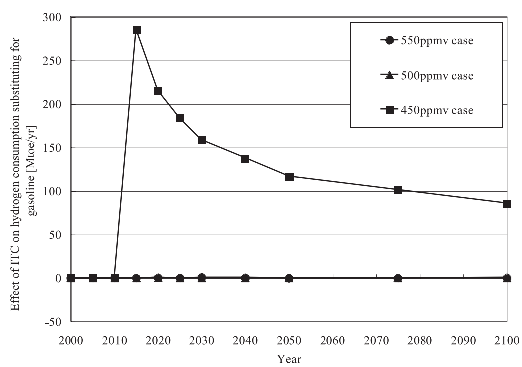
a. Power generation by Wind power



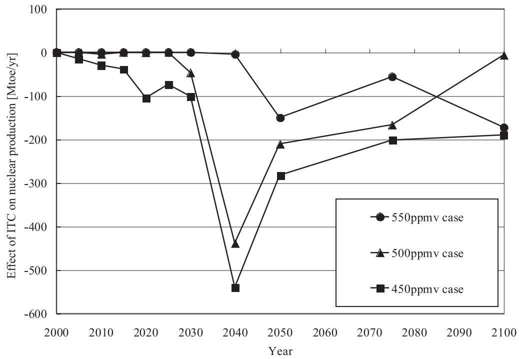
b. Power generation by PV



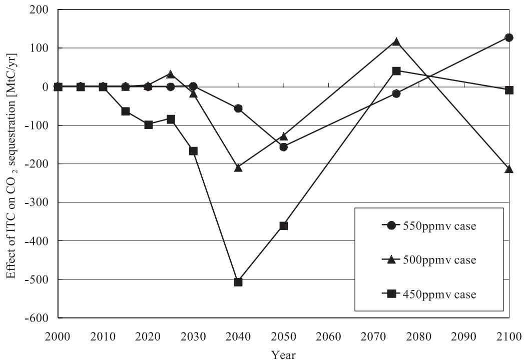
c. Hydrogen consumption substituting for gasoline



d. Nuclear



e. CO_2 sequestrations



For wind power, the effects of the learning rate change are conspicuous throughout the time span. The differences in cost due to the CO_2 stabilization level are observed mainly between 2000 and 2040, which is the same as the results of the original learning rate shown in Figure 5.

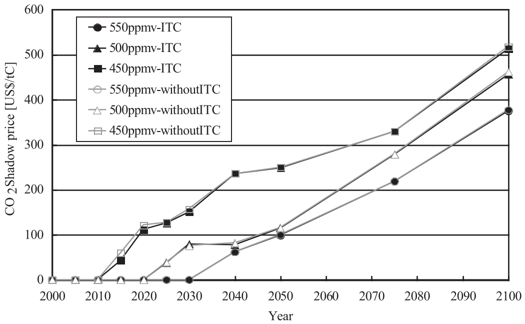
On the other hand, the differences in cost of PV due to the CO_2 stabilization level are very small and almost indiscernible. Only the changes due to the learning rate are observed. This implies that the timing of initial introduction of PV depends principally on the learning rate and not on the stabilization level. The initial cost of PV in 2000 is considerably higher than that of wind power and the utilization in 2000 is very small. In general, the cost reduction which takes place according to the learning curve in the early period is relatively large for the same ratio of increase in cumulative production.

For FCVs, a higher learning rate does not lead to a significant change in the utilization as compared to the original learning rate. The original learning rate seems to be so large that the higher learning rate does not bring about any more acceleration of utilization of FCVs further. For the cases of the lower learning rate, the delayed cost reduction of FCVs is observed for the higher CO_2 stabilization levels.

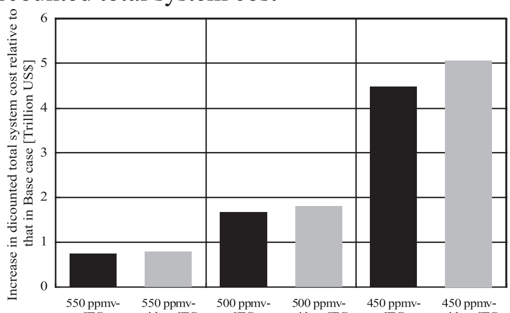
The impacts of the learning rate are relatively large, especially for immature technologies which have high cost and small utilization at the initial time point.

Figure 8. Marginal CO_2 Reduction Costs and Increase in Discounted Total System Cost Relative to that for Base Case

a. Marginal CO_2 reduction costs



b. Increase in discounted total system cost

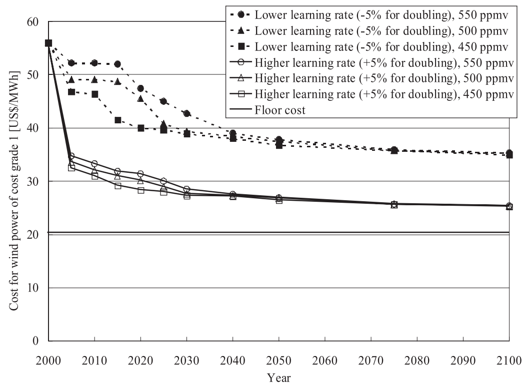


5. CONCLUSION

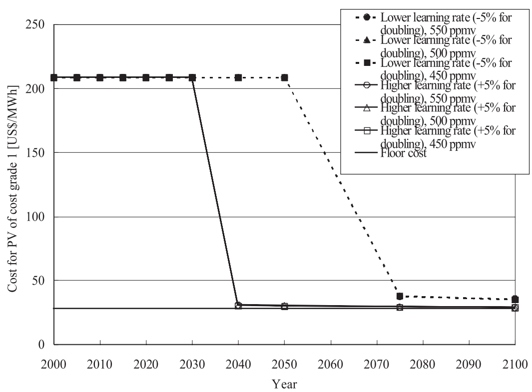
A world energy systems model was developed to explore cost effective measures for CO_2 stabilization of different levels and impacts of induced technological changes on them. The model treats technological changes endogenously only for wind power, PV and FCVs, which are mass production technologies and are expected to follow the typical learning curve with a constant learning rate. For all the other technologies, technological changes are exogenously determined. Despite the difficulties in solving the optimization model with endogenous technological changes, an acceptable solution is achieved

Figure 9. Sensitivity to the Learning Rate

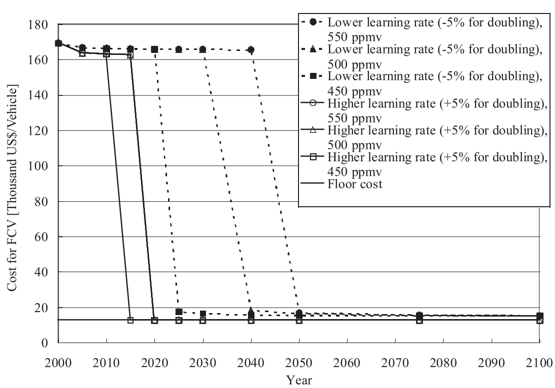
a. Wind power



b. PV



c. FCVs



with practical time through iterative model runs. Thanks to its high regional resolution, the model considers in detail, the transportation cost of energies and also regional differences in energy systems and technology level in exploration of cost effective energy systems for both non-policy case and stabilization cases of 550, 500 and 450 ppmv. The final remarks are as follows:

1) Endogenous technology learning is solved successfully through iterative model runs.
2) More nuclear and renewables, less fossil fuels and more CCS are to be used for lower levels of stabilization. The total system cost becomes larger non-linearly as the stabilization level becomes lower.
3) The effect of induced technological change is significant in terms of the amount of technology utilization, only during a time period of initial substantial introduction of technology.
4) The marginal CO_2 reduction cost or the total system cost is not influenced substantially by the ITC because the portion of endogenously treated technologies is not large in this study.
5) The determination of learning rate values should be careful because their impacts may be relatively large.

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Comparison of Climate Policies in the ENTICE-BR Model

*David Popp**

This paper uses the ENTICE-BR model to study the effects of various climate stabilization policies. Because the ENTICE-BR model includes benefits from reduced climate damages, it is possible to calculate the net economic impact of each policy. In general, only the least restrictive concentration limit is welfare enhancing. While the policies are welfare enhancing in simulations using optimistic assumptions about the potential of the backstop energy technology, such assumptions mean that the backstop is also used in the no-policy base case, so that climate change itself is less of a problem. Finally, assumptions about the nature of R&D markets are important. Removing the assumption of partial crowding out from energy R&D nearly doubles the gains from policy-induced energy R&D.

1. INTRODUCTION

ENTICE-BR is a modified version of the DICE model (Nordhaus, 1994; Nordhaus and Boyer, 2000) that includes endogenous links between climate policy and energy innovation. Like DICE, ENTICE-BR is a dynamic growth model of the global economy that includes links between economic activity, carbon emissions, and the climate. The model includes fossil fuels as an input to production, as in the more detailed RICE model (Nordhaus and Yang 1996, Nordhaus and Boyer 2000). However, ENTICE-BR retains the global framework of the DICE model, rather than dividing the world into separate regions. In this paper, I explore the effect of the various climate stabilization policies used in the Innovation Modeling Comparison Project (IMCP). I begin by discussing the basic structure of the ENTICE-BR model, focusing on how endogenous technological change is incorporated into the model. Section 3 briefly discusses calibration

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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of the model. Readers interested in more modeling and calibration details are referred to Popp (forthcoming). Section 4 presents the results of simulations of the four carbon concentration stabilization scenarios used in the IMCP: 400, 450, 500, and 550 parts per million (ppm). Section 5 concludes.

2. MODEL STRUCTURE

The ENTICE-BR model maximizes the present value of per capita utility, subject to a set of economic constraints, some of which are presented below [equations (1)-(6)].[1] Output, Q_t, is produced by a combination of labor, L_t, the physical capital stock, K_t, and effective energy units, E_t.[2] Overall technological progress comes through changes in total factor productivity, A_t. Effective energy units are a measure of the productive capabilities of three possible energy inputs: fossil fuels, F_t, a carbon-free backstop technology, B_t and knowledge pertaining to energy efficiency, $H_{E,t}$. The cost of both fossil fuels and the backstop fuel, $p_{F.t}$ and $p_{B,t}$, are subtracted from total output:[3]

$$Q_t = A_t K_t^{\gamma} L_t^{1-\gamma-\beta} - p_{F,t} F_t - p_{B,t} B_t \tag{1}$$

Effective energy units, E_t, uses a nested constant elasticity of substitution (CES) framework to aggregate the contributions of fossil fuels, the backstop energy source, and knowledge pertaining to energy efficiency. Defining a_H as a scaling factor determining the level of energy savings resulting from new energy-efficiency knowledge and Φ_t as any remaining exogenous changes in the ratio of carbon emissions per unit of carbon services, energy needs are met by consuming energy inputs or improving knowledge pertaining to energy efficiency, as shown below:

$$E_t = \left[\alpha_H H_{E,t}^{\rho_H} + \left(\left(\frac{F_t}{\alpha_\Phi \Phi_t} \right)^{\rho_B} + B_t^{\rho_B} \right)^{\rho_H/\rho_B} \right]^{1/\rho_H} \tag{2}$$

The first nest in equation (2) relates the use of energy inputs and energy efficiency improvements, while the second allows for substitution between fossil fuels and the backstop technology. This second nest, introduced in van der Zwaan et al (2002), models the backstop and fossil fuels as imperfect substitutes, allowing

1. The equations below represent portions of the model directly incorporating energy-related technological change. Details on other equations, including those linking economic activity and the environment, can be found in Popp (forthcoming).

2. For optimizing with climate policy, output is scaled by the damages caused by carbon concentrations, as shown in Nordhaus and Boyer (2000).

3. Energy consumption, represented by fossil fuel usage, F, is measured in tons of carbon. The price of fossil fuels is thus the price per ton of carbon. Backstop energy units are converted to represent the equivalence of one ton of carbon-based energy. The cost of fossil fuels evolves over time, and increases as more fossil fuels are extracted. See Popp (2004a) for more details. The costs of the backstop technology are defined below.

for "niche markets" for the backstop technology even when the price of the backstop exceeds fossil fuel prices. In each nest, the ease of substitution is represented by ρ_i.[4]

Backstop technologies are, by definition, technologies for which scarcity is not a concern. The price of the backstop technology falls over time as technology advances. Defining $H_{B,t}$ as the stock of knowledge pertaining to the backstop, and using η to represent the relationship between new knowledge and prices, the backstop price is:

$$p_{B,t} = \frac{P_{B,0}}{H_{B,t}^{\eta}} \tag{3}$$

This specification is similar to that used in experience curves, (see for example, Ibenholt, 2002). In this specification, $1\text{-}2^{-\eta}$ provides the cost reduction that occurs from a doubling of the knowledge stock. This calculation is commonly referred to as the *progress ratio.*

Technological change enters the model through the two knowledge stocks defined above. Technological advances can improve energy efficiency ($H_{E,t}$) or lower the costs of using the backstop technology ($H_{B,t}$). Similar to a physical capital stock, these knowledge stocks are created by the accumulation of previous research and development (R&D). R&D is endogenous to the model. The R&D sector is calibrated as discussed in section III, so that growth in energy R&D in the baseline business as usual simulations (BAU) are consistent with historical levels. Moreover, because R&D is endogenous, the level of R&D spending and thus the level of each knowledge stock, increases when climate policies are introduced. Using $R_{i,t}$ to represent R&D spending for either energy efficiency or the backstop technology, the knowledge stocks increase as shown below:

$$H_{i,t+1} = aR_{i,t}^{b_i} H_{i,t}^{\Phi_i} + H_{i,t}, \;\; i = E,B \tag{4}$$

The first term on the right-hand side models the process by which energy R&D, $R_{i,t}$, creates new knowledge. The parameters are chosen so that there are diminishing returns to energy research over time. This assumption is motivated by empirical

4. Note that technology enters equation (2) in one of two ways. $H_{E,t}$ represents technological improvements to energy efficiency that evolve endogenously over time. Technology also enters exogenously through Φ_t, which represents exogenous changes in the ratio of carbon emissions per unit of carbon services. Examples include changes in consumption patterns and switching to less carbon-intensive fossil fuels, such as natural gas. This remaining technological change is retained so that emissions in the baseline (no policy) simulation with R&D replicate the results of the DICE model without R&D. Because the DICE model and its variants are a one-sector macroeconomic growth model, changes in consumption patterns or substitution among types of fossil fuels are not explicitly modeled. Fortunately, Popp (2004a) shows that the percentage of exogenous changes in carbon intensity remaining does not affect the net economic impact of induced technological change, as it is the level of R&D induced between an exogenous and endogenous R&D simulation that is important. Changing the scaling factor only changes the level of emissions in each simulation, but not the *difference* between them.

work in Popp (2002). In this case, diminishing returns to R&D occur as long as both b_i and ϕ_i are between 0 and 1.

Because of the public goods nature of knowledge, the role of market failures in R&D must be considered. Virtually all empirical studies of R&D find that the social returns to R&D are greater than the private returns to R&D.[5] Since firms will invest until the private rates of return to R&D are equal to the rates of returns on other investments, underinvestment in R&D will occur. I model these positive externalities by constraining the private rate of return for R&D to be four times that of investment in physical capital. Omitting such market failures implicitly assumes that government policies, such as R&D subsidies, will sufficiently augment private R&D efforts to correct market failures.

One implication of the high social benefits to R&D is that the model must account for the opportunity cost of R&D. This is important because empirical work suggests that at least some energy R&D will replace other forms of R&D. Note that all output is devoted to either consumption, investment in physical capital, or R&D:

$$Q_t = C_t + I_t + R_{E,t} + R_{B,t} \tag{5}$$

However, this simple accounting ignores the potential effects of crowding out. The opportunity cost of a dollar of energy R&D is that one less dollar is available for any of three possible activities: consumption, physical investment, or investment in other R&D.[6] The opportunity costs of the first two are simply valued at one dollar. However, since the social rate of return on R&D is four times higher that of other investment, losing a dollar of other R&D has the same effect as losing four dollars of other investment. Thus, the cost of any research that crowds out other research is four dollars. This is modeled by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock is:

$$K_t = \{I_t - 4{*}crowdout{*}(R_{E,t} + R_{B,t})\}{+}(1\text{-}\delta)K_{t\text{-}1}, \tag{6}$$

where *crowdout* represents the percentage of other R&D crowded out by energy R&D. As in Popp (forthcoming, 2004a,b), in the base case I assume new energy R&D crowds out 50% of other R&D.

3. CALIBRATION

Popp (forthcoming) describes the basic calibration of the ENTICE-BR model. The model begins in 1995, and is solved in 10-year increments for 350 years. The model has been recalibrated slightly so that output in year 2000 is consistent

5. There is a large body of empirical work that verifies the social returns to R&D are greater than the private returns. For a discussion of this work and its implications for climate models, see Popp (2005).

6. Here, I am referring to R&D designed to increase productivity in other sectors. Accounting for the opportunity cost of reducing this research is important, since it is not explicitly included in the model.

with other papers presented in the IMCP project. As in Popp (forthcoming), parameters are chosen so that the initial elasticity of energy R&D with respect to energy prices across policy simulations is 0.35 (Popp, 2002). This elasticity is primarily controlled by the choice of ρ_H, which for this paper equals 0.38. To calibrate equation (4), the value a is also chosen so that the change in energy R&D between 1995 and 2005 in the optimal policy simulation is consistent with the elasticity of 0.35. Values of b and ϕ are chosen so that future elasticities fit the desired time path – falling slowly in the near future due to diminishing returns to R&D. The value of the scaling factor a_H is chosen so that each new dollar of energy efficiency R&D yields four dollars of energy savings.

To calibrate the backstop energy sector, initial values for backstop R&D and backstop energy consumption are needed. Following van der Zwaan et al (2002), who use results from Nakicenovic et al (1998), 4 percent of all energy consumption in 1995 comes from the backstop technology, for an initial value of 0.25 equivalent tons of carbon.[7] Specifying the initial backstop price is complicated, as a wide range of estimates exists. Moreover, the initial backstop price also defines the elasticity of substitution between backstop and fossil fuel energy sources. Following Popp (forthcoming), I consider three possible starting prices: \$400 ($\rho_B = 0.885$), \$1200 ($\rho_B = 0.542$), and \$2000 ($\rho_B = 0.383$) per carbon ton equivalent (CTE) of backstop energy. Note that lower prices imply a higher elasticity of substitution,[8] and thus yield very high elasticities for backstop energy R&D, resulting in levels of policy-induced R&D inconsistent with empirical evidence. A price of \$2000 CTE provides more reasonable elasticities of backstop energy R&D, as the level of ρ_B implied by this starting price is consistent with the level used for energy efficiency R&D. However, this price is in the upper range of current price estimates.[9]

Finally, I need a value for η, which relates human capital to backstop price decreases. Again, no good empirical estimates exist. The scenarios presented in this paper assume a value of 0.4, which implies a progress ratio of 24 percent. Popp (forthcoming) shows that the model is not very sensitive to the choice of this parameter. This surprising result occurs because changes in the price of the backstop are only significant near the point at which the backstop price approaches the cost of traditional fossil fuels. In other years, changes in this parameter have little impact. Thus, over the 350 year period simulated in ENTICE-BR, there is little impact to changing the value of η.

7. Although van der Zwaan et al do not specify the fuels represented by their backstop technology, this figure would be consistent with including hydroelectric and solar-based renewables (e.g. solar, wind, and geothermal), but not including nuclear energy. Given the political difficulties in siting new nuclear power plants, as well as the environmental costs of dealing with nuclear waste, this assumption seems practical.

8. This is because the both the elasticity of substitution and initial backstop price must be consistent with backstop usage in the base year. As the initial price falls, either the elasticity of substitution must increase, or the level of backstop usage in the base year would have to increase.

9. See footnote 18 in Popp (forthcoming) for a discussion.

4. SIMULATION RESULTS

This section simulates the effects of limiting atmospheric carbon concentrations to 400, 450, 500, or 550 ppm. I begin with results using the medium elasticity of substitution between the backstop and fossil fuels, which is the base case in Popp (forthcoming). I present sensitivity analysis on this choice, as well as examining the effect of R&D opportunity costs and R&D market imperfections. Readers interested in sensitivity analysis of other parameters are referred to Popp (forthcoming, 2004a).

Table 1 presents the net economic impact of each policy under the various scenarios. I calculate the *net economic impact* of a policy as the present value of consumption under the policy minus the present value of consumption in the base case, in which carbon emissions are uncontrolled.[10] Note that measures of output in the DICE family of models include damages from climate change. Thus, output measures include both the costs of reducing emissions and any potential benefits from these reductions. As such, unlike models that do not explicitly include damages, changes in GDP cannot be used as a measure of the cost of a policy.

Note that, with the exception of the case where the elasticity of substitution between the backstop and fossil fuels is high (and thus the starting price of the backstop is low), only the least restrictive of the climate policies enhances welfare. In the base case, the present value of consumption falls by over 25 trillion dollars for the most restrictive policy limiting concentrations to 400 parts per million (ppm). This finding is robust, as even with a low opportunity cost of research or a model that removes the imperfections in R&D markets, the net economic impact of this policy is still a loss of nearly 25 trillion dollars.

In addition to the base results, Table 1 also shows the benefits from policy-induced technological change (ITC) in the energy sector. Column 2 shows the net economic impact of each policy when technology is exogenous – that is, energy R&D levels remain at baseline levels even after climate policy is enforced. Column 3 shows the difference between columns 1 and 2, and column 4 expresses this difference as a percentage increase from the net economic impact without ITC. Because more restrictive polices induce more R&D, the gains from ITC are greater for the more restrictive policies. However, because the welfare losses are so large with the restrictive policies, the percentage gain is smaller.

While it may seem surprising that the effects of ITC are small, it is important to note that R&D occurs even in the business as usual (BAU) simulation that does not include climate policy. Thus, these welfare gains are not for the effect of technology per se, but only of the gains from the additional energy R&D that is induced by a climate policy. Table 2 shows the level of energy R&D (both backstop and energy efficiency R&D) under each policy.[11] Looking at the base

10. For the business as usual case in which emissions are uncontrolled, the model is first optimized ignoring climate damages, and output is then adjusted to account for the damages that occur from such suboptimal behavior.

11. The table also presents optimal energy R&D subsidies. These are discussed below.

Table 1. Net Impact of Stabilization Policies

Stabilization goal	(1) Net economic impact with ITC	(2) Net economic impact without ITC	(3) Gain from ITC (trillions 1995 US $)	(4) % gain from ITC	(5) Net economic impact with low R&D opportunity cost	(6) Gain from low opp cost (trillions 1995 US $)	(7) % gain from low opp cost	(8) Net economic impact with R&D subsidies	(9) Gain from R&D subsidies (trillions 1995 US $)	(10) Gain from R&D subsidies
Base -- medium elasticity of substitution										
400 ppm	-25.64	-26.62	0.98	3.7%	-24.90	0.74	2.9%	-25.41	0.23	0.9%
450 ppm	-8.19	-8.83	0.64	7.2%	-7.70	0.49	6.0%	-7.97	0.22	2.7%
500 ppm	-1.42	-1.87	0.45	24.0%	-1.05	0.36	25.7%	-1.23	0.19	13.3%
550 ppm	1.32	0.99	0.33	33.6%	1.62	0.29	22.1%	1.49	0.16	12.5%
low elasticity of substitution										
400 ppm	-35.25	-35.99	0.74	2.0%	-34.61	0.65	1.8%	-35.05	0.20	0.6%
450 ppm	-13.39	-13.87	0.48	3.5%	-12.96	0.43	3.2%	-13.19	0.19	1.4%
500 ppm	-4.39	-4.74	0.35	7.3%	-4.06	0.33	7.6%	-4.23	0.16	3.7%
550 ppm	-0.37	-0.64	0.27	41.6%	-0.09	0.28	76.0%	-0.23	0.14	37.0%
high elasticity of substitution										
400 ppm	2.83	1.92	0.91	47.4%	3.16	0.33	11.8%	2.99	0.16	5.6%
450 ppm	3.50	3.04	0.47	15.4%	3.62	0.11	3.2%	3.91	0.41	11.6%
500 ppm	3.58	3.04	0.54	17.8%	3.72	0.14	3.9%	3.91	0.33	9.2%
550 ppm	3.71	3.04	0.68	22.3%	3.93	0.21	5.7%	3.91	0.20	5.3%

The table shows the *net economic impact*, measured as the change from business as usual in the present value of consumption, for various climate stabilization scenarios. In all cases, gains are expressed in trillions of 1995 US dollars. Column (1) shows the gain with a model including policy-induced technological change, while column (2) is the gain from a model with exogenous technological change, in which energy R&D with policy is constrained to be the same as in the no policy case. Column (3) is the difference between columns (1) and (2). It is the welfare gain from including ITC in the model, measured in trillions of 1995 US dollars. Column (4) expresses this gain as a percentage increase from column (2). Column (5) presents the net economic impact from a model with no crowding out from energy R&D. Columns (6) and (7) present the marginal gain from removing crowding out, compared to the results in column (1). Finally, column (8) is the net economic impact when R&D is subsidized at its optimal level. Columns (9) and (10) present the marginal gain from these subsidies, compared to column (1).

case, note that energy R&D increases from 14.6 billion to 15.8 billion dollars in 2000 and from 48.5 to 62.8 billion in 2100 under the most restrictive policy. In contrast, energy R&D increases to just 14.9 billion in 2000 and 53.0 billion with the least restrictive policy. Thus, even with the most restrictive policy, the majority of the R&D that occurs takes place *with or without* climate policy in place.[12] Also, note the inverse relationship between the elasticity of substitution between energy sources and induced R&D. There is less energy R&D induced when the elasticity of substitution is high. However, recall that the high elasticity of substitution corresponds with an initial low backstop price. As such, the backstop price falls to a threshold below fossil fuel prices more rapidly, so that the share of energy coming from the backstop grows more quickly.

To better understand the impact of these policies, Table 3 summarizes results for four key outputs of the model: output (in trillions of 1995 US dollars), the carbon tax necessary to achieve the policy goal,[13] the percentage of energy coming from the backstop technology, and atmospheric carbon concentrations.[14] Results for each policy option, as well as a business as usual scenario that has no climate policy, are presented for each of the three initial backstop prices. The results presented include induced technological change in the energy sector.[15] Consistent with the net economic impact shown in Table 1, in most cases output is lower with policy in place. These effects are most notable in the long run, as the carbon tax necessary to limit concentrations grows over time. For the most restrictive policy, the carbon tax grows from $72.75 per ton in 2000 to $1,102.51 in 2100. In contrast, for the least restrictive policy, the carbon tax is $10.97 per ton in 2000, and just $170.23 in 2100. Still, the near-term effects of even this policy appear negative, as output in the base case remains lower, even in 2100. It is only the case of a high elasticity of substitution that output increases with a climate policy in place.

The welfare gains that occur with a high elasticity of substitution (as well as the lower carbon taxes to achieve each policy goal), occur because the high elasticity of substitution case corresponds with a lower initial backstop price. In this scenario, the backstop price falls below the price of carbon-based fuel in 2090, making it easier to achieve carbon reductions. Indeed, note that BAU carbon concentrations barely exceed 500, even in the no policy case.

12. It is important to note that the BAU scenario is calibrated beginning with 1995 energy R&D levels, and assuming that this R&D evolves over time in a way consistent with historical trends. Of course, past energy R&D has also been influenced by policy, such as country-level attempts at carbon taxes, requirements that a certain percentage of energy be produced with renewable sources, and through public funding of R&D. Thus, the BAU scenario should not be interpreted as a case with no policy, but rather a case in which current policies continue but are not augmented by more restrictive emissions limits.

13. As ENTICE-BR is a global model, permit trading is not a direct policy option. However, the carbon tax can also be seen as the permit price that would result in a global trading market.

14. Note that, except in the case of 400 ppm, the concentration constraint does not become binding until after 2100.

15. For each variable, there is little change when technology is exogenous.

Table 2. Energy R&D

Energy R&D (billions of 1995 US dollars)				
2000	2020	2050	2100	
Base -- medium elasticity of substitution				
BAU	14.61	24.89	34.51	48.51
400 ppm	15.81	29.19	44.89	62.83
with subsidies	16.51	35.19	56.48	83.85
450 ppm	15.17	26.77	38.87	60.48
with subsidies	15.59	31.11	52.03	80.57
500 ppm	14.94	25.92	36.82	57.40
with subsidies	15.18	29.12	47.75	77.80
550 ppm	14.85	25.57	35.98	52.96
with subsidies	15.00	28.20	45.35	73.44
low elasticity of substitution				
BAU	14.67	25.88	35.45	49.60
400 ppm	16.00	29.21	44.34	62.16
with subsidies	16.42	34.88	56.26	83.42
450 ppm	15.44	27.18	38.74	59.80
with subsidies	15.57	31.14	51.84	80.05
500 ppm	15.16	26.58	37.11	56.85
with subsidies	15.19	29.31	47.85	77.40
550 ppm	14.99	26.37	36.53	52.96
with subsidies	15.02	28.44	45.54	73.36
high elasticity of substitution				
BAU	14.58	24.77	34.42	48.10
400 ppm	15.51	28.15	39.97	52.81
with subsidies	15.60	31.20	47.82	69.69
450 ppm	15.01	26.41	37.98	52.83
with subsidies	15.10	28.98	46.55	69.71
500 ppm	14.88	25.73	36.32	52.34
with subsidies	15.10	28.98	46.55	69.71
550 ppm	14.84	25.55	35.85	50.76
with subsidies	15.10	28.98	46.55	69.71

The table presents total energy R&D in billions of 1995 US dollars. Lines labeled "with subsidies" present the level of energy R&D when R&D market imperfections are removed from the model.

Thus, carbon concentrations are not much higher than mandated by the two weaker policy options analyzed. This is important, as it indicates that *optimistic assumptions about the potential benefits of technology should be included not only in simulations that include a policy, but in analysis of the no-policy base case as well* (Popp, forthcoming). Thus, even without a carbon policy in place, the majority of energy comes from backstop sources by 2100. Indeed, Table 3 shows a large increase in the BAU percentage of energy coming from backstop sources for the high elasticity of substitution case between 2050, when the backstop is still more expensive, and 2100, when it is cheaper. In contrast, since the two other elasticities of substitution correspond with higher initial backstop prices, the price of the backstop does not become competitive without high carbon taxes. Thus, BAU usage of the backstop remains at 10 percent or less. As such, carbon concentrations in the BAU case range between 568 and 574 ppm by 2010, necessitating that restrictive climate policies be put in place if the stabilization goals are to be met.

Turning to sensitivity analysis of assumptions about R&D markets, columns (5)-(7) of Table 1 show the net economic impact of simulations assuming that all energy R&D is new R&D, so that no other beneficial R&D is crowded out. As shown in column (6), lowering this opportunity cost nearly doubles the benefits of ITC. For example, with the most restrictive policy in the base case, ITC increases welfare by 0.98 trillion dollars. Removing the assumption of partial crowding out leads to an additional 0.74 trillion dollars of welfare gain. As before, these effects are most important for the more restrictive policies, as they induce higher levels of R&D.

Finally, the last three columns of Table 1 show the effect of removing R&D market imperfections.[16] This can be seen as a case where the government subsidizes energy R&D at an optimal level. While this also enhances welfare, the gains are not as large as removing the assumption of crowding out.[17] Moreover, there is less variation in the gain from R&D subsidies as there are in the gains from ITC. Table 2 includes the total level of energy R&D when subsidies are included. As with policy-induced ITC, subsidies are higher under more restrictive climate policies.

5. CONCLUSION

This paper uses the ENTICE-BR model (Popp, forthcoming) to study the effects of various climate stabilization policies used in the IMCP. Because the ENTICE-BR model includes benefits from reduced climate damages, it is possible to calculate the net economic impact of each policy. Except in the case of a low initial backstop price, only the least restrictive concentration limit (550 ppm) is welfare enhancing. With a low initial backstop price, each of the climate stabilization policies is welfare enhancing. With a low backstop price, the stabilization policies imply little cost. When the backstop price is low, it becomes competitive with fossil fuels more quickly, and thus is also used in the no-policy base case.[18] As a result, carbon concentrations in the BAU scenario are lower, so that climate change itself is less of a problem. Thus, the emission reductions

16. That is, the return on energy R&D is no longer constrained to be four times that of other investments.

17. The R&D simulations include the assumption of partial crowding out. Popp (2004a) shows that this is important. There, I show that the rate of return on energy R&D is still higher than the rate of return on private investment after the restriction on returns to R&D is removed, because the optimal level of energy R&D must be low enough to account for crowing out of other investments.

18. See Popp (forthcoming) for a more detailed discussion.

Table 3. Effect of Stabilization Policies on Key Variables

	Output (trillions)				Carbon Tax			
2000	**2020**	**2050**	**2100**	**2000**	**2020**	**2050**	**2100**	
Base -- medium elasticity of substitution								
BAU	32.03	49.85	75.57	116.45	N/A	N/A	N/A	N/A
400 ppm	32.00	49.28	72.87	111.54	$72.75	$187.14	$657.81	$1102.51
450 ppm	32.03	49.69	74.79	112.89	$25.64	$63.15	$189.30	$722.10
500 ppm	32.03	49.78	75.26	114.57	$14.32	$33.53	$85.82	$394.26
550 ppm	32.03	49.81	75.40	115.79	$10.97	$24.72	$55.58	$170.23
low elasticity of substitution								
BAU	32.01	49.94	75.94	117.31	N/A	N/A	N/A	N/A
400 ppm	31.98	49.27	72.81	110.71	$83.20	$214.40	$761.89	$1459.71
450 ppm	32.01	49.75	74.98	112.69	$29.18	$72.64	$221.62	$910.49
500 ppm	32.02	49.86	75.55	114.84	$15.87	$37.71	$99.99	$487.03
550 ppm	32.02	49.89	75.73	116.37	$11.74	$26.84	$62.55	$211.53
high elasticity of substitution								
BAU	32.04	49.78	75.34	116.66	N/A	N/A	N/A	N/A
400 ppm	32.04	49.62	74.84	117.27	$21.59	$56.47	$118.04	$79.03
450 ppm	32.04	49.74	75.22	116.87	$8.56	$18.57	$36.62	$70.17
500 ppm	32.04	49.76	75.26	116.84	$8.62	$18.69	$36.84	$70.56
550 ppm	32.04	49.76	75.28	116.85	$8.63	$18.75	$36.93	$70.74

	Percentage of Energy from Backstop				Concentration (ppm)			
2000	**2020**	**2050**	**2100**	**2000**	**2020**	**2050**	**2100**	
Base -- medium elasticity of substitution								
BAU	4.2%	5.6%	7.5%	10.7%	355.11	395.24	457.98	568.03
400 ppm	5.4%	12.2%	36.8%	60.8%	355.11	381.69	399.73	400.00
450 ppm	4.6%	7.6%	14.9%	45.8%	355.11	389.64	431.59	450.00
500 ppm	4.4%	6.6%	10.6%	29.6%	355.11	392.09	443.51	498.17
550 ppm	4.4%	6.3%	9.4%	18.1%	355.11	392.87	447.61	524.15
low elasticity of substitution								
BAU	4.1%	5.1%	6.3%	8.0%	355.11	395.42	459.47	574.30
400 ppm	5.1%	9.9%	25.1%	43.9%	355.11	381.03	399.34	400.00
450 ppm	4.5%	6.7%	11.4%	31.3%	355.11	389.37	430.89	450.00
500 ppm	4.3%	5.9%	8.5%	20.3%	355.11	392.07	443.78	498.19
550 ppm	4.3%	5.7%	7.6%	12.9%	355.11	392.98	448.54	526.19
high elasticity of substitution								
BAU	4.9%	11.7%	30.1%	67.9%	355.11	394.57	448.65	504.40
400 ppm	6.7%	30.3%	77.8%	89.9%	355.11	386.52	400.00	400.00
450 ppm	5.6%	16.7%	46.9%	88.1%	355.11	391.29	432.48	446.23
500 ppm	5.6%	16.7%	46.5%	87.8%	355.11	391.80	433.86	448.48
550 ppm	5.6%	16.7%	46.4%	87.6%	355.11	391.95	434.35	449.46

The table presents the levels of key variables under different climate stabilization policies. Dollar values are presented using 1995 US dollars.

required by each concentration scenario are smaller and easier to achieve. Finally, when evaluating the potential of induced technological change to lower the costs of climate policy, assumptions about the nature of R&D markets are important. Removing the assumption of partial crowding out from energy R&D nearly doubles the gains from policy-induced energy R&D. This is important, as it suggests that models ignoring the costs of R&D necessary to develop new technologies, such as those relying solely on learning-by-doing, overstate the gains from policy-induced technological change.

ACKNOWLEDGEMENT

The author thanks Ian Sue Wing, Larry Goulder, Allan Manne and seminar participants at Stanford University and Rensselaer Poytechnic Institute for helpful comments on earlier papers using the ENTICE-BR model, and three anonymous reviewers for their comments on this paper. Janna Matlack, Ashley Walter, and Neelakshi Medhi provided excellent research assistance. As usual, any remaining errors are solely the responsibility of the author. Financial support for the development of the ENTICE-BR model was provided by the National Science Foundation under grant number SES-0001679.

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Assessment of CO_2 Reductions and Economic Impacts Considering Energy-Saving Investments

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Using a global dynamic optimization model that includes a notion of endogenous energy-saving investments, economic impacts and energy-system changes are assessed under several policy cases where CO_2 concentration is stabilized at the 450, 500, and 550 ppm levels by the year 2100. The effect of increased investments in energy-saving technologies on energy efficiency is derived exogenously from results of the AIM/Enduse model applied to Japan, then endogenized in the global dynamic optimization model.

We find that with diffusion of energy-saving technologies, GDP loss during the 21st century falls from 2.5% to 2.1% in the 450 ppm case. The impact is small for the 550 ppm case, however, because a shift to low-carbon-intensive energies such as gas and renewable energies does not occur to a significant extent under this target.

1. INTRODUCTION

The role of the diffusion of energy saving technology in achieving CO_2 emissions reductions is known to be important. In particular, investments in energy-saving technologies in the manufacturing sector can be considered key to driving down energy demand and hence CO_2 emissions in the economy. To assess energy saving as one of many options for reducing CO_2 emissions, however, it is vital to understand the interaction between investment in energy-saving technologies and improvements in energy efficiency.

When evaluating factors contributing to their reduction, CO_2 emissions are often decomposed using a simple hypothetical identity called the Kaya identity (Yamaji et al., 1991). To address the development of literature on CO_2 absorption

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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measures such as CO_2 capture and storage, the Kaya identity has been described in greater detail in recent years. For example, Kawase et al. (2005) separate CO_2 emissions into five factors: i) the ratio of net CO_2 emissions including CO_2 capture and storage to generated CO_2 emissions; ii) carbon intensity (i.e. the ratio of generated CO_2 emissions to primary energy consumption); iii) the inverse of energy conversion efficiency (i.e. the ratio of primary energy consumption to final energy consumption); iv) the aggregated energy intensity (i.e. the ratio of final energy consumption to economic activity) and v) economic activity. The extended Kaya identity used in this study is defined as follows:

$$C = \frac{C}{C_s} \bullet \frac{C_s}{Ep} \bullet \frac{Ep}{Ef} \bullet \frac{Ef}{A} \bullet A = s \bullet i \bullet e_p \bullet e_f \bullet A$$

where C is total CO_2 emissions including CCS, Cs is fossil and industrial CO_2 emissions, Ep and Ef are primary and final energy consumption respectively, A is Economic activity, s is the ratio of net CO_2 emissions to fossil & industrial CO_2 emissions, i is Carbon intensity, e_p is the inverse of energy conversion efficiency, and e_f is the aggregated energy intensity.

The first term reflects the effects of artificial absorption measures such as CO_2 capture and storage of generated CO_2 emissions. The second term represents the effects of shifting from carbon-intensive fuels to lower carbon energies. In the third term, the effects of measures for efficiency improvement in the transformation from primary energy to final energy are expressed. The fourth term describes the effects of energy efficiency improvements at the end-use points. Measures for investments in energy saving in end-use technologies – the main focus of this study – are thus reflected in the fourth term.

In order to arrive at efficient policies for CO_2 reduction, it is necessary to estimate the optimal combinations of the contributing factors described above. The timing of implementation of appropriate measures must also be explored. To obtain solutions for such issues, it is often useful to use integrated models and linkages between top-down and bottom-up models. For example, the first version of MERGE (Manne et al., 1995) – an integrated assessment in which the costs of abatement are explicitly balanced off against the benefits of reducing the impacts of climate change – links ETA-MACRO to the CLIMATE and IMPACT submodels. To give another example, the National Institute for Environmental Studies and Kyoto University have evaluated price and economic impacts of a carbon tax in Japan (Kainuma et al, 2004) by interlinking three different models: i) the AIM/Material model (Masui, 2005), a country-based computable general equilibrium model with recursive dynamics that deals not only with monetary balances but also material balances; ii) the AIM/Enduse model (Kainuma et al., 2002), a country-based bottom-up optimization model with a detailed technology selection framework and; iii) the AIM/Top-down model (Kainuma et al., 2002), a global computable general equilibrium model with recursive dynamics.

The analysis presented in this paper mainly uses a top-down model that is also linked with a bottom-up model, in order to assess CO_2 reductions and economic impacts by considering energy-saving investments. For the purpose of estimating effectiveness of energy-saving investments from a long-term perspective, the same methodology of linking models as used by AIM is adopted here. However, a different type of global model is introduced in this study for the following reason. Investments in the recursive dynamic model mentioned above is given exogenously year by year, by using appropriate investment functions. Yet, the focus here lies with endogenous energy-saving investments under various scenarios. From this viewpoint, it is more appropriate to use a dynamic model with a long-term perspective, hence the global dynamic optimization model – AIM/Dynamic-Global – is developed, with multi-regions and multi-sectors.

The AIM/Dynamic-Global model is soft-linked with the AIM/Enduse model. The former is a global dynamic optimization model that can simulate fuel selections among fossil energies such as coal, oil, gas, and renewable energies in order to assess the relationships between CO_2 generation and primary energy supply. Moreover, endogenous energy-saving investments and their effects are also embodied in the model to assess the relationships between energy demand and economic activities. The impact of investments in energy saving technologies on improvements in energy efficiency is derived by the AIM/Enduse [Japan] model – a bottom-up optimization model applied to Japan. This provides an extensive database for existing and improved technology options. Results derived from the bottom-up analysis are then applied as an input to the AIM/Dynamic-Global model in this study.

The objective of this study is to evaluate the effects of energy-saving technological changes for the reduction of CO_2 emissions, by using the AIM/Enduse model and the AIM/Dynamic-Global model. In particular, this paper focuses on the consequences of endogenous technological change in terms of the relationships between investments in energy-saving technologies and improvements in energy efficiency.

2. MODEL STRUCTURE

The model used for this analysis is a global dynamic optimization model with multiple regions and economic activities. Moreover, this model can introduce endogenous energy-saving investments and estimate their effectiveness. Figure 1 shows the overall structure of the model.

In order to maximize global utility (GU), levels of economic activities are calculated. The following are the main equations in this model:

(1) $GU = \Sigma_r\, wgt_r * RU_r$

(2) $RU_r = \Sigma_r\, udf_{t,r} * u_r\ (C_{t,r,ne}, pop_{t,r})$

$$(3)\ Y_{t,r,i} = f_{t,r,i}\,(K_{t,r,i}, L_{t,r,i}, M_{t,r,j,i}, (aeei_{t,r,i,e}\ {}^*AE_{t,r,i,e})\ {}^*E_{t,r,e,i}, \Sigma_{grd}\, EXT_{t,r,ff\in i,grd})$$

$$(4a)\ Y_{t,r,ne} + IM_{t,r,ne} = \Sigma_j\, M_{t,r,ne,j} + C_{t,r,ne} + \Sigma_j\, I_{t,r,ne,j} + ESI_{t,r,mnf\in ne} + EX_{t,r,ne}$$

$$(4b)\ Y_{t,r,ne} + IM_{t,r,e} = \Sigma_j\, E_{t,r,e,j} + C_{t,r,e} + EX_{t,r,e}$$

$$(5)\ \Sigma_r\, IM_{t,r,i} = \Sigma_r\, EX_{t,r,i}$$

$$(6)\ C_{t,r,e} = c_{t,r}\,(\Sigma_{ne}\, C_{t,r,ne})$$

$$(7)\ K_{t+1,r,i} = (1 - dep)^{ts_t}\ {}^*K_{t+1,r,i} + ts_t\ {}^*0.5{}^*\ \Sigma_{ne}\,(I_{t,r,ne,j} + I_{t+1,r,ne,j})$$

$$(8)\ \Sigma_i\, L_{t,r,i} \le lab_{t,r}$$

$$(9)\ RSV_{t+1,r,ff,grd} = RSV_{t,r,ff,grd} - ts_t\ {}^*0.5{}^*\ (EXT_{t,r,ff,grd} + EXT_{t+1,r,ff,grd})$$

$$(10)\ EK_{t+1,r,mnf} = (1 - dep)^{ts_t}\ {}^*EK_{t+1,r,mnf} + ts_t\ {}^*0.5{}^*\ (ESI_{t,r,mnf} + ESI_{t+1,r,mnf})$$

$$(11)\ AE_{t,r,mnf\in i,e} = g_{r,e}\left(\frac{EK_{t,r}}{Y_{t,r,mnf\in i}}\right)$$

$$(12)\ CO2_t = \Sigma_r \Sigma_e\, cef_e\ {}^*(\Sigma_j\, E_{t,r,e,j} + C_{t,r,e}) + othco2_t$$

Sets:

t: time period, r: region, i and j: sector and commodity, $e\in i$: energy (subset of sector, i), $ne\in i$: non-energy (subset of sector, i), $ff\in e$: fossil fuels (subset of energy, e), $mnf\in ne$: manufacturing sector (subset of non-energy, ne), grd: grade of fossil fuels.

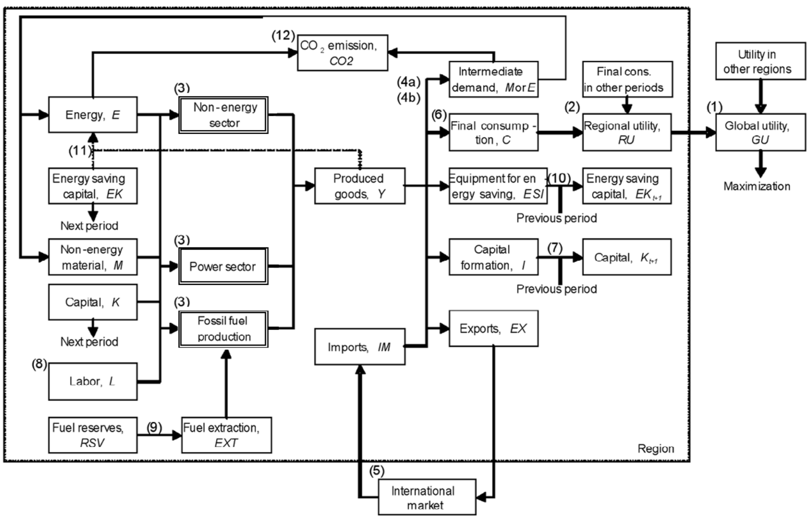
Exogenous parameters:

wgt_r: regional weight, $udf_{t,r}$: utility discount factor, $pop_{t,r}$: population, $aeei_{t,r,i,e}$: autonomous energy efficiency improvement, $lab_{t,r}$: labor supply limit, dep: depreciation rate, ts_t: time step, cef_e: carbon emission factor, $othco2_t$: CO_2 emissions from other sources.

Endogenous variables:

GU: global utility, RU_r: regional utility, $Y_{t,r,i}$: production, $C_{t,r,i}$: final consumption, $K_{t,r,i}$: capital stock, $L_{t,r,i}$: labor input, $M_{t,r,j,i}$: non-energy intermediate demand, $E_{t,r,e,i}$: energy input, $AE_{t,r,i,e}$: additional energy efficiency improvement, $EXT_{t,r,ff,grd}$: extracted fuel resources, $IM_{t,r,i}$: imports, $I_{t,r,i,j}$: fixed capital formation, $ESI_{t,r,mnf}$: capital formation for energy saving (i.e. energy-saving investments), $EX_{t,r,i}$: exports, $RSV_{t,r,ff,grd}$: fuel reserves, $EK_{t,r}$: energy-saving capital stock, CO_{2t}; global CO_2 emissions.

Figure 1. Structure of the AIM/Dynamic-Global Model



Note: The numbers (1) - (12) correspond to the equation numbers shown above. Characters in *italics* represent the variables in the equations.

2.1 Time Period, Region and Activity

The model has a dynamic optimization framework maximizing *GU*, the global discounted utility from the final consumption over the entire time period. The regional utilities calculated from Equation (2) are aggregated based on the Negishi weight (wgt_r) (Negishi, 1960; Mori, 1996) in Equation (1). The base and final years are set as 1995 and 2100 respectively. The model is solved in 5-year increments until 2000, and 10-year increments from 2000 onwards. The classifications of regions and economic activities are shown in Table 1 and Table 2 respectively. The GTAP data (McDougall et al., 1998) and IEA energy balance table (IEA, 1998a and 1998b) are calibrated to obtain the activity levels in the initial year.

Table 1. Classification to Regions

	Model regions	Group
JPN	Japan	Annex I
USA	USA	
OECD	Other OECD countries	
FSU	Former Soviet Union	
CHN	China	Non-Annex I
ROW	Rest of the world	

Table 2. Classification of Economic Activities

Sectors	Sectors	Products
Manufacturing	Manufacturing sector	Goods
Services and others	Service, agriculture, construction sectors	Services
Crude oil	Crude oil extraction	Crude oil
Oil products	Oil refinery sector	Oil products
Coal	Coal mining and products	Coal
Gas	Gas mining and products	Gas
Thermal power	Thermal power sector	Electricity
High-cost non-thermal power	Non-thermal power with high cost	Electricity
Low-cost non-thermal power	Non-thermal power with low cost	Electricity

2.2 Production Function

Equation (3) represents the production function. Capital, labor, energy, and non-energy intermediate goods are the inputs for production. For the extraction of fossil fuels, the amount of fuel deposits is also taken into account with energy types classified into coal, oil, gas, and electricity. Each sector produces a specific commodity, as shown in Table 2. Figure 2 depicts the production structure and the formulation of each production function is explained below.

2.2.1 Non-energy Sector

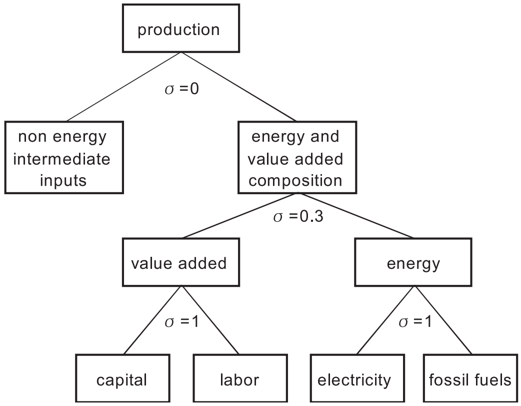
We assume the elasticity of substitution between non-energy intermediate inputs and combinations of energy and value added to be perfectly inelastic. In other words, the Leontief production function is assumed. The elasticity of substitution between energy and value added is assumed to be 0.3. Both the elasticity of substitution between capital and labor, and that between electricity and fossil fuels are assumed unit elastic.

2.2.2 Fossil Fuel Production Sector

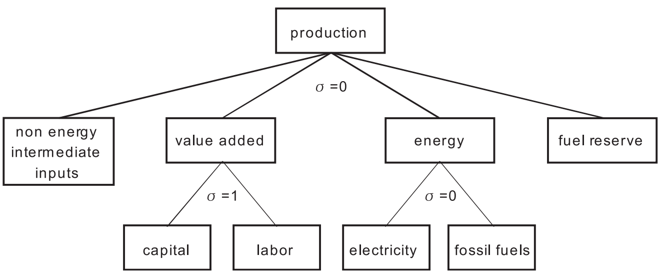
In the fossil fuel mining sector (i.e. crude oil, coal, and gas), the elasticity of substitution between value added and energy is assumed to be zero. Moreover, we assume the reserves of fossil fuels are depleted in proportion to the amount of extraction. The extraction costs in each grade and the quantities of fuel reserves are defined based on Rogner (1997). It is assumed that the combination of reserves that minimizes costs meets demand in the initial year. In addition, upper limits of recoverable reserves are introduced on fuel extraction by each grade. If fuel demand exceeds the upper boundary of the cheaper reserves, then supply taps into the next grade of reserves to meet the demand. Elasticity of substitution among different energy types is assumed to be zero in the fossil fuel production sector. Production of oil products describes the process of refining crude oil, hence no fuel reserves are consumed in production. The produced fossil fuels are either consumed directly or converted into electricity.

Figure 2. Structures of Production Activity

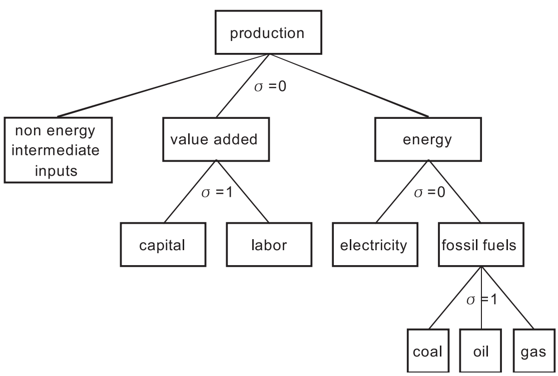
a. Production Structure in Non-energy Sector



b. Production Structure in Fossil Fuel Production Sector



c. Production Structure in Electricity Production Sectors



2.2.3 Power sectors

The power sectors are classified into the thermal power sector and other power sectors for this analysis. Like the fossil fuel production sector, we assume perfectly inelastic substitution between value added and energy. In the thermal power sector, coal, oil, and gas are treated as inputs, and electricity is calculated as an output. The fossil fuel inputs are aggregated using the Cobb-Douglas function. The non-thermal power sector can also supply electricity output, but without fossil fuel inputs. This model differentiates the non-thermal power sector into high-cost and low-cost plants. Electricity supply from low-cost plants is subject to an upper limit, whilst no such bounds are set for the high-cost type.

2.3 Supply and Demand of Commodities

Produced commodities and imported commodities are distributed into intermediate demands, final consumptions, investments (fixed capital formation), capital formation for energy-saving investments (only manufactured goods) and exports, as shown in Equations (4a) and (4b). These equations represent the non-energy and energy goods markets respectively. Upper boundaries are imposed on the ratio of imports to domestic products for non-energy goods; however, no upper limits are set for the import share of energy goods. In the international market, the total imports are equal to the total exports in each commodity, as shown in Equation (5).

2.4 Household Final Consumption

In this study, the household sector in each region is assumed to consume non-energy goods based on the Cobb-Douglas function in each period. The total present value of final demands is defined as the regional utility. Here, household energy demands are assumed to be derived demands. Hence total energy demand in this sector is calculated from the total non-energy final consumption goods as shown in Equation (6), assuming elasticity of substitution among energy types takes the value of one.

2.5 Investment and Capital Stock

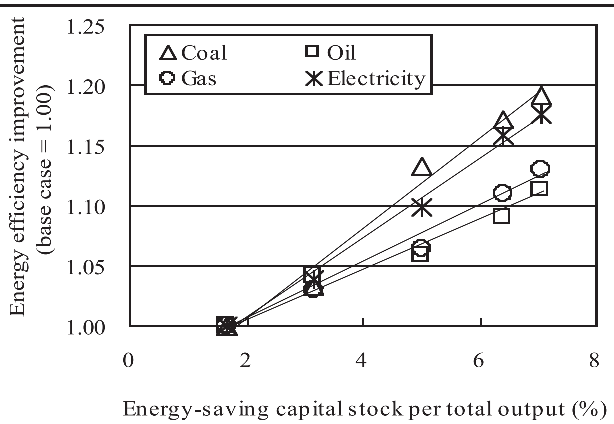
Total income of the household sector gives final demand expenditure, which can either be consumed now to increase present utility, or invested as savings to increase the future utility. The share of the capital formation of each investment good is assumed to be fixed. The investment goods are distributed to each sector and accumulated as capital stock as shown in Equation (7). The putty-clay relationship is assumed to represent the process of investment and capital stock. That is to say, investment goods can be accumulated in any sector, but they cannot be moved among the sectors after accumulation. Unconstrained labor mobility is assumed among the sectors in each region. These relationships are explained by Equation (8).

2.6 Energy-saving Investments and Features of Endogenous Technology Change

As an important policy option for reducing CO_2 emissions, the role of energy-saving investments is considered in this model. In general, the price of equipment rises with its energy-efficiency performance. In this model, such 'additional costs' paid for efficient technology are regarded as energy-saving investments. The links between energy-saving investment, accumulated energy-saving capital stock and additional energy efficiency improvement are embodied in the model as endogenous technical change. The sensitivity of equipment cost differentials to energy savings is extracted from the results of the AIM/Enduse model applied to Japan.

Figure 3 shows the results of the AIM/Enduse model in the manufacturing sector. As shown in this figure, the accumulated energy-saving capital stock per output determines the additional energy efficiency improvement in the manufacturing sector. This relationship is introduced in the global dynamic optimization model according to Equation (11), providing the soft-linkage between this dynamic optimization model and the AIM/Enduse model. Equation (10) describes the process of capital stock formation for energy saving. The energy-saving investment (ESI) and the corresponding additional energy efficiency improvement (AE) are determined endogenously. If marginal CO_2 abatement costs exceed the cost of an energy-saving investment, then the investment will be made. In this way, additional energy efficiency improvements under the CO_2 emission constraint is modeled as induced technology change (ITC).

Figure 3. Impact of Energy-saving Investments on Energy Efficiency Improvements



Note: The lines in the figure represent least-square regression in each energy use.

However, this paper considers energy-saving investments in the manufacturing sector alone. Because energy demand systems are unique to sectors, results obtained from the AIM/Enduse model cannot be generalized other sectors such as energy production and the residential. Moreover, the AIM/Enduse model simulates only technologies that are currently in use, up to the year 2030. Beyond 2030, we assume the interplay between investment, energy-efficiency and emissions reductions remains constant at 2030 levels, and that least expected technology innovation occurs until the end of the 21st century.

In addition, due to the lack of data availability in other regions, results derived from the AIM/Enduse model applied to Japan is applied globally, assuming fairly consistent energy demand systems across regions. Given that Japan's economy is among the world's most energy-efficient, this simulation thus show conservative estimates for the effects of energy-saving improvements on a global scale, because greater improvements in energy efficiency is expected to take place in regions other than Japan, especially in developing countries.

2.7 CO_2 Emissions

Equation (12) gives CO_2 emissions that result from the model. CO_2 emissions from fossil fuels combustion are taken as endogenous. Other emission sources such as land use and industrial processes are regarded as exogenous parameters. In the simulation, CO_2 emissions from these other sources are fixed during the simulated period and aggregated exogenously into global emissions.

The constraint on CO_2 emissions is introduced to stabilize atmospheric CO_2 concentration on a global scale, whilst distribution of CO_2 emissions among regions is calculated endogenously based on the criterion of equal marginal reduction cost.

3. SIMULATION RESULTS

The following scenarios are prepared for analyzing the effectiveness of energy-saving investments;

1) Reference case: No constraint on CO_2 emissions and no energy-saving investment.
2) Reference case with energy-saving investments: No CO_2 constraint but introduction of energy-saving investments.
3) CO_2 stabilization case without energy-saving investments: introduction of CO_2 constraint to stabilize CO_2 emissions at the 450, 500 or 550 ppm levels without energy-saving investments.
4) CO_2 stabilization case with energy-saving investments: introduction of CO_2 constraint to stabilize CO_2 emissions at the 450, 500 or 550 ppm levels with energy-saving investments.

In the "reference case", endogenous technology change is not taken into account. In scenario 2, if the price increase due to depletion of fossil fuel resources is sufficiently high, investments in energy-saving technologies will be made. In the case of "CO_2 stabilization case without energy-saving investments," a fuel transition will be the major countermeasure to reduce CO_2 emissions. On the other hand, under the "CO_2 stabilization case with energy-saving investments" scenario, induced technological change will occur to improve energy-efficiency and achieve stabilization targets – hence ITC plays an important role.

Parameters including autonomous energy efficiency improvements are calibrated to reproduce the level of CO_2 emissions and GDP proposed by the Innovation Modeling Comparison Project (IMCP) for the reference case. CO_2 emissions from land use and industrial processes in the initial year are adjusted to meet the proposed CO_2 emissions. Figure 4 shows the main simulation results of

Figure 4. Results of Simulations of the Reference Scenario (Area Charts) and Trajectories Proposed by the IMCP (Line Charts)

Figure 4-(a) GDP

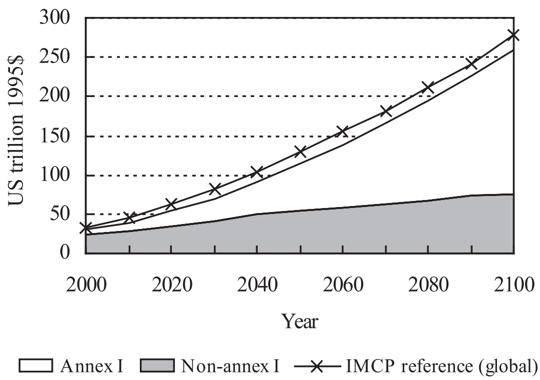
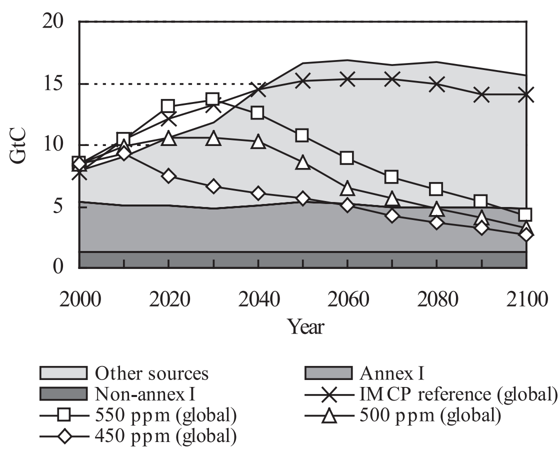


Figure 4-(b) CO_2 emissions



the reference scenario and trajectories of CO_2 stabilization scenarios proposed by the IMCP. Here, the area charts represent the results for Annex I and Non-Annex I groups in the reference case. Trajectories of emissions under various climate policy targets are also depicted by the line charts in Figure 4(b).

The simulations in this study consider three CO_2 concentration stabilization policy scenarios: stabilization at 450, 500, and 550 ppm by the year 2100. Since this model does not include a module for calculating CO_2 concentration, we estimate corresponding global CO_2 emissions scenarios exogenously. For CO_2 reduction simulations, two scenarios—with and without energy-saving investments—are examined in this study.

3.1 Cases without Energy-saving Investments

Figures 5 and 6 show the estimate percentage GDP reductions and the marginal abatement cost of CO_2 respectively. In the 450 ppm scenario, total GDP falls by 2.46% compared to the reference scenario over the course of the century, under a 5% annual discounted rate. Under this stringent policy scenario, marginal abatement cost of CO_2 reaches 1700 US$/tC in the year 2100. For the 550 ppm stabilization scenario on the other hand, discounted GDP loss is 0.85% compared to the reference scenario and marginal abatement cost of CO_2 in 2100 is 76 US$/tC. Under the high CO_2 constraint, fossil fuel supply decreases as shown in Figure 7. This implies that mild constraints such as the 550 ppm stabilization case could be achieved by moderate fuel switching. To achieve the 450 ppm scenario, however, requires a drastic fuel transition implying higher costs.

Figure 5. GDP Reductions Relative to the Reference Case During the 21st Century (Discount Rate: 5%/year)

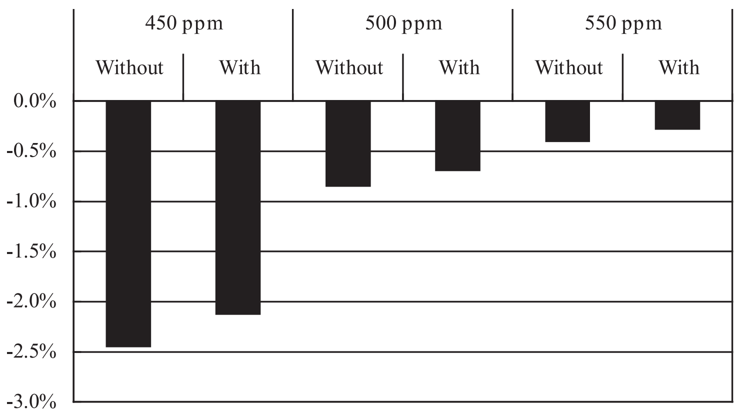


Figure 6. Changes in Marginal Cost of Reducing CO_2 Emissions

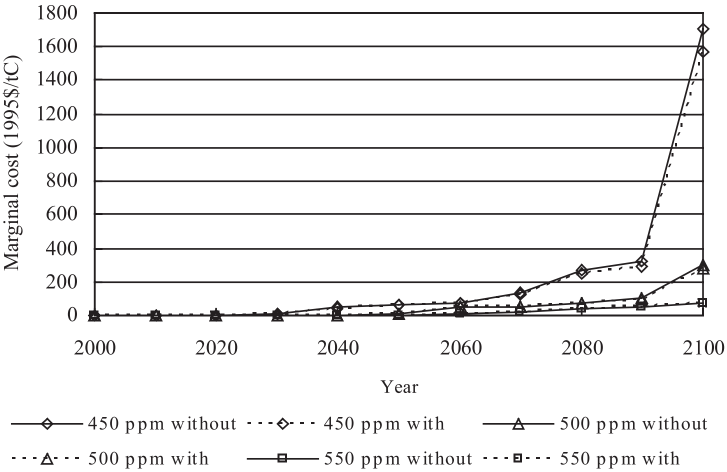
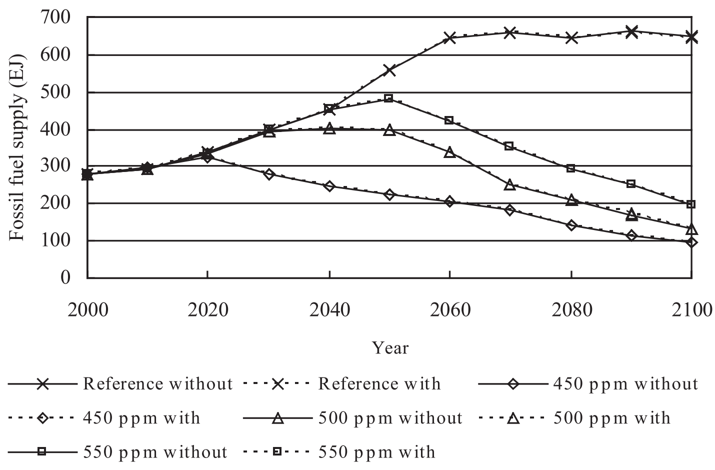


Figure 7. Changes in Fossil Fuel Supply



3.2 Cases with Energy-saving Investments

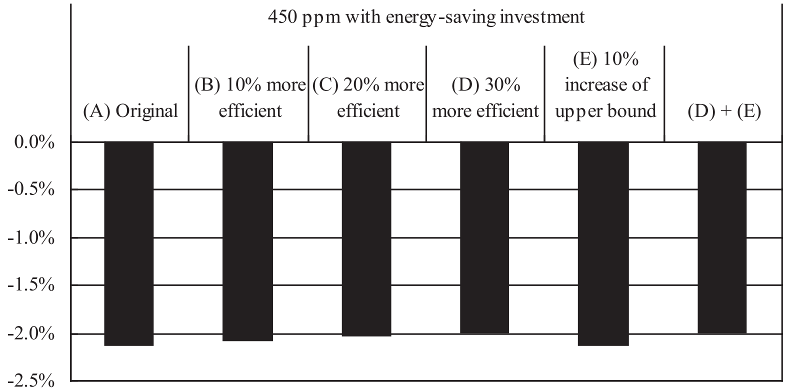
Since energy-saving investments are limited to the manufacturing sector, the effect of the endogenizing energy-saving investments in the overall framework does not appear significant. In the 450 ppm stabilization scenario with energy-saving investments, such investments occur from 2010 onwards. Compared to the same stabilization case without endogenous energy-saving investments, energy-saving investments as a proportion of global GDP increase in the region of 0.2 to 1.0%. For the 450 ppm stabilization case with energy-saving investments, manufacturing production will increase by between 0.017% and 2.3%. Moreover, these manufacturing production activities will induce service demands by between 0.086% and 0.49%. In terms of GDP loss, the simulation shows that existing advanced technologies have the potential to decrease estimated GDP loss from 2.5% to 2.1% for the 450 ppm stabilization case.

Compared to the case without, marginal CO_2 abatement costs in the case with energy-saving investments fall by between 6.3% to 11%, after the year 2040. In terms of marginal abatement cost per ton of CO_2, energy-saving investments proves a far cheaper option at 4 $/t-C to 135$/t-C compared to the case without. In addition, the additional demand generated by energy-saving investments also contributes to reduce GDP loss due to its income effect.

In contrast, the impact of energy-saving investments in the 550 ppm stabilization scenario is small, because a shift to low-carbon-intensive energies such as gas and renewable energies does not occur to a significant extent under this target. Therefore, fuel switching emerges as the foremost important transition to reduce CO_2 emissions in the economy. As expected, signals for such transition, for example encouraging greater energy-saving investments are stronger under the more stringent CO_2 reduction targets.

Figure 8 shows result of the sensitivity analysis carried out to test the responsiveness of GDP levels to varying levels of energy efficiency improvements under the 450 ppm scenario. As energy-efficiency improves by 10%, 20% and 30% compared to the base case shown in Figure 3, GDP loss is reduced by only a small amount. Even if the upper bound of the additional energy efficiency improvement is expanded by 10% compared to the base, it shows only a small impact on percentage GDP change. This is because, as is mentioned in section

Figure 8. GDP Changes Compared to the Reference Case Under the Assumption of Additional Energy Efficiency Improvement (Period: During 21st Century, Discount Rate: 5%/year)



2.6, energy-saving investments described in equation (11) are introduced only in technologies in use in the manufacturing sector. As a result, even a 30 % additional improvement in energy efficiency in the manufacturing sector creates no technological breakthrough. To cut the GDP loss, not only improvements in existing practical technologies, but the development of new cost-effective technologies is also necessary.

4. CONCLUSION

This model simulation focused on the consequences of endogenous investment in energy-saving technologies and evaluated the impact of such investments for reaching different CO_2 reduction targets. This study took into account, energy-saving investments in the manufacturing sector, but not in other sectors such as energy production and the residential sector. In addition, because of the lack of available data for other regions, sensitivity of energy-saving investments to energy efficiency improvements in Japan were applied globally in this model.

Despite the restrictive assumptions, simulation results found that when CO_2 concentration was set at the 450 ppm stabilization level, discounted total GDP loss during the 21st century relative to that of the reference scenario decrease from 2.46% to 2.12% with investments in energy-saving technologies. However, in the 450 ppm case, reducing GDP loss further requires development of new cost-effective technologies in addition to development of existing ones. The impact of energy-saving investments in the 550 ppm case is relatively small, however, because shifts to low-carbon-intensive energies such as gas and renewable energies occur to a lesser extent.

In order to stabilize the global mean temperature increase at 2°C, the National Institute for Environmental Studies and Kyoto University suggest that it is necessary to stabilize total greenhouse gas (GHG) emissions at around the 475 ppm level, based on the results of the AIM/Impact[Policy] model (Hijioka et al., 2006). In order to achieve this target at minimum costs, the role of energy-saving investments is significant.

Issues arising for further research include improving understanding of the impacts of energy-saving investments, regional disaggregation and activity disaggregation. In particular, having region and sector specific sensitivities of investment level on energy-efficiency improvements would provide more comprehensive estimations. Moreover, there is room for further tests on the robustness of the simulation results taking into account, future uncertainties over fossil fuel reserves, the use of low-cost non-thermal power plants and energy supplies in general. A more detailed assessment of technologies (both existing and new) is necessary to improve long-term climate stabilization scenarios. Lastly, linkages of the model to non-CO_2 GHG emissions are also important. To address these issues, further studies including a linkage to the AIM/Impact policy model are planned for the assessment of climate policies.

ACKNOWLEDGEMENT

This research was funded by the Global Environment Research Fund.

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The Dynamics of Carbon and Energy Intensity in a Model of Endogenous Technical Change

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In recent years, a large number of papers have explored different attempts to endogenise technical change in climate models. This recent literature has emphasized that four factors – two inputs and two outputs – should play a major role when modeling technical change in climate models. The two inputs are R&D investments and Learning by Doing, the two outputs are energy-saving and fuel switching. Indeed, R&D investments and Learning by Doing are the main drivers of a climate-friendly technical change that eventually affect both energy intensity and fuel-mix. In this paper, we present and discuss an extension of the FEEM-RICE model in which these four factors are explicitly accounted for. In our new specification of endogenous technical change, an index of energy technical change depends on both Learning by Researching and Learning by Doing. This index enters the equations defining energy intensity (i.e. the amount of carbon energy required to produce one unit of output) and carbon intensity (i.e. the level of carbonization of primarily used fuels). This new specification is embodied in the RICE 99 integrated assessment climate model and then used to generate a baseline scenario and to analyze the relationship between climate policy and technical change. Sensitivity analysis is performed on different key parameters of the energy module in order to obtain crucial insights into the relative importance of the main channels through which technological changes affects the impact of human activities on climate.

1. INTRODUCTION

Controlling the influence of human activities on climate is not an easy task. The international agreement reached in Kyoto that has so far come into force will have a very small impact on greenhouse gas (GHG) atmospheric

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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concentrations. Stabilizing these concentrations at, for example, twice the pre-industrial levels requires per capita global emissions to peak and then decline to (at least) half their 1990 value by the end of the twenty-first century (Cf. Bosetti, Galeotti and Lanza, 2004). This seems to be feasible only through drastic technological change in the energy sector, leading to the substitution of obsolete and dirty technologies with cleaner ones. There are therefore no substitutes for policy in directing innovation efforts toward fostering economic growth and helping the environment at the same time.

All the above remarks are reflected in climate models, the main quantitative tools designed either to depict long-run energy and pollution scenarios or to assist in climate change policy analysis. Indeed, these models have traditionally accounted for the presence of technical change, albeit usually evolving in an exogenous fashion. More recently, however, models have been proposed where technology changes endogenously and/or its change is induced by deliberate choices of agents and government intervention. Both bottom-up and top-down models – a long standing distinction in energy-economy-environment modeling – have been recently modified in order to accommodate forms of endogenous technical change. As it turns out, the bottom-up approach has mostly experimented with the notion of Learning by Doing, while a few top-down models have entertained the notion of a stock of knowledge which accumulates over time via R&D spending.[1]

The purpose of this paper is to present and test a new climate model which accounts for various features of technical change. In the new model, dubbed FEEM-RICE v.3, changes in technology affect the economy and climate through modifications of both the energy intensity of production and the carbon emission intensity of energy consumed. The driver of these intensity ratios is a new variable, deemed Energy Technical Change Index (*ETCI*), which is a convex combination of two stocks, an abatement-based one and an R&D-based one. These stocks are designed to capture the two main modes of endogenous technical change, Learning-by-Doing (*LbD*) and Learning-by-Researching (*LbR*).

Crucial technical change parameters are calibrated in order to obtain a baseline which reproduces the SRES B2 emission scenario (as in Boyer and Nordhaus, 2000) with technical change having both an exogenous and an endogenous component. When stabilization scenarios are simulated, an induced technical change part gets added to those two components. In order to better understand the model structure, we also carry out a number of optimization runs in which key technical change parameters are modified and their impact on energy and carbon intensity are quantified. This sensitivity analysis enables us to test the robustness of the model and to identify the main parameters driving our main results.

1. A review of the recent literature on the role of technical change in the economics of climate change and on the incorporation of induced technical change in climate-economy models can be found in Carraro and Galeotti (2002, 2004); Clarke and Weyant (2002); Löschel (2002).

The remainder of the paper is as follows. Section 2 presents the FEEM-RICE v.3 model and provides a short technical description of how technical change has been modeled. Section 3 describes the baseline calibration process. Section 4 presents our main results and the conclusions arising from our sensitivity analysis. In section 5, some policy remarks and suggestions for further research close the paper.

2. MODELING INDUCED TECHNICAL CHANGE: THE FEEM-RICE V.3 MODEL

The FEEM-RICE v.3 model is an extended version of the RICE 99 model by Boyer and Nordhaus (2000).[2] RICE 99 is a Ramsey-Koopmans single sector optimal growth model suitably extended to incorporate the interactions between economic activities and climate. There is one such model for each of the eight macro regions into which the world is divided: USA, Other High Income countries (OHI), OECD Europe (Europe), Russia and Eastern European countries (REE), Middle Income countries (MI), Lower Middle Income countries (LMI), China (CHN), and Low Income countries (LI).

Within each region a central planner chooses the optimal paths of two control variables, fixed investment and carbon energy input, so as to maximize welfare, defined as the present value of per capita consumption. The value added created via production (net of climate change) according to a constant returns technology is used for investment and consumption, after subtraction of energy spending. The technology is Cobb-Douglas and combines inputs from capital, labour and carbon energy together with the level of technology. In RICE 99, population (taken to be equal to full employment) and technology levels grow over time in an exogenous fashion, whereas capital accumulation is governed by the optimal rate of investment.

The production function of the original RICE 99 model is (n indexes regions, t time periods):

$$Q(n,t) = A(n,t)[K_F(n,t)^{1-\gamma-\alpha_n} CE(n,t)^{\alpha_n} L(n,t)^{\gamma}] - p_n^E\, CE(n,t) \qquad (1)$$

where Q is output (gross of climate change effects), A is the exogenously given level of technology and K_F, CE and L are the inputs from physical capital, carbon energy and labor, respectively, and p^E is fossil fuel price. Carbon emissions are proportional to carbon energy, that is:

$$E(n,t) = \zeta(n,t)\, CE(n,t), \qquad (2)$$

where E is industrial CO_2 emissions, while ζ is an idiosyncratic carbon intensity ratio which also exogenously declines over time. In this way, Boyer and Nordhaus (2000)

2. RICE 99 is an extension of the RICE 96 model described in Nordhaus and Yang (1996).

make the assumption of a gradual, costless improvement of the green technology gained by the agents as time goes by. This treatment of technical change appears inadequate for a model designed to study issues related to climate change.

In this paper we present and apply a new model in which technical change is endogenous and responds to climate policy as well as to other economic and policy incentives. Therefore, both endogenous and induced technical change effects will be taken into account. In FEEM-RICE v.3, we consider simultaneously both *LbD* and *LbR* as inputs of endogenous and induced technical change and we focus on the effects of technical change on both the energy intensity of production and the carbon intensity of energy use. These features of the model allow us to address both energy-saving and energy-switching issues. To clarify this aspect it is perhaps useful to refer to a time-honored concept in environmental economics, namely the Kaya's identity, which in the present specific case reads as follows:

$$E\_TOT(t) = \sum_n \left(\frac{E(n,t)}{CE(n,t)} \right) \left(\frac{CE(n,t)}{Q(n,t)} \right) \left(\frac{Q(n,t)}{L(n,t)} \right) L(n,t), \tag{3}$$

where E_TOT is world emissions, CE is carbon energy, and L is population. Hence, world emissions are a product of two 'forces': techno-economic forces, given by carbon intensity (E/CE) and energy intensity (CE/Q), and socio-economic forces, given by per capita output (Q/L), as well as demographic dynamics L. In addition to socio-economic forces – income and population – which are commonly modeled in endogenous growth models, our model allows us to endogenise both techno-economic forces, namely energy and carbon intensity.

The main novelty of our formulation is given by the relationship between technical change and both Learning-by-Researching and Learning-by-Doing *at the same time*. We assume that energy-saving and climate-friendly innovation is brought about by R&D spending which contributes to the accumulation of the stock of existing knowledge.[3] In addition to this Learning-by-Researching effect, the model also accounts for the effect of Learning-by-Doing, now modeled in terms of cumulated abatement efforts. Thus, our index of technical change, *ETCI* (Energy Technical Change Index), is defined as a convex combination of the stocks of knowledge and abatement:

$$ETCI(n,t) = K_R(n,t)^c \, ABAT_S(n,t)^d, \tag{4}$$

where $K_R(n,t)$ is the stock of knowledge and $ABAT_S$ represents the stock of cumulated abatement. This, in turn is defined as:

3. Therefore, the focus is on energy-related R&D. It has to be pointed out that analysing R&D expenditure is complicated because (i) R&D is not always amenable to measurement and (ii) there is a great deal of uncertainty in the ability of R&D to generate technological change. These words of caution should be therefore borne in mind by the reader when going through the paper.

$$ABAT_S(n,t+1) = \delta_A ABAT_F(n,t) + (1-\delta_B)ABAT_S(n,t), \tag{5}$$

where $ABAT_F$ is the abatement flow, δ_A is the learning factor, i.e. the amount of abatement which translates into a learning experience, and δ_B being the depreciation rate of cumulated experience. The stock of knowledge $K_R(n,t)$ accumulates in the usual fashion:

$$K_R(n,t+1) = R\&D(n,t) + (1-\delta_R)K_R(n,t), \tag{6}$$

where R&D represent investments in energy R&D, δ_R is the depreciation rate of knowledge. Without loss of generality we assume that $d = (1\text{-}c)$.

How does our index of energy technical change affect the rest of the economy? The variable *ETCI* is assumed to affect both energy intensity (i.e. the quantity of energy required to produce one unit of output) and carbon intensity (i.e. the level of carbonization of primarily used fuels). As seen in equation (1), the factors of production are labour, physical capital and carbon energy. Let us first consider the effect of technical progress on factor productivity (the energy-intensity effect). In our model, the production function (1) is replaced by the following equation:

$$Q(n,t) = A(n,t)[K_F(n,t)^{1-\alpha_n(ETCI)-\gamma} CE(n,t)^{\alpha_n(ETCI)} L(n,t)^{\gamma}] - p_n^E CE(n,t), \tag{1'}$$

where:

$$\alpha_n = \alpha_n[ETCI(n,t)] = \frac{\vartheta_n}{2-\exp[\beta_n ETCI(n,t)]}, \tag{7}$$

and θ_n and β_n are region specific parameters, calibrated to have – in the base year – α_n exactly as in the original formulation of the production function. Thus, an increase in the endogenously determined *ETCI* reduces – *ceteris paribus* – the output elasticity of the energy input. It is worth noting that in (1'), the Hick's neutral component of technological progress, A, accounts for a fraction of technical change which evolves exogenously, thus following an explicit suggestion by Clarke and Weyant (2002).

Let us now turn to the effect of energy technical change on the carbon intensity of energy consumption. As shown in (2), effective energy results from both fossil fuel use and (exogenous) technical change in the energy sector. In our model, we assume that *ETCI* serves the purpose of reducing, *ceteris paribus,* the level of carbon emissions. More precisely, equation (2) is replaced by:

$$E(n,t) = h[CE(n,t), ETCI(n,t)] = \varsigma(n,t)\left(\frac{1}{2-\exp[\psi_n ETCI(n,t)]}\right)CE(n,t) \tag{2'}$$

Again, parameters in Equation (2') have been calibrated in order to replicate the base year in the original formulation. Here an increase in *ETCI* progressively reduces the amount of emissions generated by a unit of fossil fuel consumed. Finally, we recognize that R&D spending absorbs some resources.

In order to account for the difference between private and public return to investments in R&D, we follow Popp (2004) and model the positive externality of knowledge creation by assuming that the return on R&D investment is four times higher than the one in physical capital. At the same time, the opportunity cost of crowding out other forms of R&D is obtained by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock for final good production becomes:

$$K_F(n,t+1) = K_F(n,t)\,(1-\delta) + I(n,t) - 4*\lambda*R\&D(n,t)), \tag{8}$$

where λ, the crowding out parameter, represents the percentage of other R&D crowded out by energy R&D.

The optimal dynamic path of all variables of the model is determined by solving an intertemporal optimization problem. Control variables (physical investments, R&D investments and energy demand) are computed within a game-theory framework. Each country plays a non-cooperative Nash game in a dynamic setting which yields an Open Loop Nash equilibrium.

3. CALIBRATION OF THE BASELINE

To further clarify our formulation of endogenous and induced technical change, let us highlight the dynamic interrelationships between the different variables and their role in the model. First of all, let us notice that *R&D* is a control variable, whereas stock of knowledge and cumulated abatement are state variables. Therefore, *R&D* can be used strategically by regulators in each region of the model, whereas *LbD* is an output of the regulator's strategic behavior. This is quite clear at the beginning of the game (see Figure 1). At stage one, only *LbR* through R&D investments occurs. This modifies our index of energy technical change *ETCI* and yields some amount of abatement, i.e. some abatement experience which becomes *LbD*. Both *LbR* and *LbD* then affect *ETCI* in the subsequent stages.

In short, the fundamental driver of technical progress is R&D investment. This induces knowledge accumulation and experience in emission abatement in various regions of the world. In turn, these variables move technology towards a more environment-friendly dynamic path.

Our quite general solution to account for endogenous and induced technical change comes obviously at a cost. Basically, little information to calibrate the model parameters is available. The best strategy we can follow is to calibrate parameters in order to replicate, in the baseline, emissions of the SRES B2 scenario (IPCC, 2000), which are also the baseline emissions in the original RICE 99 model by Boyer and Nordhaus (2000).

Given the high degree of freedom characterizing the calibration process, there exist many distinct baseline models representing different interpretations of what role the exogenous and endogenous components should play in the baseline.

We emphasize this fact by using two versions of the FEEM-RICE v.3, called FAST and SLOW FEEM-RICE. The two versions primarily differ in the value of the learning factor, δ_A, defined as the rate at which accumulation of past abatement becomes effective experience. Therefore, it represents the effectiveness of Learning by Doing. In particular the FAST version of the model assumes a 10% learning factor as opposed to the 5% learning factor of the SLOW version. In addition to this, the two versions of the model differ in the magnitude of the crowding out effect of investment in energy R&D on other research investments, which in turn controls for the profitability of R&D investments. Differences in these two key features imply a substantially different contribution of the exogenous component – the declining trend in carbon intensity ratio, described by $\zeta(n,t)$ in Equation (2')- versus the endogenous component of technical change in the baseline (see Table 3). A comparison of the two versions – also with respect to the original RICE 99 model and with respect to FEEM-RICE without endogenous technical change – is shown in Tables 1 and 2. In particular, the percentage change cumulated in year 2105 with respect to base year 1995, both of the energy intensity and of the carbon intensity ratios are presented.

Notice that, in the original RICE 99 model, technical change was not only exogenous, but was also assumed to display its effects almost exclusively on carbon intensity. By contrast, in our new model, both carbon intensity and energy intensity are modified by the presence of an index of energy technical change, which is

Figure 1. The Structure of Technical Change in FEEM RICE v.3

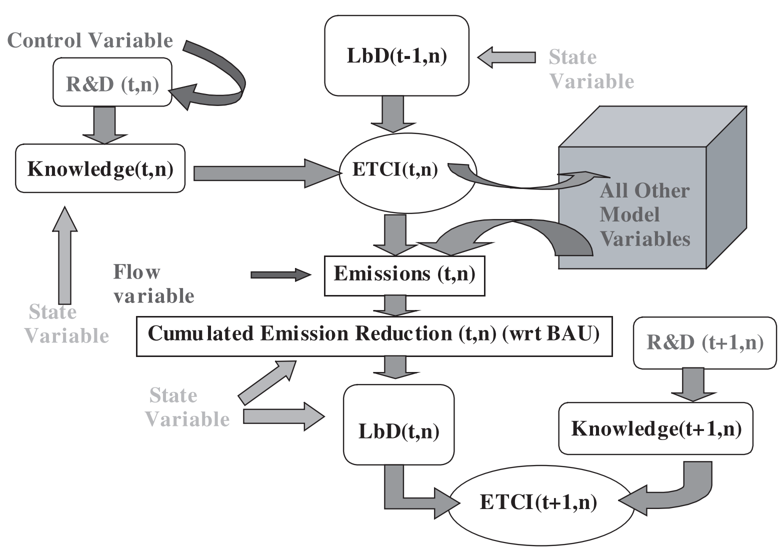


Table 1. Contributions of Different Technical Change Components to Lowering Carbon and Energy Intensity in the FAST Version of FEEM-RICE v.3: 1995-2105 Cumulated Effects

Baseline	Nordhaus RICE 99	FEEM-RICE v.3 with Exogenous TC	FAST FEEM-RICE v.3	FEEM-RICE with only Learning by Researching*
Carbon Energy/Production	-2.74%	-10.59%	-26.92%	-10.79%
Carbon Emissions/Carbon Energy	-66.52%	-40.77%	-66.14%	-49.01%

Table 2. Contributions of Different Technical Change Components to Lowering Carbon and Energy Intensity in the SLOW Version of FEEM-RICE v.3: 1995-2105 Cumulated Effects

Baseline	Nordhaus RICE 99	FEEM-RICE v.3 with Exogenous TC	SLOW FEEM-RICE v.3	FEEM-RICE with only Learning by Researching*
Carbon Energy/Production	-2.74%	-6.83%	-13.76%	-7.13%
Carbon Emissions/Carbon Energy	-66.52%	-51.59%	-59.47%	-54.29%

* The scenario in which we consider only Learning by Researching without any consequent Learning by Doing effect must be considered as a benchmark case in which we set to zero the coefficient relating the amount of cumulated abatement to the dynamics of our index of energy technical change.

Table 3. Exogenous and Endogenous Share of Total Energy Technical Change Measured as the Effect on the Carbon Intensity Index in the Baseline Scenario (1995-2105)

Baseline	Exogenous TC	Endogenous TC
FAST FEEM-RICE v.3	62%	38%
SLOW FEEM-RICE v.3	87%	13%

endogenous and depends on both R&D investments and Learning by Doing effects. The balance between the effect on carbon intensity and the one on energy intensity depends on the parameters β and ψ that have been calibrated to reproduce Boyer and Nordhaus (2000)'s baseline scenario. A careful sensitivity analysis on these two coefficients has been performed. Results are reported below.

In addition, the endogenous component is larger in the FAST version of FEEM RICE v.3 than in the SLOW version (see Table 3). The reason is the enhanced effectiveness of energy technical change in the FAST version, where energy R&D crowds out a smaller amount of other types of R&D and where LbD is faster.

Finally, notice that the effects shown in Table 1-3 refer to the baseline scenario without any stabilization target and/or climate policy. More relevant effects on and of technical change will be shown in the next section where the control variables will be optimized to achieve a stabilization target and to maximize welfare. In this new context, more technical change will become optimal (namely more R&D investments). Therefore, the endogenous component of energy technical change will be integrated by an induced component (which therefore reduces the share of the exogenous component. See Table 4 below). The FEEM-RICE v.3 model enables us to disentangle the three components of technical change and to quantify the induced (additional) R&D investments in new energy technologies that it would be optimal to carry out in order to achieve a given stabilization target.

4. INDUCED ENERGY TECHNICAL CHANGE AND THE COST OF GHG STABILIZATION

The model briefly described in the previous two sections has been used to analyze the economic implications of stabilizing emissions at three different target levels: 450, 500 and 550 ppm in 2100.[4] In this section we present only some of the results that we obtained, with the objective of clarifying the properties of the model more than providing an exhaustive economic and environmental analysis of our optimization runs. Therefore, we will limit our analysis to the SLOW version of the model, which is less optimistic with respect to the future evolution of technical change.

When simulating a scenario with an imposed constraint on carbon concentrations, there will be some additional effort to be undertaken by the central planner of each region in order to limit their share of emissions. We refer to the associated additional technical change as induced technical change.

First of all, let us assess how technical change reacts to the introduction to more stringent policy objective. From Table 4 and from Figure 2, it is clear that more ambitious targets imply an increasing investment in energy R&D and a greater incidence on the endogenous and induced components of energy technical change. In particular, the share of induced technical change becomes 13.8% in the 450 ppm scenario, whereas the endogenous component (including the induced one) doubles with respect to the one in the baseline scenario. In addition, as visible in Figure 2, not only a more stringent constraint on the stabilization level implies increasing cumulated investment in energy R&D, but also the distribution over time of these investments is extremely influenced. While in the case of a 450 ppmv stabilization target a dramatic and immediate increase in investment

4. Let us underline that the model is not a multi gas model and therefore accounts for CO2 emissions only.

Table 4. Exogenous, Endogenous and Induced Share of Total Energy Technical Change Measured as the Effect on the Carbon Intensity Index in the Three Stabilization Scenarios (1995- 2105). SLOW Version of FEEM-RICE v.3

SLOW FEEM-RICE	Exogenous TC	Endogenous TC	Induced TC
450 ppm scenario	74.8%	11.4%	13.8%
500 ppm scenario	75.9%	11.6%	12.5%
550 ppm scenario	79.4%	12.1%	8.5%

Table 5. Endogenous and Induced Share of Total Energy Technical Change Index. Percentage Variation between 1995 and 2105. SLOW Version of FEEM-RICE v.3

SLOW FEEM-RICE	Endogenous TC	Induced TC
450 ppm scenario	24%	76%
500 ppm scenario	29%	71%
550 ppm scenario	37%	63%

in energy R&D would be required, in the other two cases this effect would be procrastinated to later periods (2025).

Our index of energy technical change *ETCI* strongly increases as a reaction to the stabilization target. *ETCI* reaches a peak after the mid of next century as a consequence of the large R&D investments that countries find it optimal to carry out from 2020 to 2050. Even though the model takes into account crowding effects in R&D investments and even though the focus is only on energy R&D and the related knowledge accumulation, the path of technical change which is necessary to stabilize GHG concentrations at 450 ppm seems unlikely to be realistic. Also notice that between 2/3 and 3/4 of the change in *ETCI* is induced by the imposition of a stabilization target (see Table 5). This again shows that R&D investments three of four times larger than those in the baseline would be necessary to achieve a stabilization target.[5]

If we look at costs, the impact of stabilization targets does not seem to be high, at least as far as cost are measured by GDP losses (see, for example, Figure 3 for the more ambitious and costly target). There are two reasons. First, in the model GDP losses are lowered by the positive effects of stabilization on the environment (in our model lower concentrations imply lower GDP losses). Second, losses in terms of consumption are compensated by an increase in investments,

5. In this paper, we use a macro model of the world economy in which there is only one type of energy R&D investment. Therefore, it is not possible to identify which technologies/sectors R&D investments should focus on, or have been channeled to in order to achieve reductions in carbon and energy intensities.

Figure 2. The Dynamics of ETCI in the Three Stabilizations Scenarios. SLOW Version of FEEM RICE v.3

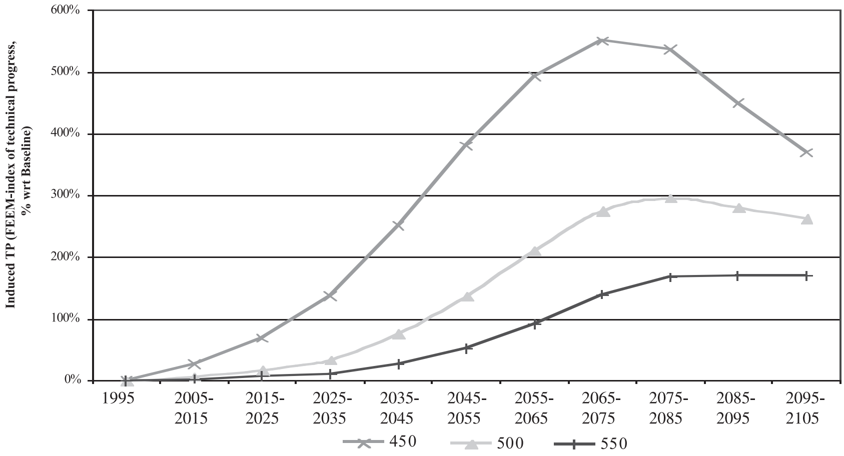
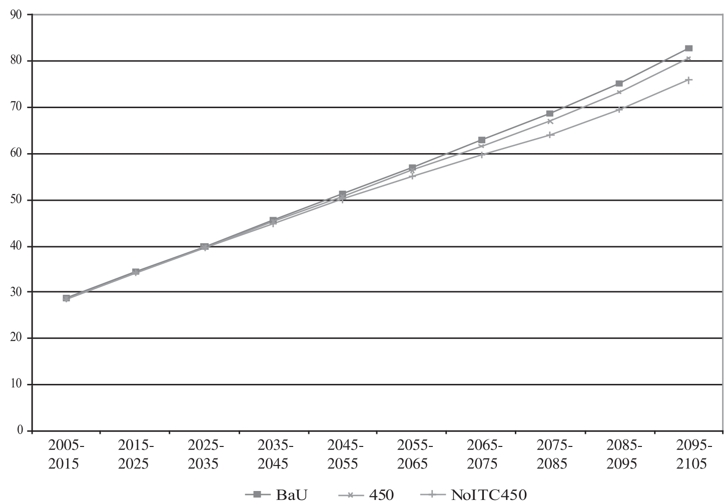


Figure 3. The GDP Cost of Stabilizing GHG Concentrations at 450 ppm with and without Induced Technical Change (1990 USD in MER)



in particular investments in R&D. Similar conclusions can be shown if costs are measured in terms of welfare losses (see Figure 4).

Finally, given the uncertainty on some crucial parameters of the model, we carried out an extensive sensitivity analysis that helped us to check the robustness of the model and of the conclusions that can be derived by using our model. Again, we cannot show all results. We focus therefore on the main

Figure 4. Welfare Cost of Stabilizing GHG Concentrations with and without Induced Technical Change. SLOW Version of FEEM RICE v.3

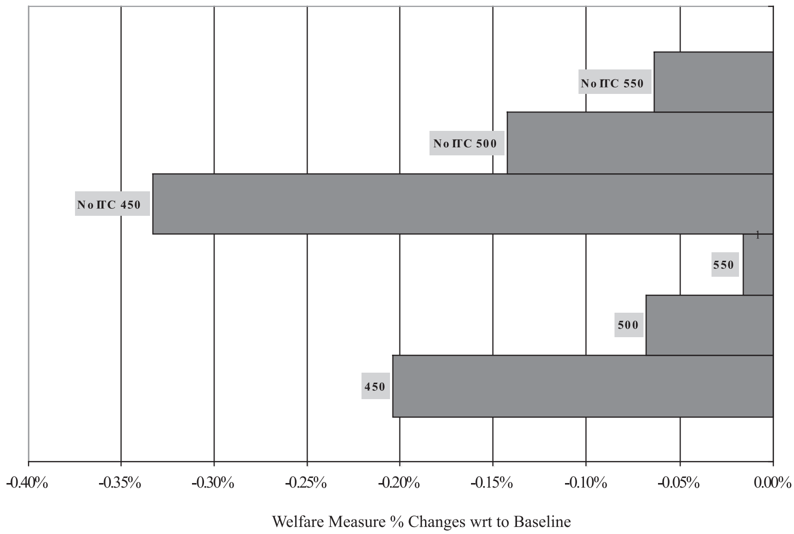
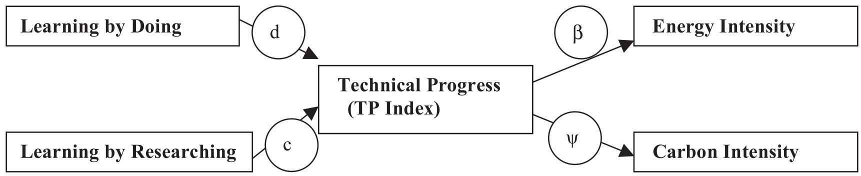


Figure 5. The Crucial Parameters of the Endogenous/Induced Technical Change Model



parameters that define our specification of endogenous technical change. In particular, through the parameter c we control for the role of researching vs. learning in the process of technical change, whereas through the parameters β and ψ we control for the impact of technical progress on energy intensity and carbon intensity respectively (see Figure 5). Again we show results only for the SLOW version of FEEM RICE v.3. The initial values of the main parameters are shown in Table 6 below.

The most important conclusion is the high sensitivity of R&D expenditure with respect to the coefficients β, ψ, c. The less effective is technical change in reducing GHG emissions the higher the increase in energy-related R&D expenditure which is necessary to stabilize GHG concentrations.

Table 6. Initial Parameter Values for the Technical Change Module of the Model

Parameter	β(n)	ψ(n)	c	δ_R	δ_A	δ_B	d
Value	(0.1-0.2)	(0.9-1.2)	0.5	0.05	0.05	0.05	1-c

Extensive sensitivity analysis has been performed on the parameters *β*, *ψ* and *c*. Results are shown in Tables 7-9.

Table 7. Sensitivity with Respect to Energy-Saving Effect Controlling Parameter. Percentage Change Relative to the Central Value Case

β	**- 0.05**	**central value**	**+ 0.05**	**+ 0.1**
Atmospheric concentration of carbon (GTC) in 2100	1.29%	-	-1.30%	-3.18%
Atmospheric temperature (deg C) in 2100	0.94%	-	-1.13%	-2.78%
R&D Expenditure as % of GDP (1990 USD in MER).	-6.75%	-	45.22%	116.05%

Table 8. Sensitivity with Respect to Fuel-Switching Effect Controlling Parameter. Percentage Change Relative to the Central Value Case

ψ	**- 0.4**	**- 0.2**	**central value**	**+ 0.2**	**+ 0.4**
Atmospheric concentration of carbon (GTC) in 2100	2.69%	1.29%	-	-1.16%	-2.21%
Atmospheric temperature (deg C) in 2100	1.86%	0.94%	-	-0.92%	-1.81%
R&D Expenditure as % of GDP (1990 USD in MER).	-15.58%	-6.75%	-	5.18%	9.15%

Table 9. Sensitivity with Respect to Different ETCI Formulations. Percentage Change Relative to the Central Value Case

	c = 0.0	**c =.25**	**central value**	**c = 0.75**	**c = 1.00**
Atmospheric concentration of carbon (GTC) in 2100	-2.52%	-0.90%	-	1.27%	0.27%
Atmospheric temperature (deg C) in 2100	-2.25%	-1.05%	-	1.00%	-0.29%
R&D Expenditure as % of GPD (1990 USD in MER).	-99.77%	-57.39%	-	61.66%	316.60%

5. CONCLUDING REMARKS

In the model presented in this paper, both Learning by Researching and Learning by Doing are explicitly accounted for through an index of energy technical change. Moreover, our index of technical change affects both the relationship between the variables of the macro-dynamic model and energy intensity and the one with carbon intensity. R&D investments induce the developments of environment-friendly technologies through which GHG emission abatement can be undertaken. At the same time, these abatement activities increase experience and produce learning, which enhance the effectiveness of environment-friendly technologies in reducing GHG emissions. The emission reduction takes place through both energy-saving and fuel-switching effects. In the model, the different components of technical change have a differentiated impact on both effects.

The model has been used to assess the economic costs of achieving different stabilization targets. Our results suggest that these costs can be small, if adequate R&D investments can be financed and undertaken. Therefore, models in which technical change is exogenous and/or stabilization targets induce no change in the optimal trajectory of energy-related innovation are likely to overestimate the actual stabilization costs.

An extensive sensitivity analysis with respect to the main parameters of our 2x2 formulation of technical change has been carried out. This sensitivity analysis has shown the robustness of the model when parameters are changed around the calibrated values and the consistency of the results when large changes in the parameters are imposed.

The next steps in our research agenda can be described as follows. It would be useful to extend the model in order to include a non-energy sector, thus making it possible to have a better representation of fuel-switching dynamics. Second, the possibility of a growing effectiveness of carbon sequestration technologies could be accounted for in the model. Finally, and most importantly, stochastic components of the process of technical change – and therefore uncertainty – must be modeled to develop a more realistic analysis of climate policy.

ACKNOWLEDGEMENTS

This paper is part of the research work being carried out by the Climate Change Modelling and Policy Research Programme at Fondazione Eni Enrico Mattei and has been prepared for the Innovation Modeling Comparison Project. Comments from Barbara Buchner, Francesco Bosello and an anonymous referee are gratefully acknowledged. The authors are also grateful to Reyer Gerlagh and Sjak Smulders for useful conversations on how to model technical change. The usual disclaimer applies.

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Mitigation Strategies and Costs of Climate Protection: The Effects of ETC in the Hybrid Model MIND

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MIND is a hybrid model incorporating several energy related sectors in an endogenous growth model of the world economy. This model structure allows a better understanding of the linkages between the energy sectors and the macro-economic environment. We perform a sensitivity analysis and parameter studies to improve the understanding of the economic mechanisms underlying opportunity costs and the optimal mix of mitigation options. Parameters representing technological change that permeates the entire economy have a strong impact on both the opportunity costs of climate protection and on the optimal mitigation strategies e.g. parameters in the macro-economic environment and in the extraction sector. Sector-specific energy technology parameters change the portfolio of mitigation options but have only modest effects on opportunity costs e.g. learning rate of the renewable energy technologies. We conclude that feedback loops between the macro-economy and the energy sectors are crucial for the determination of opportunity costs and mitigation strategies.

1. SETTING THE SCENE

The Innovation Modeling Comparison Project (IMCP) explores the consequences of endogenous technological change (ETC) for the economics of stabilizing atmospheric carbon dioxide (CO_2) concentration. This paper contributes to the IMCP by presenting an analysis of technological change, both at different levels and in different sectors of the Model of Investment and technological Development (MIND). MIND combines an intertemporal endogenous growth model of the macro-economy with sector-specific and technological details taken

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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from the field of energy system modeling. In particular, we explore the impact of endogenous technological change on opportunity costs and mitigation strategies within the framework of a social cost-effectiveness analysis.

We explore the impact of ETC in a social cost-effectiveness framework because we want to understand how technological change is induced by climate policy. Several studies have already incorporated aspects of ETC in this framework (Buonanno et al, 2003; Chakravorty et al, 1997; Goulder and Mathai, 2002; Kypreos and Barreto, 2000; Nordhaus and Boyer, 2000; Nordhaus, 2002; Popp, 2004a; 2004b). The added value of MIND arises mainly from two features. First, we incorporate a wide spectrum of relevant mitigation options, including improvement of energy efficiency, carbon capture and sequestration (CCS), renewable energy technologies, and traditional non-fossil fuels (exogenous time series for large hydropower and nuclear). Second, technological change in MIND has an endogenous formulation with R&D investments in labor and energy productivity, learning-by-doing, and vintage capital in the different energy sectors. We believe that including these features of ETC is essential for the assessment of macro-economic mitigation costs and the portfolio of mitigation options. MIND is a hybrid model merging features from bottom-up and top-down models. It resembles a bottom-up model because it comprises several energy sectors. However, compared to energy system models, the technologies are represented at a more aggregated level. In MIND, these sectors are embedded within a macro-economic environment, in order to evaluate the feedbacks between the macro-economy and the energy sector (see Manne et. al. 1995 for an example of a similar exercise). We will show that these feedbacks are crucial for an understanding of opportunity costs and mitigation strategies in an economy faced with climate policy.

The next section briefly introduces the model and its calibration, highlighting the improved treatment of CCS in MIND 1.1. Section 3 discusses technological change within MIND, forming the main part of this paper. Section 4 draws conclusions.

2. THE MODEL STRUCTURE OF MIND 1.1

The model equations of MIND are introduced and discussed in Edenhofer, Bauer and Kriegler (2005). The model version 1.0 presented therein has been extended by Bauer (2005), to replace exogenous scenarios of Carbon Capture and Sequestration (CCS) with a technologically detailed, endogenous treatment of the CCS option (model version 1.1). This study uses MIND 1.1, adapted slightly to meet the requirements of the IMCP, and enhanced by a more sophisticated carbon cycle (Hoos et al. 2001). The following section provides a summary of the model structure and parameter calibrations. Model equations are restricted to the parameters treated in the sensitivity analysis and parameter studies in this article; for a comprehensive discussion of the model structure we refer to Edenhofer et al. (2005) and Bauer (2005).

MIND is an integrated assessment model comprising a model of the world economy drawing specific focus on the energy sector, and a climate module computing global mean temperature changes. MIND therefore allows us to assess the impacts of constraints to climatic change on the economy in cost-effectiveness analysis.

MIND models economic dynamics by adopting an endogenous growth framework. It calculates time paths of investment and consumption decisions that are intertemporally optimal. The objective is to maximize social welfare, defined as the present value of utility (pure rate of time preferences is 1%), which is a function of per capita consumption exhibiting diminishing marginal utility. Most economic activity is subsumed in an aggregate CES production function (equation 1), the output Y_A of which describes the gross world product (GWP).[1]

$$Y_A = \phi_A[\xi_A^L(A * L_A)^{-\rho_A} + \xi_A^E(B * E)^{-\rho_A} + \xi_A^K \mathrm{K}_A^{-\rho_A}]^{-1/\rho_A} \quad (1)$$

The income share related parameters ξ_A are calibrated so that the actual income shares of labor L_A, energy E, and capital K_A relate to each other at the ratio of 66:4:30. Total factor productivity Φ_A is a fixed scalar calibrated to a value where the historical output of 2000 is reproduced. The elasticity parameter ρ_A determines the elasticity of substitution $\sigma_A = (1+\rho_A)^{-1}$. In some integrated assessment models, the elasticity of substitution between capital and energy is 0.4 for developed countries and 0.3 for developing countries (Manne et al, 1995). We have chosen an overall elasticity of substitution for all three factors of $\sigma_A = 0.4$. Labor L_A is described by an exogenous population scenario adopted from the common POLES/IMAGE baseline (CPI, Vuuren et al. 2003). Capital stock K_A is built up through investments and depreciates at a rate of 5 %. The initial value of K_A is derived from Y_A and an estimated capital coefficient. Capital coefficients were computed from the OECD database and from PWT6.1 for different countries. Their values agglomerate around 2.5. Since energy sector capital is separate from K_A, we assume a lower capital coefficient of 2.0. Variables A and B denote the productivities of labor and energy, respectively, and are stock variables determined by R&D investments according to equation (2):

$$\frac{\dot{A}}{A} = \alpha_A \left(\frac{RD_A}{Y} \right)^{\gamma_A}, \qquad with\ A(t = \tau_1) = A_0 \quad (2)$$

$$\frac{\dot{B}}{B} = \alpha_B \left(\frac{RD_B}{Y} \right)^{\gamma_B}, \qquad with\ B(t = \tau_1) = B_0 \quad (3)$$

RD_A and RD_B are investment flows controlled by the central planner. The parameters γ_A and γ_B (where $0<\gamma_A<1$. $0<\gamma_B<1$) model the decreasing marginal productivity of R&D investments. They are assumed to take the values of 0.05

1. MIND is implemented in discrete time steps of 5 years. In the model equations of this text we present the more intuitive continuous formulations, e.g. in case of derivatives.

and 0.1, respectively. Parameters α_A and α_B determine the productivity of R&D investments. They are calibrated at a rate such that spending 1 % of the GWP on energy R&D increases the energy efficiency parameter by 2.25 %; when 2.5 % of GWP is spent on labor R&D, the labor efficiency parameter increases by 2 %.

The energy input to aggregate production, E, is an additive composite of fossil energy, renewable energy, and traditional non-fossil energy, with the latter given exogenously. Fossil energy is produced from energy conversion capital and primary energy input in a CES production function. Fossil resources are converted to primary energy using an exogenous assumption about the carbon/energy ratio of the fossil fuel mix, its availability being described by a model of resource extraction. Resource R is extracted by capital K_{res}, the average productivity of which is subject to a scarcity effect ($\kappa_{res,s}$) and a learning-by-doing effect ($\kappa_{res,l}$):

$$R = \kappa_{res} K_{res} \tag{4}$$

$$\kappa_{res} = \kappa_{res,s}\, \kappa_{res,l} \tag{5}$$

The initial resource extraction is $R = 6.4$ GtC (SRES), assumed to be produced by a capital stock of $K_{res} = 5$ trillion \$US. This determines $\kappa_{res,l}$ because $\kappa_{res,s}$ is normalized to unity.

The scarcity effect $\kappa_{res,s}$ is determined by the marginal costs of resource extraction C_{res}^{mar}:

$$\kappa_{res,s} = \frac{\chi_1}{C_{res}^{mar}} \tag{6}$$

In equation 6, parameter χ_1 as well as the marginal costs in 2000 are set to \$113. During the simulation, marginal costs C_{res}^{mar} increase with cumulative resource extraction CR_{res} according to equations 7 and 8.

$$C_{res}^{mar} = \chi_1 + \chi_2 \left(\frac{CR_{res}}{\chi_3} \right)^{\chi_4} \tag{7}$$

$$CR_{res}(t) = \int_{\tau_1}^{t} R(t')dt', \text{ with } CR_{res}(t = \tau_1) = 0 \tag{8}$$

Parameter χ_1 denotes initial costs of the fossil resource, the exponent χ_4 captures the curvature of the function (i.e. the timing of increasing costs), and χ_2 gives the marginal costs once the amount described by χ_3 has been extracted. We parameterize this function according to Rogner's (1997) empirical assessment of world hydrocarbon resources, and arrive at the values $\chi_2 = 700$, $\chi_3 = 3500$ and $\chi_4 = 2$.

The learning-by-doing effect of capital productivity $\kappa_{res,l}$ depends on the ratio of actual resource extraction $E_{res,l}$ to initial resource extraction $E^0_{res,l}$.

$$\dot{\kappa}_{res,l} = \frac{\kappa_{res,l}}{\tau_{res,l}\,\kappa^{max}_{res,l}}(\kappa^{max}_{res,l} - \kappa_{res,l})\left(\left[\frac{E_{res,l}}{E^0_{res,l}}\right]^{\beta_{res,l}} - 1\right) \tag{9}$$

$$with \;\; \kappa_{res,l}(t = \tau_1) = \kappa^0_{res,l}$$

The factor $\beta_{res,l} = 0.4$ dampens the learning-by-doing effect: a rapid increase in extraction induces a loss in productivity gains relative to the same increase in extraction spread over a longer time period. Furthermore, productivity gains from learning saturate when productivity approaches its maximum value $\kappa^{max}_{res,l}$ which is set to twice its initial value. Parameter $\tau_{res,l}$ determines the speed of learning and is set to 100 years.

Renewable energy E_{ren} is produced by capital Kap_{ren} which is employed at $FLH_{ren} = 2190$ full load hours per year.

$$E_{ren}(t) = FLH_{ren} * Kap_{ren}(t) \tag{10}$$

$$Kap_{ren}(t) = \int_{t_0}^{t} \omega(t - t')\,\kappa_{ren}(t')\,I_{ren}(t')dt' \tag{11}$$

The available renewable energy capital stock in each point in time is determined by summing over the investments into renewable energy I_{ren} in preceding time steps multiplied with the productivity of installed capital κ_{ren}. Depreciation is modeled by weights ω which determine the fraction of capital that still remains. ω_1 to ω_7 are set to 1.0, 0.9, 0.8, 0.7, 0.5, 0.15, 0.05, and $\omega_i = 0$ if $i > 7$. This allows to model different capital productivities for different vintages of the capital stock. Capital productivity κ_{ren} indeed changes in time because the costs of renewable energy equipment c_{ren} decrease, subject to learning-by-doing.

$$\kappa_{ren} = \frac{1}{c_{ren}(t) + c_{floor}} \tag{12}$$

The inverse of floor costs $c_{floor} = 500$ US\$/kW constrains capital productivity from above, while c_{ren} starts out at $c_{ren} = 700$ US\$/kW and decreases with cumulative installed capital $CKap_{ren}$:

$$CKap_{ren} = \int_{\tau_0}^{t} Kap_{ren}(t')dt' \tag{13}$$

The following equation describes the dynamics of learning-by-doing in the renewable sector:

$$c_{ren,t} - c_{ren,t-1} = c_{ren,0}\,CKap^{-\mu_{ren}}_{ren,0}\,(CKap^{-\mu_{ren}}_{ren,t} - CKap^{-\mu_{ren}}_{ren,t-1})$$

$$\times \left(\frac{CKap_{ren,t-1}}{CKap_{ren,t}} \right)^{\beta_{ren}} \tag{14}$$
$$with\ c_{ren}(t = 0) = c^0_{ren},$$

The learning parameter μ_{ren} determines the learning rate *lr* and reflects a learning rate of 15 %, i.e. investment costs decrease by 15 % with every doubling of cumulative installed capacity. Parameter β_{ren} within the last factor of the right hand side of the equation causes a dampening similar to $\beta_{res,l}$ in the learning-by-doing equation of the fossil resource extraction (equation 9). Set to $\beta_{ren} = 0.4$, it prevents learning that is too fast.

There are three sources of carbon dioxide emissions: fossil fuel combustion, leakage from sequestered CO_2, and emissions from land-use and land-use change. The latter are described by an exogenous time series. Since fossil resources are measured in tons of carbon, resource use *R* and emissions *Em* coincide, except for land-use emissions and Carbon Capturing and Sequestration (CCS):

$$Em(t) = R(t) + LULUC(t) - R_{cap}(t) + LEAK(t), \tag{15}$$

where R_{cap} denotes the amount of CO_2 captured in a given year and *LEAK* denotes leakage.

CCS is modeled as a chain process distinguishing six steps: CO_2 is captured at point sources (1) and transported via pipelines to sequestration sites (2). There, the CO_2 needs to be compressed (3) before it is injected into the sequestration site (4). Then, it either remains in the site (5) or leaks into the atmosphere (6). Processes 1-4 are capital intensive and are modeled as capital stocks representing available capacities for the individual processes. Capacities are built up by investments according to the following equation:

$$K_{pq}(t) = \int_{t_0}^{t} \omega_q(t - t')\, \iota^{-1}_{pq}(t')\, I_{pq}(t')dt' \tag{16}$$

Variables K_{pq} denote the capacities, index *p* denotes the process step, and the index *q* denotes different investment alternatives such as one of five distinct capture technologies or one of six distinct sequestration alternatives. Weighting parameters ω introduce a depreciation scheme for different vintages of the capital stocks, similar to equation (11) in case of renewable energy. Investments are denoted I_{pq} and the investment costs are ι_{pq}. Investment costs for capturing capacity range from ~100 \$US/tC to ~450 \$US/tC depending on the specific capture technology. When the productivity of CCS investments is varied in parameter studies later on in this paper, the same relative change is applied to the investment costs for each technology.

In addition to the limitation inflicted by the necessity to build up capacity, the amount of carbon that may be captured is limited by a static and a dynamic constraint. The static constraint limits the amount of carbon which can be captured from a large power plant as a fraction of the resource use in the business-as-usual scenario. The dynamic constraint defines an upper limit of investments into the specific capture technologies in each period. The upper limit is defined as a share of the investments in the power generation sector. The rationale is that the capability of retrofit investments in large power plants depends on the total amount of investments undertaken in the power generation sector.

The injection of CO_2 into particular sequestration sites demands two types of facilities: compressors and injection wells (steps 3 and 4). The modeling approach takes into account that both facilities demand investments and secondary energy. In steps 5 and 6, the modeling approach considers the capacity constraint of each sequestration alternative *j* and leakage of sequestered carbon: Leakage is described by a rate, and the capacity of each sequestration alternative is the upper bound for the cumulative amount of CO_2 that is injected into each sequestration alternative.

3. THE ROLE OF ENDOGENOUS TECHNOLOGICAL CHANGE IN MIND

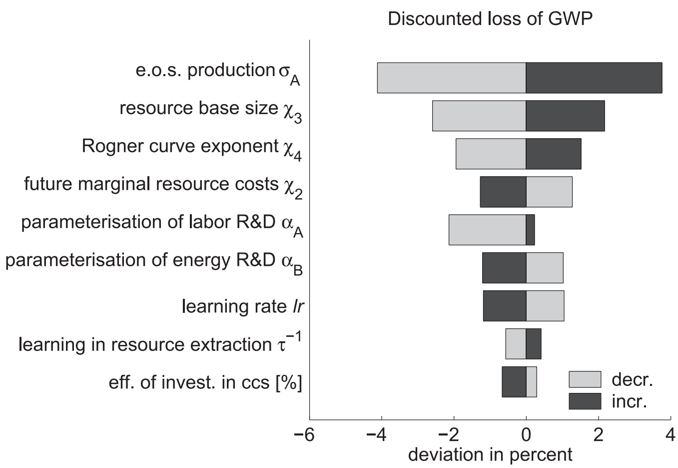
In what ways does endogenous technological change matter in policy scenarios computed with MIND? In the following sections, we explore this question using sensitivity analysis and miscellaneous parameter studies (see Bauer et al, 2005 for initial parameter studies with MIND). In the sensitivity analysis, we rank important technology-related model parameters according to their influence on two model outputs: the opportunity costs of climate protection and the mix of options used for CO_2 mitigation. We then study the effect of parameter variations on the same model outputs and analyze the underlying economic dynamics. All model runs stabilize atmospheric CO_2 concentration level at 450 ppm.

3.1 Local Sensitivity Analysis

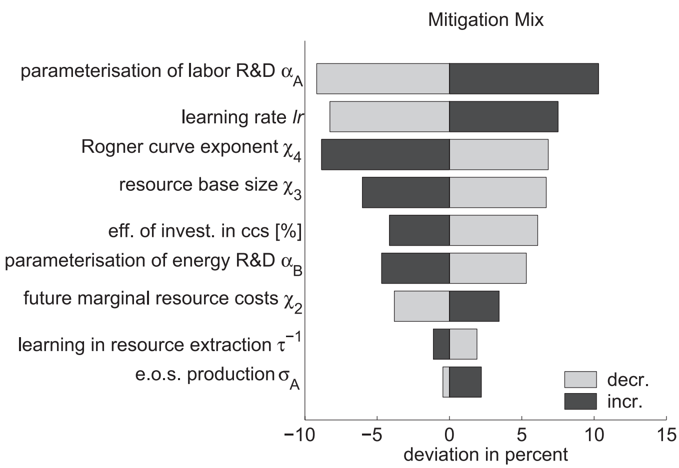
Figure 1a and 1b show the influence of important parameters of MIND on opportunity costs of climate policy (1a) and on the mix of mitigation options (1b). The former are measured as losses of gross world product (GWP), accumulated from 2000 to 2100 and discounted to present value at a rate of 5 %, relative to the business-as-usual scenario. The latter is represented by the ratio of the two dominant options, renewable energies and CCS, where a ratio of unity implies that the same amount of CO_2 reductions may be attributed to each of the mitigation options. Parameter influence is measured by the response of the model to a 5 % variation of the parameter. Taking the set of parameters from the model calibration as the starting point, we vary one parameter at a time, hence the effects reflect local sensitivity. As local sensitivity analysis assesses parameter sensitivity at only one point in parameter space it neglects the fact that sensitivities may vary tremendously at other points in parameter space. Using a measure of global sensitivity, i.e. a measure that takes into account simultaneous variation of several parameters, is preferable as it provides a remedy to this shortcoming.

Figure 1. Sensitivity Analysis

1a.



1b.



Figures 1a and 1b show the influence of important technological parameters on opportunity costs and mix of mitigation options, respectively. Metric is the deviation of the output in response to an up to 5% increase (decrease) of the parameter. The parameter "e.o.s. production" refers to the elasticity of substitution σ_A in aggregate industrial production, i.e. production of the gross world product.

However, local sensitivity analysis is used in this paper for the following two reasons. Firstly, the model response to a change in a single parameter, *ceteris paribus* , is an intuitive measure. Secondly, the computational burden for a local analysis is much lower. To emphasise, while this analysis sheds light on the influence of parameters and the potential influence of their uncertainties on model results, we do not explicitly test parameter uncertainties. Therefore, we make no statements about the relative importance of parameters in contributing to the uncertainty of computed results, but rather, about the ir potential to impact results themselves.

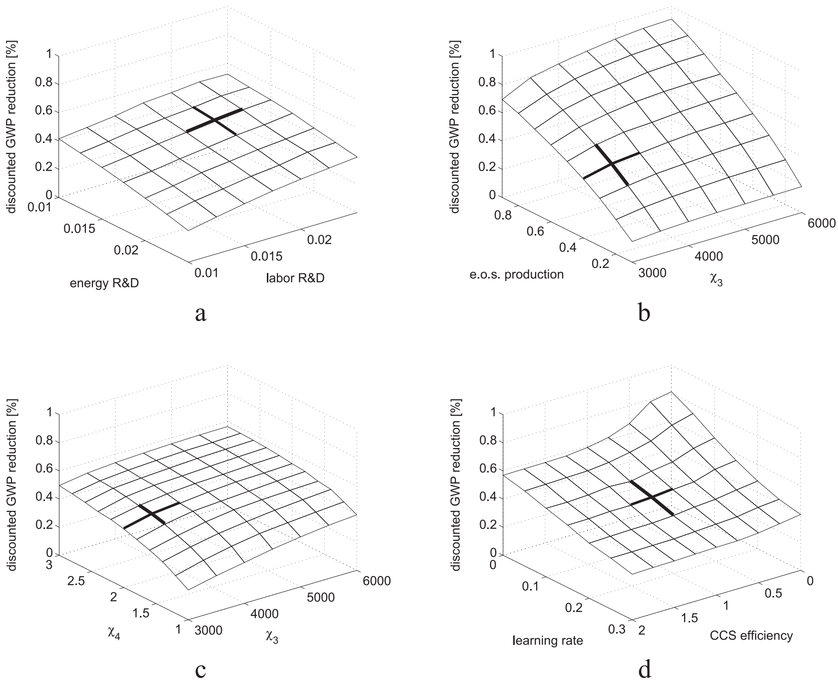
As Figure 1a indicates, the greatest influence on opportunity costs is exerted by the elasticity of substitution σ_A, followed by the parameters describing the availability of fossil resources, and the effectiveness of R&D investments in labor productivity. The latter and the top three parameters have a positive effect on costs, i.e. costs increase with the parameters, whereas the assumption of high marginal future fossil resources costs have a negative effect. Productivity of energy efficiency R&D and the learning rate of the renewable energy technologies rank next, followed by two more sector specific parameters, the learning parameter in fossil resource extraction and the efficiency of investments in CCS. Overall, the relatively small responses of the model to parameter variations (less than 5%) improves the confidence in the robustness of the computed opportunity costs. In the next two sections we will explore the reasons for this observation, and evaluate the role of technological change in deriving these results.

Figure 1b depicts the influence of parameters on the mix of mitigation options. It is immediately evident from a comparison between Figure 1a and Figure 1b that the ranking of parameters has changed. Most notably, the elasticity of substitution has dropped to the bottom rank, and two resource related parameters, χ_2 and χ_3, also emerge to fall in ranking. Conversely, the parameterization of labor R&D, the learning rate of renewable technologies, and the efficiency of CCS investments have risen in the hierarchy. Overall, the mitigation mix is more sensitive (with variations up to 10 %) than the mitigation costs in Figure 1a. This result comes as no surprise. Since GWP losses are closely related to social welfare, the maximization of which is the objective of MIND, GWP loss is deliberately kept to a minimum. The mix of mitigation options, on the other hand, is endogenously determined to minimize costs. It is intuitive that a change in the parameter values alters the competitiveness of mitigation options, hence its impact on the mitigation mix is significant.

3.2 Determinants of the Opportunity Costs

This section takes a closer look at the opportunity costs of climate protection. We present parameter studies varying two parameters simultaneously. This enables us to discuss the effects of varying these parameters, as well as analyzing the interdependencies between them, hence taking a first step beyond a local sensitivity analysis presented in Section 3.1. To an extent, this analysis remains very much local in character since many parameters remain fixed at their default levels. However, restricting the variation to two parameters at a time enables an intuitive graphical presentation of the results, which provides deeper and useful insights into the workings of MIND.

Figure 2. Parameter Studies of Mitigation Costs



Figures in this panel show discounted gross world product loss (discount rate is 5 %) for several parameter studies. In figure 2a, energy R&D and labor R&D refer to the productivity of investment into research that enhances the efficiency of the corresponding factor. In 2b, e.o.s. production refers to the elasticity of substitution in the aggregate industrial production sector. Parameters χ_3 and χ_4 in figure 2b and 2c refer to the size of the fossil resource base and the exponent of the Rogner curve, respectively. Figure 3d treats the learning rate of renewable technologies and the efficiency of investments in CCS technology. The pairs of default parameter values are indicated with a bold cross.

We start out by taking a look at the engine of endogenous growth in MIND: R&D investments that drive labor and energy efficiencies. Figure 2a displays the productivity of these investments. While the two parameters are similar with respect to the process they describe – accumulation of a knowledge stock increasing the productivity of an input factor to aggregate production – their effects on opportunity costs are contrary. An enhanced effectiveness of labor productivity R&D raises costs, while better energy efficiency R&D reduces GWP losses. This is due to opposite effects on the mitigation gap, i.e. the discrepancy of CO_2 emissions between business-as-usual and climate policy scenarios. More effective labor R&D stimulates additional economic growth and implies higher CO_2 emissions in the baseline. More effective energy R&D investments, on the other hand, facilitate much better energy efficiency in the baseline, and hence lowers CO_2 emissions.

The mitigation gap characterizes the challenge for the economy facing climate protection goals and manifests itself in the opportunity costs.

Figure 2b compiles two parameters with an effect of the second type: the elasticity of substitution in the aggregate production sector, and the estimated size of the available fossil resources. Figure 2b shows that costs increase with the elasticity of substitution. This too can be attributed to baseline effects: higher elasticity of substitution implies a more flexible production technology which induces higher economic growth in the business-as-usual scenario. Therefore, achieving 450 ppm requires a substantial departure from the baseline and is relatively costly. A variation of the resource base has a bigger impact on the mitigation costs if the elasticity of substitution is relatively high. Low values of the elasticity of substitution hinder economic growth and consequently imply a lower demand for energy. At low energy demand, relaxing the scarcity of the resource has a smaller effect. In general, a larger resource base allows higher economic growth in the business-as-usual case. When climate policy constrains resource use, it devaluates exhaustible resource as an economic asset and diminishes the rent income of their owners. The loss of rent income increases with the resource base because a relatively cheap and abundant resource can no longer be used as input in production.

We take yet a closer look at the fossil resource base. Figure 2c studies the variation of the size of the resource base χ_3 and parameter χ_4. Parameter χ_4 as well as the resource base are proxy variables for the technological progress in the extraction sector. Increasing χ_3, i.e. assuming more abundant resources, results in cheaper short to medium term supply of the fossil resource. Increasing χ_4 trades a slow and steady increase of the marginal costs for a steeper increase at a later time – thus making the resource cheaper and more easily available in the short to medium term. High values of χ_4 allow higher economic growth in the business-as-usual case and induce a relatively large mitigation gap. For high values of χ_4 the marginal costs of extraction are essentially constant. Under this condition, an increased resource base has moderate impact on macro-economic mitigation costs. For low values of χ_4, an increased resource base has a slightly higher impact on the macro-economic costs because marginal improvements in extraction already increase the shadow price of the resource. This parameter study shows that climate protection becomes relatively costly if there is a high rate of technological progress in the exploration and extraction of fossil fuels. Accelerated technological progress in the extraction sector makes climate policy more costly, because such policy devaluates assets (resources and capital stock in the corresponding sectors). Therefore, special attention ought to be paid to assumptions about resource availability and their uncertainties.

Contrary effects can be observed if technological progress decreases the costs of mitigation technologies. The impact on opportunity costs is shown in Figure 2d. We explore two parameters which are both closely related to mitigation options: the efficiency of investments into Carbon Capture and Sequestration technologies (CCS) and the learning rate of renewable energy technologies.

Varying these two parameters shifts the competitive advantage between the two mitigation options and, consequently, the extent to which they are used. It turns out that the efficiency of CCS investments has no strong impact on the overall opportunity costs if the learning rate of renewable energy technologies is relatively high. The reason is that renewables are modeled as a backstop technology, i.e. as a carbon-free energy source, and need no non-reproducible input for energy production. In contrast to the renewables, CCS investments only bridge from the fossil fuel age to a carbon-free era. CCS makes the transition of the energy system smoother but has severe limitations if fossil fuels become more costly because of increasing marginal extraction costs at the end of the 21st century. At the same time, renewable energy becomes cheaper because of learning-by-doing. It is plausible that this effect cannot be altered by high efficiencies of CCS investments. At low learning rates of the backstop technology, CCS becomes more important.

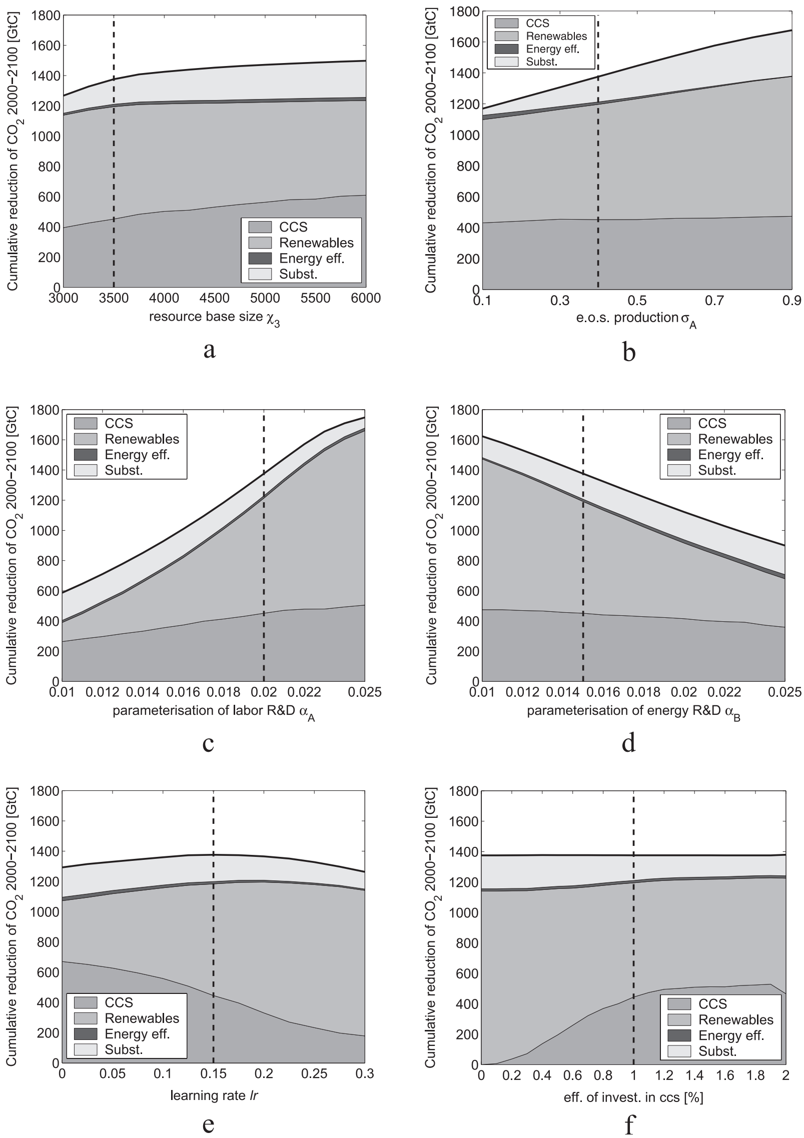
3.3 Mitigation Strategies

In this section we analyze the impact of the same parameters explored in the previous section on the option portfolio of an optimal mitigation strategy. Mitigation options are compared on the basis of the amount of CO_2 that they enable the economy to reduce. For the CCS option, this is straightforward: it is simply the amount of captured and sequestered CO_2 (less the amount that leaks from the sequestration site). In case of energy related mitigation options, i.e. renewable energy and energy efficiency improvements, the corresponding amount of "mitigated CO_2 emissions" was derived from the equivalent amount of energy from fossil fuels. In , the degree of efficiency on converting primary into final energy is determined endogenously in the production function of the fossil sector. In this ex post analysis, however, we estimate the "equivalent" amount of fossil energy by assuming a fix coefficient. The remaining mitigation options, namely energy savings by substitution of energy at the levels of energy transformation and aggregate production, are visualized as the difference to the total reduction of CO_2.

Figure 3a shows that the amount of CCS within the portfolio of mitigation options increases with the assumed resource base. The cumulative amount of CO_2 reduced by renewables within the next century decreases, energy efficiency remains constant and energy savings increase. An increasing resource base implies increasing rents for the owners. This increasing rent income makes CCS a more profitable option. Due to high economic growth and relatively cheap fossil fuels, the return on investment in renewables falls short of the returns on CCS investments.

In figure 3b, energy savings (reduction of energy consumption by substituting energy by capital in different sectors) become more profitable if the elasticity of substitution increases; at the same time, the importance of energy efficiency decreases.

Figure 3. Parameter Studies of Mix of Mitigation Options



Figures 3a-f show how the mix of mitigation options varies in parameter studies. CO_2 reductions caused by avoiding the use of fossil fuels (renewable energy, energy efficiency improvements, and substitution) are estimated from the alternative use of fossil fuels. Dashed lines indicate the default parameter value.

A more surprising result is obtained in figure 3c and 3d. In figure 3c an increasing productivity of R&D investment in labor enhancing activities also increases the share of renewables in the mitigation portfolio. The explanation is as follows: economic growth induces additional energy demand that is met by carbon-free technologies. Due to high economic growth, marginal extraction costs of fossil fuels increase sooner, and thus CCS is less competitive compared to renewables. In contrast, when R&D investments in energy efficiency become more productive, the mitigation gap shrinks, and the share of renewables within the mitigation portfolio decreases (3d). Interestingly, changes in the productivity of energy R&D investments affect the baseline rather than providing a more attractive mitigation option. In this study, the energy efficiency parameter varies from 63 to 245 % of its regular value in 2100 in the baseline, the latter implying that energy use in 2100 is decreased by 60%. Climate policy, however, only induces 0.4 to 2.7 % additional increases of the efficiency parameter. To sum, higher energy efficiency and a lower baseline for economic growth reduce the demand for renewables. The importance of the renewable energy option depends heavily on the underlying economic growth path.

As figure 3e shows, high learning rates in the renewable energy sector reduce the optimal amount of CCS substantially. In that sense CCS can be seen as a joker-option if the learning rate of the renewables is relatively low. It is also remarkable that energy savings are less important when the learning rate is relatively high because the energy demand can be met by the carbon-free renewables. Learning-by-doing reduces the price of electricity produced by renewables and increases the demand for renewables which reduces their costs further. This feedback loop makes CCS less important. As figure 3f indicates, this effect can be counteracted by an increasing efficiency of CCS-investments.

4. CONCLUDING REMARKS

In what ways does technological change matter? Our analysis shows that technological change works in two "directions": we identify technological progress that permeates the entire economy and technological progress that is restricted in its effects to a single sector. Examples for such sector-specific technological change are learning-by-doing effects associated with renewable energy technologies and resource extraction, as well as technological progress in CCS, here modeled via its investment efficiency. In , parameters associated with such sector specific technological change have a significant impact[2] on the optimal mix of mitigation options. For example, an increased learning rate increases the share of renewables, and improved investment efficiency in CCS increases the share of CCS within the entire portfolio of mitigation options (Figures 1b and

2. We refer to the impact of a parameter in terms of a relatively large potential influence, i.e. a large sensitivity of results to changes of this parameter. Recall, however, that the actual uncertainty about parameters is not taken into account.

3ef). However, these parameters are less important in determining the overall opportunity costs of climate protection which measure the impact on the overall economy (Figure 1a).

In contrast, there is technological change with significant impact on the macro-economic growth process, evident in its influence on opportunity costs. Such technological change is described by parameters of the macro-economic environment, like the elasticity of substitution, and the parameters characterizing the effectiveness of labor- and energy R&D investments. Labor R&D investments in particular have a strong influence on macro-economic growth as well as the mix of mitigation options. Progress in resource extraction is an example of sector-specific technological change with a macro-economic impact. This progress is characterized by the parameters of Rogner's scarcity curve and has been shown to exert a significant influence on opportunity costs. The most prominent effect of these parameters is their impact on the baseline.

We conclude that feedbacks between the macro-economy and the energy system are crucial for determining mitigation costs and the development of the mitigation portfolio in time. The case of technological change in resource extraction shows how sector-specific processes may exert significant influence on the macro-economy, while the impact of labor R&D productivity on the share of renewable energy is an example of macro-economic influence on a distinct sector.

This has strong implication for policy. A sector-specific policy that fosters technological change in the extraction sector induced by increasing prices in the oil or gas market would increase the opportunity costs of climate protection. A policy that increases the economy-wide energy efficiency in all energy related sectors would reduce the costs of climate protection substantially. Enhancing technological change in the extraction sector makes sense, if decision makers intended only to increase energy security. Analysis here highlights that the impact of such a policy on the opportunity costs of climate protection must also be taken into account.

The results presented here indicate that partial-equilibrium models omitting intertemporal and inter-sectoral aspects can be misleading for designing a climate and energy policy. Thus, they stress the utility of hybrid models incorporating endogenous technological change at the sector level as well as at the macro-economic level. Moreover, hybrid models pose a coherent framework not only for the assessment of the opportunity costs and portfolios of mitigation strategies, but also for the design of climate and energy policy instruments.

ACKNOWLEDGEMENTS

We are grateful to Elmar Kriegler for productive discussions and helpful comments on earlier version of this paper. This work was funded by the Volkswagen Foundation, Project II/78470, which we gratefully acknowledge.

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ITC in a Global Growth-Climate Model with CCS: The Value of Induced Technical Change for Climate Stabilization

*Reyer Gerlagh**

We assess the effect of ITC in a global growth model, – DEMETER-1CCS – with learning-by-doing, where energy savings, energy transition and carbon capturing and sequestration (CCS) are the three main options for emissions reductions. The model accounts for technological change based on learning by doing, embodied in capital installed in previous periods. We run five scenarios: one baseline scenario with no climate change policy and four stabilization scenarios in which atmospheric CO_2 concentrations are stabilized at 550, 500, 450, and 400 ppmv. We find that the timing of emissions reductions and the investment strategy is relatively independent of the endogeneity of technological change. More important is the vintages' structure of production. ITC does reduce costs by approximately a factor of 2, however, these benefits only materialize after some decades.

1. INTRODUCTION

Until recently, most economic assessments of climate-change policies neglected effects on economic performance through policy-induced technological development. This omission was in some ways not surprising, given the substantial gap in the understanding of determinants for both the level and direction of technological change. Although analysis of technological change induced by prices changes in factors of demand has been made as early as the 1960s (e.g. Kennedy 1964), it was not until the 1990s that the topic attracted wide debate.

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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In recent years, a stream of so-called endogenous-growth models have been developed, describing cumulative knowledge as a major determinant of long-term economic growth (Aghion and Howitt, 1992; Mankiw, 1995). Environmental economics has applied insights from the macro-economic literature on aggregate growth to build theoretic models of innovation in relation to environmental policy (Gradus and Smulders, 1993; Bovenberg and Smulders, 1995, 1996; Verdier, 1995; Beltratti, 1997; Smulders, 1999; Goulder and Mathai, 2000; Carraro et al, 2003; Smulders and de Nooij, 2003; Nakada, 2004). Notably, there have been wide applications of these insights to economic models that assess the interplay between energy use, climate change, climate policy and technological change (Carraro and Galeotti, 1997; Goulder and Schneider, 1999; Nordhaus, 2002; Manne and Richels, 2002; van der Zwaan *et al*, 2002; Gerlagh and van der Zwaan, 2003, 2004; Buonanno et al, 2003; Popp, 2004; Gerlagh, 2004; Gerlagh et al; 2004, Gerlagh and Lise, 2005).

Analysis of this kind commonly finds the inclusion of technical change decreases costs of emission reductions. How substantial these cost reductions are, compared to an analysis without induced technological change (ITC), remains a subject for debate (Fischer and Morgenstern, 2003; Goulder, 2004). Some authors suggest that ITC substantially cuts costs (Manne and Richels, 2002, Gerlagh and van der Zwaan 2003) or even renders a double dividend by having positive impact on both income and the environment (Carraro and Galeotti, 1997). In contrast, the others are more pessimistic and claim that ITC has a relatively small impact relative to that of factor substitutions for a given technology (Goulder and Schneider, 1999; Nordhaus, 2002). This paper contributes to the latter literature, assessing the effect of ITC in a global growth model with learning-by-doing, where energy savings, energy transition, and carbon capturing and sequestration (CCS) form the main options for emissions reductions. We specifically assess the required investments portfolio in fossil fuel, non-carbon energy sources and CCS to reach various stabilization targets, and its relation to enhanced learning.

The outlay of the paper is as follows. In Section 2, we present our model, DEMETER-1CCS. It is a growth model with learning-by-doing for fossil fuels and non-carbon energy, containing a decarbonisation option through CCS, and a simple climate module. The model is an extension of the DEMETER model used widely for climate change policy analysis (van der Zwaan et al, 2002; Gerlagh and van der Zwaan, 2003, 2004; Gerlagh et al, 2004). This section presents the primary equations. Welfare and profit functions and first order conditions are given in the appendix. Section 3 briefly elaborates on the calibration issues. In Section 4, we present and discuss calculations for a benchmark and various stabilization scenarios. Section 5 draws conclusions.

2. DEMETER-1CCS: MODEL STRUCTURE

The DEMETER model has featured in a number of publications (van der Zwaan et al, 2002; Gerlagh and van der Zwaan, 2003; Gerlagh and van der

Zwaan 2004; Gerlagh et al, 2004). The model presented here extends the DEMETER-1 model with a description of carbon capturing and sequestration. The model has 30 distinct time periods of five years, each denoted by t=1,…,30. The model distinguishes one representative consumer, three representative producers (also referred to as sectors) and a public agent that can set emission taxes to reduce carbon dioxide emissions. Producers of the final good or consumption good, of energy based on fossil-fuel technology and of energy based on carbon-free technology are denoted by superscripts $j=C,F,N$, respectively. The final good is produced by sector $j=C$, where output is denoted by Y^C. The same good is used for consumption, investments I in all three sectors and for operation and maintenance M (as usually distinguished in energy models, cf. McDonald and Schrattenholzer, 2001) in both energy sectors $j=F,N$ (1). We also distinguish a separate carbon capture and storage (CCS) activity for which investments and maintenance are required. We assume there is one representative consumer who maximizes welfare subject to a budget constraint (2), where W is total welfare, ρ is the pure time preference and C_t / L_t is consumption per capita. For the three sectors, we assume a representative producer who maximizes profits subject to production constraints (6)-(12) given below. Intertemporal profits are equal to intertemporal revenues, which for the consumer goods producer, consists of output Y_t^C, while expenditures consists of investments, I_t^C (one period ahead), labour L_t at wage w_t, fossil-fuel energy Y_t^F at price μ_t^F, and carbon-free energy, Y_t^N at price μ_t^N (3). For the non-carbon energy producers, profits are equal to the value of output minus investments and maintenance costs (4). For the fossil fuel energy producer, the cash flows equation (4) is adjusted to account for additional costs of investments and maintenance for *CCS*, and for the carbon tax levied on emissions (5).

$$C_t + I_t^C + I_t^F + I_t^{CCS} + I_t^N + M_t^F + M_t^{CCS} + M_t^N = Y_t^C. \tag{1}$$

$$\text{Max } W = \sum_{t=1}^{\infty} (1+\rho)^{1-t} L_t \, 1\text{n}(C_t / L_t), \tag{2}$$

$$\text{Max } \sum_{t=1}^{\infty} \beta_0^t (Y_t^C - I_t^C - w_t L_t - \mu_t^F Y_t^F - \mu_t^N Y_t^N), \tag{3}$$

$$\text{Max } \sum_{t=1}^{\infty} \beta_0^t (\mu_t^N Y_t^N - I_t^N - M_t^N). \tag{4}$$

$$\text{Max } \sum_{t=1}^{\infty} \beta_0^t (\mu_t^F Y_t^F - I_t^F - M_t^F - I_t^{CCS} - M_t^{CCS} - \tau_t Em_t^F). \tag{5}$$

To describe production, DEMETER-1CCS accounts for technology that is embodied in capital installed in previous periods. It therefore distinguishes between production that uses the vintages of previous periods, and production that uses the newest vintage for which the capital stock has been installed in the directly preceding period. The input and output variables, as well as prices, associated with the most recent vintages are denoted by tildes (~). For every vintage, the production of the final good uses a capital-labor composite, $\tilde{Z}_t$, and a composite measure for energy services, $\tilde{E}_t$, as intermediate inputs (6), where A_t^1 and A_t^2 are technology coefficients, and γ is the substitution elasticity between $\tilde{Z}_t$ and $\tilde{E}_t$. Notice that the Lagrange variable for the profit maximization program is given between brackets. The capital-labor composite $\tilde{Z}_t$ has fixed value share α for capital (7). Note that new capital is by definition equal to the investments of one period ahead, $\tilde{K}_t^j = I_{t-1}^j$.

We model energy services $\tilde{E}_t$ as consisting of a CES aggregate of energy produced by the sectors F and N (8), where σ is the elasticity of substitution between F and N.

One part of production employs the new vintage, the other part employs the old capital stock that carries over from the previous period. All flows, output, use of energy, labor, and the output of emissions are differentiated between old and new vintages. The input/output flow in period t is equal to the corresponding flow for the new vintage, plus the corresponding flow for the old capital stock of the previous period, times a depreciation factor $(1-\delta)$,[1] (9), (10), (11), and (12).

$$\tilde{Y}_t^C = ((A_t^1, \tilde{Z}_t)^{(\gamma-1)/\gamma} + (A_t^2, \tilde{E}_t)^{(\gamma-1)/\gamma})^{\gamma/(\gamma-1)} \qquad (\tilde{\lambda}_t) \qquad (6)$$

$$\tilde{Z}_t = (I_C^{t-1})^{\alpha} (\tilde{L}_t)^{1-\alpha}, \qquad (\tilde{\theta}_t) \qquad (7)$$

$$\tilde{E}_t = ((\tilde{Y}_t^F)^{(\sigma-1)/\sigma} + (\tilde{Y}_t^N)^{(\sigma-1)/\sigma})^{\sigma/(\sigma-1)} \qquad (\tilde{\chi}_t) \qquad (8)$$

$$Y_t^C = (1-\delta)\, Y_{t-1}^C + \tilde{Y}_t^C, \qquad (\tilde{\lambda}_t) \qquad (9)$$

$$Y_t^j = (1-\delta)\, Y_{t-1}^j + \tilde{Y}_t^j, \qquad (\tilde{\mu}_t^j; j=F,N) \qquad (10)$$

$$L_t^j = (1-\delta)\, L_{t-1}^j + \tilde{L}_t, \qquad (\tilde{w}_t) \qquad (11)$$

$$Em_t = (1-\delta)\, Em_{t-1} + \tilde{E}m_t, \qquad (\tilde{\tau}_t) \qquad (12)$$

Both energy producers, the fossil fuel sector, $j=F$, and the non-fossil fuel sector, $j=N$, are treated almost symmetrically. The only difference is in the costs and the option for fossil-fuel energy producers to decarbonize through carbon capturing and storage. We first describe the production process for the non-fossil fuel sector. Production of energy, $\tilde{Y}_t^j$ $(j=F,N)$, requires investments I_{t-1}^j (in the previous period) and maintenance costs, M_t^j, see (10), (13), (14), (15), and (16). Each new vintage with output $\tilde{Y}_t^j$ requires a certain effort, measured through the variable Q, which is proportional to investments (one period ahead) and maintenance costs (13), where the variable h_t^j is a measure of technology variable over

1. Though the vintage structure is an important extension with respect to many other global integrated assessment models, it is still limited in the sense that the model does not distinguish between capital with low depreciation rate (e.g. electricity plants) and capital with high depreciation rate (e.g. personal cars). All capital stocks have an expected lifetime of 1/δ (15 years), and an average capital age of slightly below 1/2δ, due to the higher share of young vintages in a growing economy.

time, and a^j and b^j measure the constant investment and maintenance share in production costs.

$$Q_t^j = h_t^j \tilde{Y}_t, \qquad (\phi_{j,t};\, j=F,N) \qquad (13)$$

$$I_{t-1}^j = Q_t^j \,/\, a^j, \qquad (\zeta_{j,t};\, j=F,N) \qquad (14)$$

$$\tilde{M}_t^j = Q_t^j \,/\, b^j. \qquad (\eta_{j,t};\, j=F,N) \qquad (15)$$

$$M_t^j = (1 - \delta)\, M_{t-1}^j + \tilde{M}_t^j. \qquad (\xi_{j,t};\, j=F,N) \qquad (16)$$

We assume that knowledge is a public good that is non-rival and non-exclusive. Thus firms will not internalize the positive spill-over effects from their investments in their prices. Hence, the productivity parameter h_t^j is treated as exogenous by the firms, and the individual firms are confronted with constant returns to scale. Profit maximization of (4) subject to (10), (13), (14), (15), and (16) gives zero profits. First order conditions are listed in the appendix.

Energy production based on fossil fuels can be confronted with a carbon tax levied on carbon dioxide emissions, and producers can choose to decarbonize energy through CCS. Carbon dioxide emissions, Em_t, are proportional to the carbon content of fossil fuels, denoted by ε_t^F, but part of emissions, *CCSR*, is captured through a carbon capturing and storage activity (17). The variable *CCSR* can be understood as the carbon capturing and sequestration ratio. When convenient, we use the acronym *CCS* for the carbon capturing and storage activity, measured in metric tons of carbon, and *CCSR* for the ratio of emissions prevented through this activity. The tildes on top of the variable denote that emission intensities are vintage specific. Alternatively, we can interpret the *CCSR* variable in a broader perspective as a broad decarbonization measure, where ε_t^F is the carbon intensity of a benchmark fuel mix that is optimal without carbon tax, and *CCSR* includes all activities that reduce carbon dioxide emissions including fuel-switching options.

Similar to the production of energy described above, the carbon capturing and sequestration process is described through an effort variable Q_t^{CCS}, which is assumed a second order polynomial function of the share of carbon that is captured and sequestered:

$$\tilde{E}m_t = \varepsilon_t^F\,(1 - CCSR)\,\tilde{Y}_t^F. \qquad (\tilde{\tau}_t) \qquad (17)$$

$$Q_t^{CCS} = h_t^{CCS}\,(CCSR_t + 1/2\kappa\, CCSR_t^2)\,\varepsilon \tilde{Y}_t^F, \quad (\phi_{j,t};\, j=CCS) \qquad (18)$$

Investments and maintenance costs are described through the same equations as for the production process: (14), (15), and (16). The quadratic costs curve implies that the amount of carbon that is captured and not emitted is linear in the carbon tax.

2.1. Technological Change

The DEMETER-1CCS model incorporates various insights from the bottom-up literature that stress the importance of internalizing learning-by-doing effects in climate change analyses. Energy production costs decrease as the experience increases through the installation of new energy vintages. In this version of DEMETER, the endogenous modeling of learning-by-doing is limited to the energy sectors; we have not included learning effects for overall productivity and energy efficiency. Thus, A_t^1 and A_t^2 as employed in (6) are exogenously determined by a benchmark (business as usual) growth path.

For energy production and CCS, the variable h_t^j measures the state of technology. More specifically, it defines the costs of one unit of output $\tilde{Y}_t^F$ as compared to potential long-term costs. For example, $h_t^j=2$ means that one unit of energy output of sector j costs twice as much investments and maintenance as compared to the situation in the far future when learning effect reaches its maximum value.

To capture the process of gaining experience and a decreasing value of h_t^j, we introduce the variable X_t that represents experience; it represents accumulated installed new capacity (vintage) at the beginning of period t. For energy production, the new capacity is equal to the output of the new vintage (19). For carbon capturing and sequestration, the new capacity is the amount of emissions prevented (20). Furthermore, we use a scaling function that returns the value for h_t^j as dependent on cumulative experience at the beginning of the period, X_t^j (21). Our scaling function satisfies $\partial h_t^j / \partial X_t^j \leq 0$, that is, production costs decrease as experience increases, and we assume $h_t^j=1$ for $X_t^j \to \infty$ that is, production costs converge to a strictly positive floor price (minimum amount of input associated with maximum learning effect) given by the levels of a_∞^j and b_∞^j. Finally, we assume a constant learning rate for technologies at the beginning of the learning curve (that is, for small values of X), captured by the power d^j. This means that, initially, production costs decrease by a factor $2^{-dj}=(1-lr)$, where lr is the so-called learning rate, for every doubling of installed capacity. Such decreases have been observed empirically for a large range of different technologies (IEA/OECD, 2000).

$$X_{t+1}^j = X_t^j + \tilde{Y}_t^j. \qquad (j=F,N) \qquad (19)$$

$$X_{t+1}^{CCS} = X_t^{CCS} + CCSR_t \varepsilon_t \tilde{Y}_t^F. \qquad (20)$$

$$h_t^j = c^j(1-d^j)(X_t^j)^{-dj} + 1, \qquad (j=F,N,CCS) \qquad (21)$$

2.2. Climate Change

Emissions are included in the model through equations (12) and (17). The carbon cycle and climate change dynamics are included by linking emissions to atmospheric, upper ocean, and lower ocean CO_2 storage, and ocean and global average surface temperature, following the RICE model (Nordhaus and Boyer 2000).

3. CALIBRATION AND DATA FOR NUMERICAL ANALYSIS

For all parameters but for CCS, an extensive discussion on calibration issues can be found in earlier papers on the DEMETER 1 model (van der Zwaan et al, 2002; Gerlagh and van der Zwaan, 2003; Gerlagh et al, 2004; Gerlagh and van der Zwaan, 2004).[2] Here we confine ourselves to the parameters that affect CCS. CCS costs consist of three parts: capturing of carbon, that is the separation and compression, its transport, and its storage. For a fossil fuel fired electricity plant, capturing carbon form the major share of total costs. For this process, only limited commercial experience is available and the range of costs quoted in the literature is large, dependent on specific capture technology and the power plant. However, the capture technology part in CCS systems is similar to more common technologies used for sulphur and nitrous oxides removal from flue gases. World-wide, the costs of applying these technologies have decreased considerably over the past decades (Rubin et al, 2004a and 2004b) and learning rates for capital costs of 11% and 12% were found. As DEMETER does not differentiate between carbon capture and storage, we assume that CCS as one process will have approximately the same technological progress characteristics with a 10% learning rate.[3] Still, application of the learning rate requires an estimation of the initial level of cumulative experience and the initial costs per ton of carbon. To estimate initial cumulative experience, we consider existing carbon dioxide storage e.g. the Sleipner project (0.2-0.3 MtC/yr), the Weyburn project (1-2 MtC/yr) and West Texas (5-10 MtC/yr), and assume that experience has cumulated to about 20 MtC/yr of CCS capacity installed.

Some applications of CCS can increase the output of oil fields, and this option leads to low-cost opportunities. Therefore, in the first period, we assume that some CCS activities are employable at net costs of around 10 $/tC avoided. When CCS is employed at larger scale, it is assumed that costs increase to 150$/tC

2. In Gerlagh and van der Zwaan (2004) an extensive sensitivity analysis is carried out with respect to most parameters. It was found that the value for the substitution elasticicty between both capital-labour and energy services (0.4) was of minor importance to the results, while costs of stabilization targets were shown to be sensitive with respect to changes in the substitution elasticity between conventional and renewable energy sources (3.0). Also, the learning rate for non-carbon energy sources turned out a crucial parameter for many of the results. The real interest rate (5 per cent annually) has been shown to be important for the timing of emission reductions, but not for other features.

3. Two comments to note here. First, note the 10% learning rate for CCS in contrast to the assumed 20% learning rate for both fossil fuels and non-carbon energy production. We notice, however, that due to the very large initial stock of cumulated fossil fuel capacity, for fossil fuel energy production, the effective learning is very modest. Second, for CCS we assume a floor price of 10% of costs in the first period. That is, future costs of CCS can decrease by 90% compared to the costs in the first period, keeping all other things equal. In all simulations, cost never fall below 35% of first-period costs. In this sense, the floor price has no effect on results. See also Gerlagh and van der Zwaan (2004) for details explaining how the choice of floor price for non-carbon energy has very limited effect on results.

if CCS is applied to all fossil fuel electricity generation, about one third of total energy demand in primary energy equivalents.[4] For the intermediate range, we assume the amount of CCS applied is linear in the carbon tax. These values imply that the application of a full-cost CCS system typically adds some 2-5 cent/kWh to the costs of electricity. In our main analysis, we also assume CCS can be extended to the non-electricity sector at linearly increasing marginal costs per amount of carbon captured. We thus implicitly include hydrogen from fossil fuels as an option for transportation fuels, and a switch to electric-based heating as another option. In the appendix, we show results under the alternative assumption where CCS is physically and/or economically infeasible outside the electricity sector.

4. SIMULATION RESULTS

In this section, we report on the model results of emission stabilization scenarios and how they vary with and without endogenous technological change. The overall objective of this part is to analyze the impact of technological change on crucial economic variables like gross world product (GWP), consumption, and investment strategies, that is the composition of the portfolio of technologies subject to emission stabilization scenarios. Due to limited space, we cannot elaborate on a full sensitivity analysis or parameter study. We refer to Gerlagh and van der Zwaan (2004) and Gerlagh et al, (2004) for a discussion on sensitivity of results with respect to various parameters, including the elasticity of substitution between the fossil fuel and non-carbon energy source and the learning rates.

We have run five scenarios, one baseline or ‘business as usual’ (BAU) scenario in which climate change policy is assumed absent, and four stabilization scenarios in which atmospheric CO_2 concentrations are stabilized at 550, 500, 450, and 400 ppmv (Figure 1). Given the inertia of the energy system, e.g. due to past investments in capital for fossil fuel production and fossil fuel combustion, even a very stringent climate change policy does not cause emissions to drop to zero immediately. Even when emissions immediately fall (Figure 2), the inertia of the climate system makes it impossible not to overshoot the 400 ppmv target. Therefore, for the 400 ppmv scenario, we require the atmospheric stabilization target to be binding from 2100 onwards. Consequently, in the last decades of the 21st century, emissions fall short of the steady state level that is consistent with a stable 400 ppmv concentrations, and can increase somewhat from 2100 onwards. From Figure 2, we also notice that the timing of emission reductions is relatively independent of the endogeneity of technological change. ITC leads to a fall in future abatement costs because of decreasing costs for non-carbon energy sources and CCS options, and such would be consistent with a delay in abatement. On the other hand, the beneficial learning spill-over effect from early abatement justi-

4. The IPCC (Intergovernmental Panel on Climate Change, Working Group III) is currently assembling a comprehensive overview of CCS technologies and their costs. Our linear supply function is an important extension to Ha-Duong and Keith (2003) and Keller et al (2003), who both assume constant costs of 75 and 100 $/tC, respectively.

fies early action. The numerical results suggest that these two forces are about in balance.[5] It turns out that the vintages, structure of production is more important from the timing perspective. One has to wait for new vintages of capital that are either less energy intensive or based on carbon-poor energy sources, before emissions can drop. Consequently, emission reductions are somewhat delayed. Also, as we know from the literature, the discount rate employed will have a certain effect on timing.

Figure 1. Atmospheric CO_2 Concentration

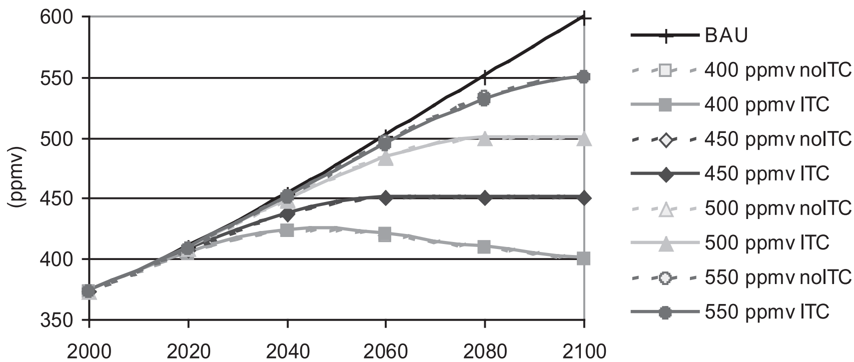
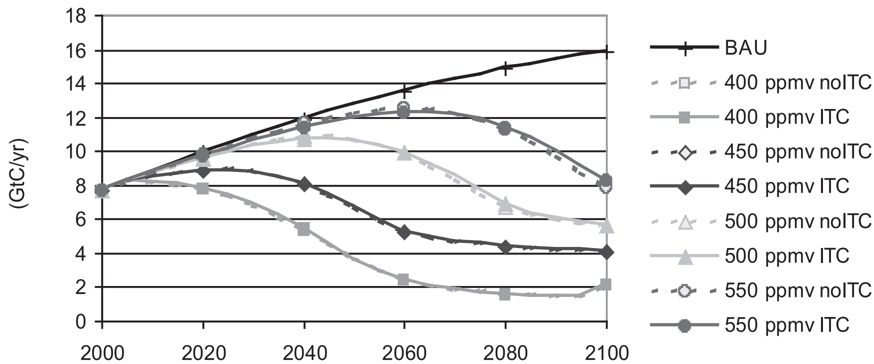


Figure 2. Global CO_2 Emissions



5. A common thought, based on the analysis by Goulder and Mathai (2000), is that the modeling of R&D implies a delay in abatement in contrast to learning by doing. We need to understand, however, that this result depends on the assumption that the R&D knowledge stock is cumulated over time, only to be used in a distant future, whereas learning by doing is associated with immediate abatement. In a second-best model where R&D is only carried out when innovations pay off in the short term, it is unclear whether ITC will imply an advance or a delay of abatement.

The model recognizes three basic mechanisms for emissions reduction: energy savings, a transition towards renewables, and carbon capturing and sequestration of fossil fuels. The latter two options both contribute to a decarbonisation of the energy system. Figure 3 compares energy savings and decarbonization of energy in one chart. The figure shows that, for the first decades (one marker per 20 years), both options are equally important. But over time, the curve bends to the left, signifying that energy decarbonisation becomes a more important mechanism.

Figure 4 zooms in on the contribution of CCS on emission reductions; it portrays the annual amount of carbon captured and sequestered. After comparison of this figure with the emissions in Figure 2, we see that CCS substantially contributes to the emission reduction effort.

Figure 3. Mechanisms for Emission Reductions (% change relative to BAU)

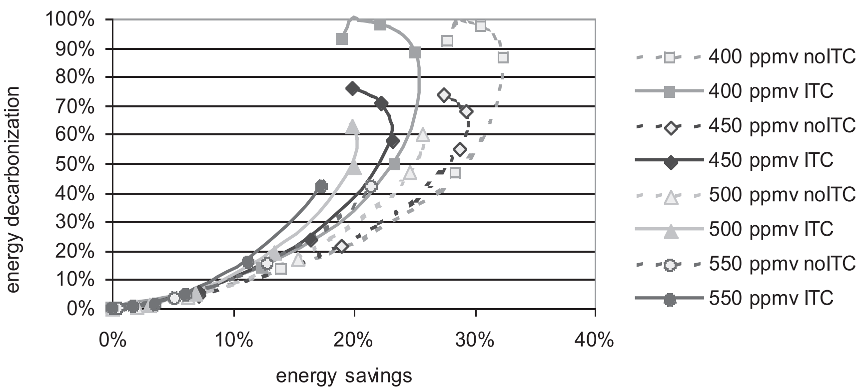


Figure 4. Carbon Capture and Sequestration

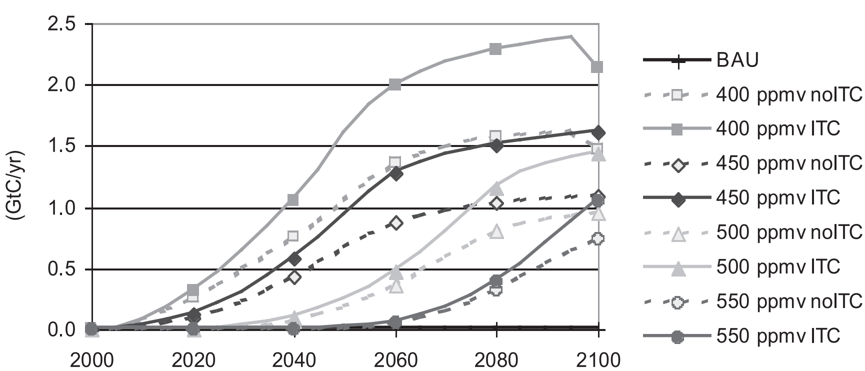
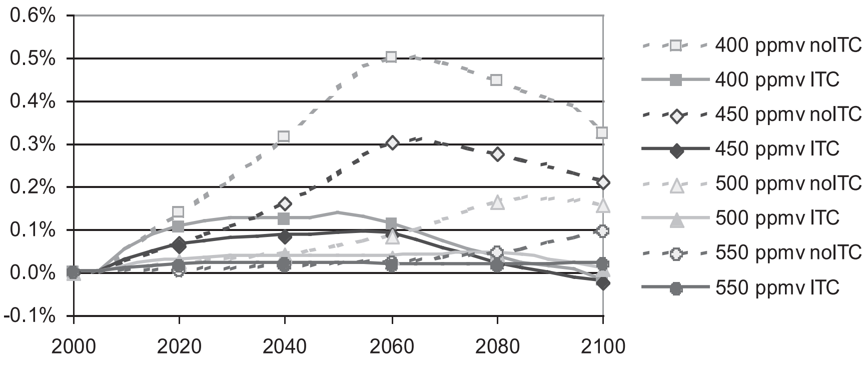


Figure 5 presents the costs of stabilization in terms of loss of Gross World Product (GWP) relative to the baseline scenario, while Figure 6 shows the costs in terms of loss of consumption. Comparing the two figures, an outstanding result is that consumption losses exceed GWP losses by about factor 2. The reason for this is that a stabilization policy substitutes investments for consumption (Figure 7). Carbon capturing and sequestration requires substantial investments (Figure 9), which counts as part of production so that it does not lead to a decrease in output, but it goes at the cost of consumption. Investments in fossil fuel energy supply decrease under a stabilization policy (Figure 8), but this is more than offset by increased investments in non-carbon energy sources (Figure 10). Not only are non-carbon energy sources more expensive then fossil fuels, but they also require a larger share of investments compared to maintenance costs.

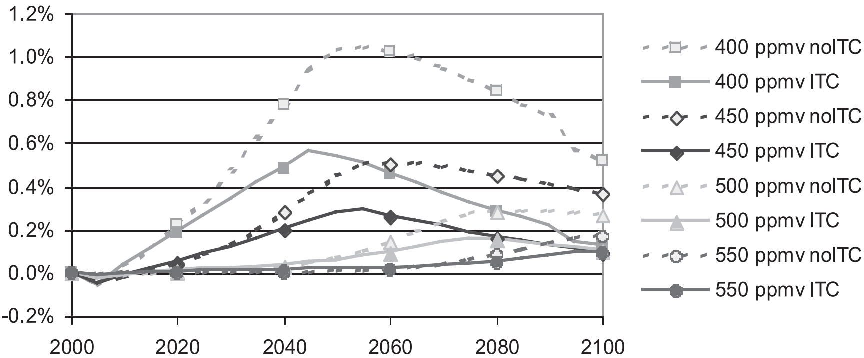
Another conclusion we can draw from Figure 5 and Figure 6 is that, first, ITC reduces costs by about factor 2, but these benefits only materialize after some decades.[6] The first twenty years, from 2000 to 2020, ITC has almost no effect on costs, but thereafter, the extra investments in CCS and non-carbon energy sources start to pay off, when they have contributed to an increase in knowledge, and consequently, to lower energy costs. By 2100, in all four stabilization scenarios, under ITC, GWP is almost unaffected or is even increased compared to the baseline. In the two most-stringent stabilization scenarios, investments in technological change clearly start to pay off as consumption losses decrease during the second half of the 21st century.

Figure 5. Loss of Gross World Product Compared to BAU



6. For an extensive comment on the level of the costs of stabilization compared to other models, see Gerlagh and van der Zwaan (2003, p.40).

Figure 6. Loss of Consumption Compared to BAU



When we specifically look at the implications of ITC on the investment strategy, we find limited effects only. Basically, investments in fossil fuels under ITC exceed the levels without ITC (Figure 8). The obvious reason is that ITC leads to an increase in costs of fossil fuels because of the foregone learning when the economy substitutes away from fossil fuels. On the other hand, because ITC reduces the costs of CCS and non-carbon energy sources, investments can slightly fall (Figure 9 and Figure 10). The changes brought about by ITC are, however, insubstantial compared to the significance of the stabilization target, especially in earlier decades. On the aggregate level, emission reductions require an increase in investments, and ITC slightly softens this need (Figure 7).

Figure 7. Total Investments per GWP

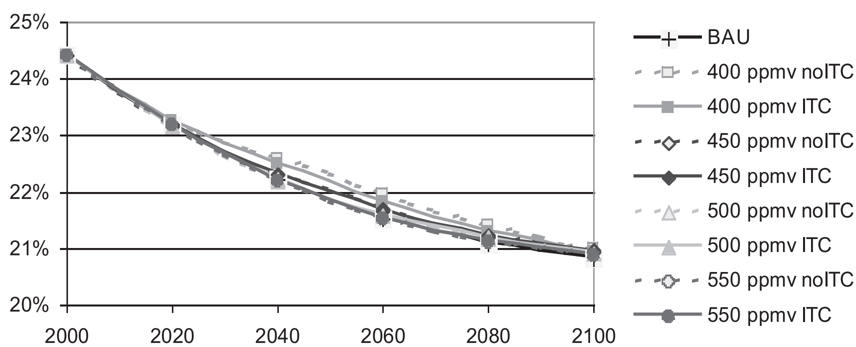


Figure 8. Investments in Fossil Fuels Energy per GWP

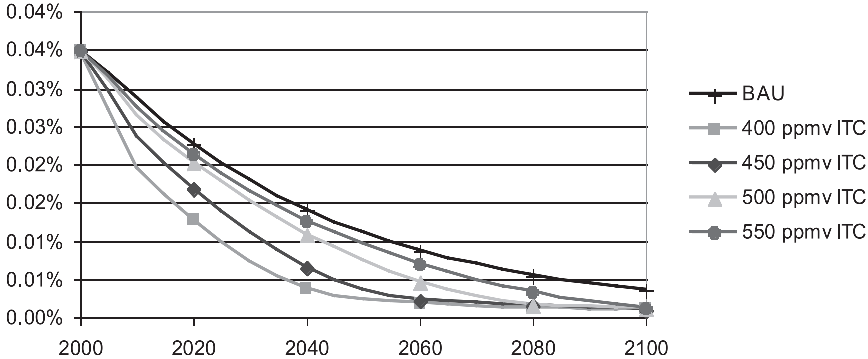


Figure 9. Investments in CCS per GWP

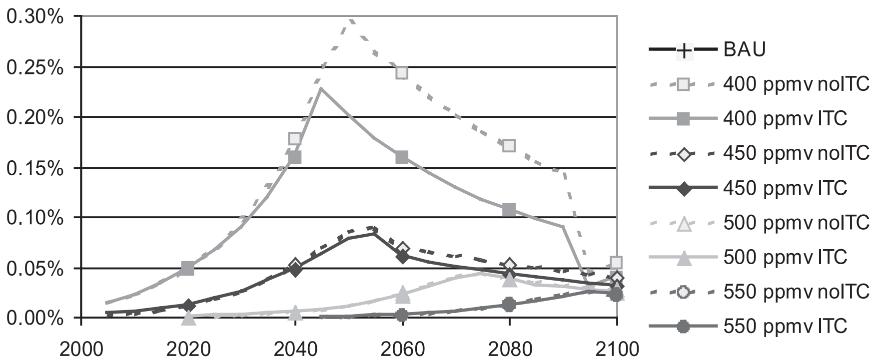
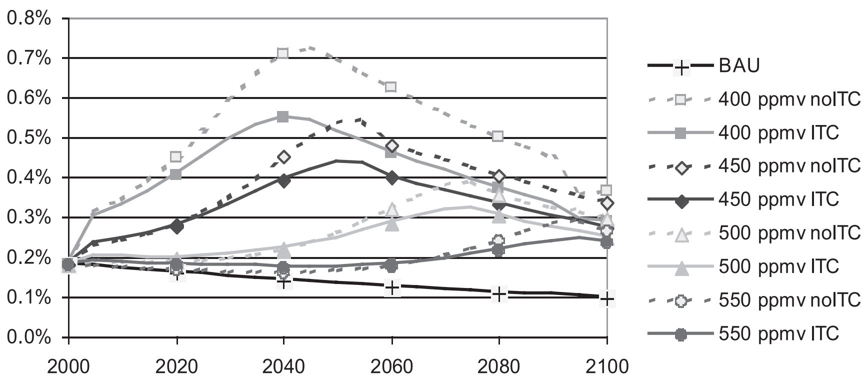


Figure 10. Investments in Non-Carbon Energy Technology per GWP



5. CONCLUSION

In this paper, we developed a global growth model with learning-by-doing for fossil fuel energy supply, non-fossil fuel energy supply, and CCS. The results obtained from assessment of the implications of ITC on output, consumption, and investments using this model suggest that ITC does not substantially affect climate stabilization strategy. Regardless of technology adjustments, it remains unchanged that, to bring about large reductions in carbon dioxide first requires substantial energy savings, applying CCS to fossil fuels and a move away from fossil fuels towards alternative energy sources. The recognition of ITC, however, has drastic implications to the costs of climate stabilization policies. When acknowledging that technologies respond to the economic incentives induced by policy, long-term costs of emissions reductions come down substantially. Viewing climate stabilization as a pillar towards the goal of sustainable development in the long-run horizon, the cost of transition into a low-carbon economy need not be a lasting burden on global economic growth.

ACKNOWLEDGEMENTS

The author thanks the Netherlands Organization for Scientific Research (NWO) for financial support under contract nr. 016.005.040. I am grateful to Ottmar Edenhofer and Claudia Kemfert for organizing the IMCP (Innovation Modelling Comparison Project) workshop, 23rd-24th February 2005, Berlin, where this paper was presented, and to the participants for their comments. I want to thank Bob van der Zwaan who has provided most of the calibration data for the CCS technology, and I also thank two anonymous reviewers for their time and suggestions that helped to improve the presentation of the paper.

APPENDIX 1. CONSTRAINTS ON CCS

In the main text, we extend the CCS option outside the 35% share of energy (in primary energy equivalents) typical for electricity. Here we present the results when we assume that CCS can be applied only to 35% of total fossil fuel energy production. In general, results hold constant under this assumption. The timing of emissions reductions and the investment strategy remains relatively independent of the endogeneity of technological change. ITC reduces costs by approximately a factor of two in the long term. The graphs specifically addressing the contribution of CCS to emission reductions, however, change substantially. Figure 11 shows a strong decrease in CCS activities for the more stringent atmospheric targets, compared to the scenarios where CCS is constrained to 35% of fossil fuel energy production (Figure 4). Remarkably, the maximum flow of carbon captured and stored is lower under the more stringent targets compared to the less stringent scenarios. This result may seem counter-intuitive at first glance. However, it can be reasoned as follows: the lower the atmospheric target, the lower the share of fossil fuels in the energy mix, and the earlier CCS reaches its maximum level of 35% of total fossil fuel energy supply. Due to the constraint, investments in CCS also drop, compared to the central scenarios (Figure 12 vs. Figure 9).

Figure 11. Carbon Capture and Sequestration, Under CCS Constraint

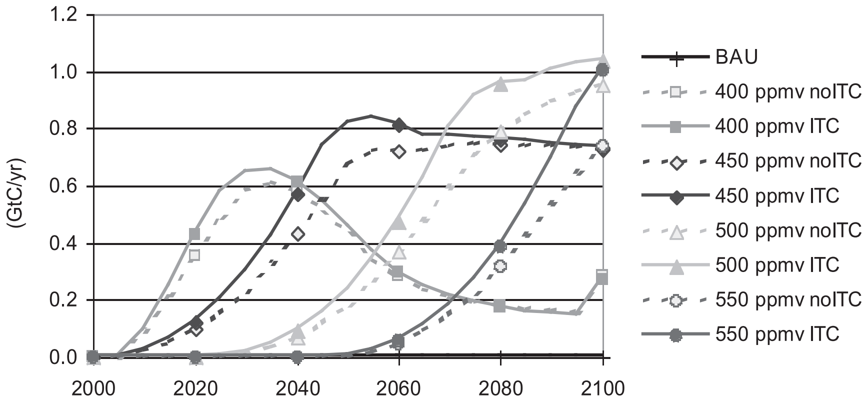
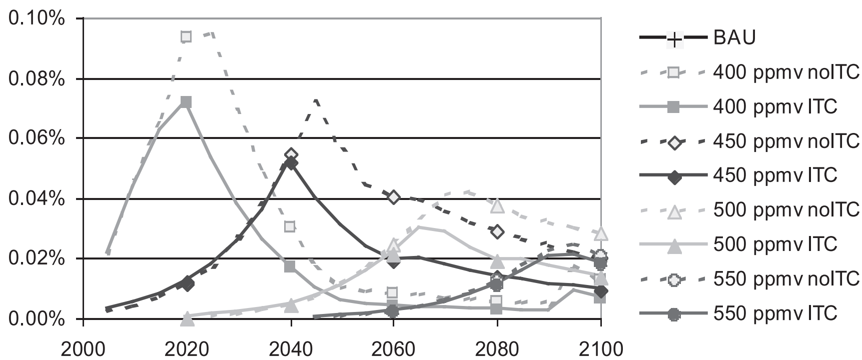


Figure 12. Investments in CCS as % of GWP, under CCS Constraint



APPENDIX 2. FURTHER MODEL CONDITIONS

First Order Conditions

Welfare optimization gives the Ramsey rule as a first-order-condition for consumption, (22), where β_t is the price deprecation factor from period t to t+1. Maximizing net profits (3), subject to the constraints (6)-(12) yields the following first order conditions for Y_t^C, $Y_t^j(j=F,N)$, L_t, Em_t, $\tilde{Z}_t$, I_t^C, $\tilde{L}_t$, $\tilde{E}_t$, $\tilde{Y}_t^j$:

$$\beta_t = (C_t / L_t) / ((1+\rho)(C_{t+1} / L_{t+1})) \,. \tag{22}$$

$$\tilde{\lambda}_t = (1-\delta)\,\beta_t \tilde{\lambda}_{t+1} + 1, \qquad (Y_t^C), \tag{23}$$

$$\mu_t^j = (1-\delta)\,\beta_t\,\tilde{\mu}^j_{t+1} + \mu_t^j. \qquad (Y_t^j,\, j{=}F{,}N), \tag{24}$$

$$\tilde{w}_t^j = (1-\delta)\,\beta_t\,\tilde{w}^j_{t+1} + w_t^j. \qquad (L_t), \tag{25}$$

$$\tau_t = \tilde{\tau}_t - (1-\delta)\,\beta_t\ \tilde{\tau}_{t+1}. \qquad (Em_t), \tag{26}$$

$$\tilde{\theta}_t = \tilde{\lambda}_t^2\ (A_t^1)^{(\gamma-1)/\gamma} + (\tilde{Z}_t / \tilde{Y}_t^C)^{-1/\gamma} \qquad (\tilde{Z}_t), \tag{27}$$

$$1 = \beta_t \tilde{\theta}_{t+1}\ \alpha\, \tilde{Z}_{t+1} / I_t^C \qquad (I_t^C), \tag{28}$$

$$\tilde{w}_t \tilde{L}_t = (1-\alpha)\ \tilde{\theta}_t \tilde{Z}_{t+1}. \qquad (\tilde{L}_t), \tag{29}$$

$$\tilde{\chi}_t = \tilde{\lambda}_t^2\ (A_t^2)^{(\gamma-1)/\gamma} + (\tilde{E}_t / \tilde{Y}_t^C)^{-1/\gamma} \qquad (\tilde{E}_t), \tag{30}$$

$$\tilde{\mu}_t^j = \ \tilde{\chi}_t\, (\tilde{Y}_t^j / \tilde{E}_t)^{-1/\sigma}. \qquad (\tilde{Y}_t^j;\, j{=},N,F) \tag{31}$$

where the variables associated with the first order conditions are given between brackets, $\tilde{\lambda}_t$ is the shadow price for $\tilde{Y}_t^C$, that is the Lagrange variable for (9) which is the same as the Lagrange variable for (6), $\tilde{\mu}_t^j$ is the shadow price for $\tilde{Y}_t^j$, and the Lagrange variable for (10), $\tilde{w}_t$ is the shadow price for $\tilde{L}_t$, and the Lagrange variable for (11), $\tilde{\theta}_t$ is the shadow price for the labour/capital composite $\tilde{Z}_t$ and the Lagrange variable for (7), $\tilde{\chi}_t$ is the shadow price for the energy composite $\tilde{E}_t$ and the Lagrange variable for (8).

The non-carbon energy producers maximize net profits (4) subject to (10), (13), (14), (15), and (16). Calculating the first order conditions for Y_t^j, $\tilde{Y}_t^j$, Q_t^j, $\tilde{M}_t^j$, I^j_{t-1}, and M_t^j, we find (24) and

$$\tilde{\mu}_t^N = h_t^N \phi_t^N, \qquad (\tilde{Y}_t^N) \tag{32}$$

$$\phi_t^j = \zeta_t^j + \eta_t^j, \qquad (Q_t^j,\, j{=}F{,}N{,}CCS) \tag{33}$$

$$\xi_t^j = b^j + \eta_t^j, \qquad (\tilde{M}_t^j,\, j{=}F{,}N{,}CCS) \tag{34}$$

$$1 = a^j \beta_t\, \zeta^j_{t+1}, \qquad (I_{t-1},\, j{=}F{,}N{,}CCS) \tag{35}$$

$$\tilde{\xi}_t^j = (1-\delta)\,\beta_t \tilde{\xi}^j_{t+1} + 1, \qquad (M_t^j,\, j{=}F{,}N{,}CCS) \tag{36}$$

where $\tilde{\mu}_t^j$ is the shadow price for $\tilde{Y}_t^j$, and the Lagrange variable for (10), ϕ_t^j is the shadow price of Q_t^j and the Lagrange variable of (13), ζ_t^j and η_t^j are the Lagrange variables of (14), and (15), and $\tilde{\xi}_t^j$ is the shadow price of $\tilde{M}_t^j$.

The fossil fuel energy producers maximize net profits (5) subject to (10), (12), (13), (14), (15), (16), (17), and (18). Calculating the first order conditions for Y_t^j, Q_t^j, $\tilde{M}_t^j$, I_{t-1}^j, M_t^j, $\tilde{Y}_t^j$, and $CCSR_t$, we find (24) for $j=F$, (33), (34), (35), and (36) for $j=F,CCS$, and

$$\tilde{\mu}_t^{\,F} = h_t^F \phi_t^F, + (1 - CCSR_t)\tilde{\tau}_t\, \varepsilon_t^F + h_t^{CSS}\, \phi_t^{CSS}\, \varepsilon_t^F\, (CCSR_t + \tfrac{1}{2}\kappa\; CCSR_t^2) \quad (37)$$

$$(1 + \kappa\; CCSR_t)\; \phi_t^{CSS}\, h_t^{CSS} \geq \tau_t \perp CCSR_t \geq 0, \quad (38)$$

respectively, where the Lagrange variable of (16), $\tilde{\tau}_t$ is the shadow price for $\tilde{Em}_t$ and the Lagrange variable for (12), which has the same value as the Lagrange variable for (17).

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Decarbonizing the Global Economy with Induced Technological Change: Scenarios to 2100 using E3MG

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This paper reports how endogenous economic growth and technological change have been introduced into a global econometric model. It explains how further technological change might be induced by mitigation policies so as to reduce greenhouse gas emissions and stabilize atmospheric concentrations. These are the first results of a structural econometric approach to modeling the global economy using the model E3MG (energy-environment-economy model of the globe), which in turn constitutes one component in the Community Integrated Assessment System (CIAS) of the UK Tyndall Centre. The model is simplified to provide a post-Keynesian view of the long-run, with an indicator of technological progress affecting each region's exports and energy use. When technological progress is endogenous in this way, long-run growth in global GDP is partly explained by the model. Average permit prices and tax rates about \$430/tC (1995) prices after 2050 are sufficient to stabilize atmospheric concentrations at 450ppm CO_2 after 2100. They also lead to higher economic growth.

1. INTRODUCTION

As part of the research program at the Tyndall Centre, a world macroeconomic model, E3MG, is being developed to investigate policies for climate change mitigation and sustainable development within an Integrated Assessment Modeling system. In coupling economic models with atmosphere-ocean models of climate change, long timescales are necessary because changes in CO_2 concentrations enhance the greenhouse effect over time periods of 50-100 years and more.

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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In projecting into the future, the approach of this paper is first to consider the past. Looking back over the last 200 years, the socio-economic system has been characterized by ongoing fundamental change, rather than convergence to any equilibrium state. Maddison (2001) takes a long view of global economic growth over the last millennium. He finds growth rates to be very different across countries and over time, and ascribes the comparatively high rates of growth to technological progress and diffusion. The increase in growth rates that emerged in Europe since 1500, and that became endemic from 1820, were founded on innovations in banking, accounting, transport, military equipment, scientific thinking and engineering. He also finds that inequalities between nations in per capita GDP have increased (in particular since WW2), not diminished over time. These three features of growth (diversity across nations and time periods, technological progress, and increasing inequalities) are evident in the scenarios reported below. These ideas are supported by quantitative studies identifying the causes of economic growth, e.g. Denison (1985) finds that three causal factors associated with technological progress[1] (capital, economies of scale and knowledge) account for 57% of growth. More recently, Wolff (1994a, 1994b) has found strong correlations between investment embodying technological change and growth in OECD economies.

Technology is important for climate change analysis for two reasons: first, technology has allowed anthropogenic climate change to happen; and second, a change to a modern, low-carbon society may well require widespread development and deployment of new, low-carbon technologies. Such large-scale changes have been a feature of 'advanced' society in the last 200 years. Widespread use of both coal and oil were part of transformations of economies and societies. In modeling these processes, we have combined an econometric, long-run model with an energy technology model to derive the benefits of moving from a baseline to stabilization targets of 550, 500 and 450 ppmv CO_2, using the instruments of permit trading and carbon taxes, with and without incorporation of endogenous technical change.

2. INCORPORATION OF ENDOGENOUS TECHNICAL CHANGE IN E3MG

In modeling long-run economic growth and technological change, we have followed the "history" approach[2] of cumulative causation and demand-

1. Denison's study of US growth 1929-1982 attributes the average long-run rate of about 3%pa to six factors: about 25% to labour at constant quality, about 16% to improvements in labour quality as from education, 12% to capital, 11% to improved allocation of resources, e.g. labour moving from traditional agriculture to urban manufacturing, 11% to economies of scale and 34% to growth of knowledge.

2. This is in contrast to the mainstream equilibrium approach (see DeCanio, 2003 for a critique) adopted in most economic models of the costs of climate stabilisation. See (Weyant, 2004) for a discussion of technological change in this approach. Setterfield (1997) explicitly compares the approaches in modeling growth and Barker (2004) compares them in modeling mitigation.

led growth[3] (Kaldor, 1957, 1972, 1985; Setterfield, 2002), which focuses on gross investment (Scott, 1989) and trade (McCombie and Thirwall, 1994, 2004), and in which technological progress is embodied in gross investment. Long-run growth and structural change through socio-technical systems, called 'Kondratiev waves', are described by Freeman and Louçã (2001) and modeled by Köhler (2005). Growth in this approach is dependent on waves of investment in new technologies.

The study reported below is the first to use a large-scale econometric model with a dynamic structure, which is both sector and region specific, to model these processes. It involves the use of econometric estimation to identify the effects of endogenous technological change (ETC) on energy and export demand and embed these in a large post-Keynesian non-linear simulation model. In addition, a treatment of substitution between fossil and non-fossil fuel technologies is employed, accounting for non-linearities resulting from investment in new technology, learning-by-doing, and innovation. This treatment allows policy measures for induced technological change[4] (ITC) to be modeled. The model has been developed in the traditions of the Cambridge dynamic model of the UK economy (Barker and Peterson, 1987) and the European model E3ME (Barker, 1999). The effects of technological change modeled this way may turn out to be sufficiently large in a closed global model to account for a substantial proportion of the long-run growth of the system. The approach has been developed to include the bottom-up energy technology model (ETM) within the top-down highly disaggregated macroeconomic model, E3MG. Thus, like the studies (Nakicenovic and Riahi, 2003; and McFarland, et al., 2004) which are also based on the linkage of top-down and bottom-up models, our modeling approach avoids the typical optimistic bias often attributed to a bottom-up engineering approach, and unduly pessimistic bias of typical macroeconomic

3. The theoretical basis of the approach is that economic growth is demand-led and supply-constrained. Growth is seen as a macroeconomic phenomenon arising out of increasing returns (Young, 1928), which engender technological change and diffusion, and which proceeds unevenly and indefinitely unless checked by imbalances. Clearly growth can increase only if labour and other resources in the world economy can be utilised in more productive ways, e.g. with new technologies and/or if they are otherwise underemployed in subsistence agriculture or unemployed. One implication of the theory is that investment induces the requisite voluntary saving, i.e. "Mr Meade's Relation" holds (Dalziel and Harcourt, 1997). Palley (2003) discusses how long-run supply is affected by actual growth. In contrast, the modern theory of supply-side economic growth assumes full employment and representative agents, and optimises an intergenerational social welfare function (see Aghion and Howitt, 1998). It goes back to Solow (1956, 1957), with endogenous growth theory developed by Romer (1986, 1990).

4. In the models, exogenous or autonomous technological change is that which is imposed from outside the model, usually in the form of a time trend affecting energy demand or the growth of world output. If, however, the choice of technologies is included within the models and affects energy demand and/or economic growth, then the model includes endogenous technological change (ETC). With ETC, further changes can generally be induced by economic policies, hence the term induced technological change (ITC); thus ITC implies ETC throughout the rest of this paper.

approaches. The advantages[5] of using this combined approach have recently been reviewed (Grubb et al., 2002).

The version of E3MG used in this study includes a partial treatment[6] of endogenous technological change in 3 ways:

i. the sectoral energy demand equations include indicators of technological progress in the form of accumulated investment and R&D, such that extra investment in new technologies induces energy saving
ii. the sectoral export demand equations include the same indicators, such that the extra investment induces more exports and therefore investment, trade, income, consumption and output in the rest of the world and
iii. the ETM incorporates learning curves through regional investment in energy generation technologies that depend on global scale economies.

These long-run energy and export demand equations are of the form given in equation (1), where X is the demand, Y is an indicator of activity, P represents relative prices (relative to GDP deflators for energy and to sectoral competitors' prices for exports), TPI is the Technological Progress Indicator, the β are parameters and the ε errors. TPI is measured by accumulating past gross investment enhanced by R&D expenditures (Lee, Pesaran and Pierce, 1990),[7] with declining weights for older investment. The indicators are included in many equations in the model, but only those for energy and exports are analyzed here. All the variables and parameters are defined for sector i and region j.

$$X_{i,j} = \beta_{o,i,j} + \beta_{1,i,j}Y_{i,j} + \beta_{2,i,j}P_{ij} + \beta_{3,i,j}(TPI)_{i,j} + \varepsilon_{i,j} \tag{1}$$

In both sets of equations, $\beta_{2,i,j}$ are restricted to be non-positive, i.e. increases in prices reduce the demand (for energy demand, see surveys in Atkinson and Manning, 1995 and Graham and Glaister, 2002; for export demand, price elasticities are reported in the literature cited below). In the energy equations $\beta_{3,i,j}$ are estimated

5. There are also disadvantages. The coupled model is highly non-linear with the possibility of instabilities, multiple solutions and discontinuities. The solution is simplified by adopting the smooth transitions assumed by Anderson and Winne (2004), but local instabilities remain. We are intending to tackle this problem by using the multiple solution techniques of a Bayesian uncertainty analysis.

6. A full treatment will include the effects of increasing returns and technological progress on many other variables in the model, including imports, consumption, employment and prices.

7. This is an indirect measure assuming that new techniques are embodied in gross investment including R&D, so that the stock of techniques is found by accumulating this investment, allowing for their obsolescence by the declining weights. Arrow (1962, p.157) used cumulative gross investment as a measure of experience in learning by doing, and the measure also finds empirical support in Schmookler's (1966) correlations between patents and gross investment 1873-1940 in several sectors. Increases in R&D unaccompanied by new investment (i.e. pure, unapplied knowledge) has no special effect on supply in the model.

to be negative, i.e. more TPI is associated with energy saving;[8] and in the export equations $\beta_{3,i,j}$ are estimated to be positive, i.e. more TPI is associated with higher exports. These parameters are constant across all scenarios.

The effect of investment and R&D on export performance, which drives our long-run results, goes back to Posner's technological gap theory (1961). Since the 1990s they have been the topic of substantial empirical research, and the effects have been found for different countries and regions at the individual plant, industrial sector and macro economy levels. Roper and Love (2001) use micro-level data to compare export performance for UK and German manufacturing plants and find "strong and consistent evidence that innovation, however measured, has a systematic effect on both the probability and propensity to export." Greenhalgh (1990) and Greenhalgh et al (1994) find significantly positive effects of R&D for over 30 UK industries' net exports. Wakelin (1998) in a study of 22 industries in nine OECD countries finds effects of different technological indicators on trade, suggesting that the choice of index is important. Magnier and Toujas-Bernate (1994) find evidence of the innovation effects on exports for nine EU countries. Fagerberg (1988) and León-Ledesma (2000) both find support for a positive effect of OECD trading partners' R&D on their exports. There is a potential two-way causation between exports and investment, but the estimations of the E3MG export equations protect against both spurious correlations (by using cointegration techniques) and the simultaneity between the dependent and the explanatory variables (by using instrumental variables or some other means).[9]

The explanation of growth being explored in E3MG is that higher investment and/or R&D is associated with higher quality and innovatory products and therefore exports, and that the extra demand for exports in world markets is matched by extra demand for imports, which are normally constrained by the balance of payments (McCombie and Thirlwall, 2004), i.e. the extra exports weaken the constraints. For the extra demand for exports to be effective in the long run, there must also be an increase in supply, which in the model is realized by economies of specialization and scale in production and higher employment and labor productivity. This study assumes that the drivers of prices and wages

8. There is an ongoing debate on how to include the effects of technological change in energy demand equations, with the main contenders being asymmetric price elasticities, time trends and (as in E3MG) direct measures in the form of the TPI. It seems clear that it will be difficult to distinguish between the explanations in the time-series analysis. See (Gately and Huntington, 2002; Griffin and Schulman, 2005; and Huntington 2005).

9. The literature on the effect is clear on the direction of causation: R&D and R&D-inspired investment in the exporting country leads to higher exports. Causation is very difficult to prove in macroeconomic behaviour, but there are convincing results at the micro level. Two independent, explicit and thorough studies of the direction of causation from innovation to export performance using German microeconomic data come to the unambiguous conclusion that the direction of causation is from R&D innovation to export volumes (Ebling and Janz, 1999; Lachenmaier and Wößmann, 2004). However these studies are concerned with R&D expenditure and other measures of innovation rather than R&D-enhanced gross accumulated investment, the indicator of technological progress adopted in E3MG. There is a close relationship between market R&D expenditures and gross investment so it is very difficult to distinguish separate effects in empirical work.

are largely exogenous (except for energy and technology prices) and that capacity utilization remains at "normal" levels. The modeling explains how low-carbon technologies are adopted as the real cost of carbon rises in the system, with learning by doing reducing capital costs as the scale of adoption increases. A rise in the costs of fossil fuels resulting from increases in CO_2 permit prices and carbon taxes thus induces extra investment in low-carbon technologies, and this is larger and earlier than the investment in conventional fossil technologies in the baseline. The carbon tax revenues and 50% of the permit revenues are assumed to be recycled in the form of lower indirect taxes. The outcome is that the extra investment and implied accelerated technological change in the stabilization scenarios leads to extra exports and investment more generally, and higher economic growth.

The bottom-up annual, dynamic energy technology model ETM (Anderson and Winne, 2004), has been extended to cover lags between orders for plant and the year when the new plant comes on stream and a rolling 7-year-ahead cost-benefit analysis of system requirements for each region. It is based on the concept of a price effect on the elasticity of substitution between competing technologies. Existing economic models usually assume constant elasticities of substitution between competing technologies. ETM is designed to account for the fact that a large array of non-carbon options is emerging, though their costs are generally high relative to those of fossil fuels. However, costs are declining relatively with innovation, investment and learning-by-doing. The process of substitution is also argued to be highly non-linear, involving threshold effects. The ETM simulates the process of substitution, allowing for non-carbon energy sources to meet a larger part of global energy demand as the price of these sources decrease with investment, learning-by-doing, and innovation. The model considers 26 separate energy supply technologies, of which 19 are carbon neutral. Investment shares in energy generation technologies are based on the following equation:

$$S_{it} = S_{it-1} + a_i S_{it-1} \left(\hat{S}_{it-1} \left(1 + S_{it-1} - \textstyle\sum_i S_{it-1}\right) - S_{it-1}\right)\left(P_{it} - P_{it-1}\right) \qquad (2)$$

where S is market shares in new investment in technology i, $\hat{S}_{it}$ is a maximum share attainable by any given technology and P is the price ratio of technology i to a marker technology (typically CCGT) . A similar representation, although simpler and more stylized, is adopted for the switch from gasoline to battery-powered vehicles rechargeable from the electricity grid. Thus ETM provides a simple model of the process of switching from a marker technology to the possible substitutes. This substitution process may be accelerated if an emission permit scheme is implemented, so that technological change leads to reductions in the use of fossil fuels by power generation, with associated reductions in emissions of greenhouse gases.

Cumulative emissions of CO_2 to 2100 are derived from the MAGICC model as used by the IPCC (Watson et al., 2001). It is a set of linked reduced form models emulating the behavior of a GCM, comprising coupled gas-cycle, radiative forcing, climate and ice-melt models integrated into a single package.

It calculates the annual-mean global surface air temperature and sea-level implications of emission scenarios for greenhouse gases and sulphur dioxide. The E3MG model is used to derive a cost-effective emission pathway which keeps cumulative emissions within the limits prescribed by the MAGICC model. Costs of stabilization are then calculated relative to the baseline. The emission pathways that come from E3MG are then put back into MAGICC to check that, with the new profile, the same concentrations are achieved. Many other studies of stabilization costs (e.g. Nakicenovic and Riahi, 2003; Van Vuuren et al., 2004) also use the MAGICC climate model to represent the relationship between emissions and concentrations. Although MAGICC and E3MG both model emissions scenarios detailing non-CO_2 greenhouse gases, we do not consider the costs of reducing these gases and their effects in this analysis.[10]

The analysis requires a set of assumptions, in addition to the usual ones for an econometric model, e.g. that a long-run solution exists, to reduce the complexity of the problem. The main ones adopted for the results reported below are as follows:

1) Population growth and migration are exogenous at baseline levels, and the assumption is adopted of sufficient labor being available from productivity growth or structural change to meet the demand for products. After 2050, the economic growth rate in all the scenarios slows down to match a slower growth in population. Throughout the century it is assumed that the workforce in developing countries will move from traditional, rural sectors, to urban and modern sectors.
2) Monetary and fiscal policy. Independent central banks are assumed to hold the rate of consumer price inflation constant. Ministries of Finance maintain a long-run fiscal balance by combining lower-non-carbon prices and reductions in costs from new technologies, sufficient to prevent any extra long-run inflation from the change in the tax regime. The increase in the costs of carbon-based products is offset by a decrease in the costs of non-carbon-based products. This implies that interest rates and exchange rates remain more or less at baseline levels in all the scenarios
3) The econometric equations in the model are reduced to two sets: energy and export demand. The energy technologies in the model are also reduced to two sets: those for the electricity sector and, in a simpler form, those for road vehicles. Except for investment by the electricity and vehicles industries, other behavioral equations are treated as being in fixed proportions to their main determinants.
4) The emission permit scheme and the carbon taxes have their effects in raising prices of energy products in proportion to their carbon content where ever they are imposed, and revenues are recycled as

10. If the CO_2 emission pathway does not result in stabilisation in the full integrated analysis, policy parameters are adjusted in E3MG until a consistent solution is achieved.

reductions in indirect taxes to maintain fiscal neutrality. The high rates required, especially for 450ppm, may prove impractical, if not politically impossible. Thus the scenarios show how high the emission prices and tax rates have to rise to achieve the targets.

4. ESTIMATION, CALIBRATION AND CRITICAL VARIABLES

The industrial and energy/emissions database[11] covering the years 1971-2001 is drawn from OECD, IEA, GTAP, RIVM, and other national and international sources and processed to provide comprehensive and consistent time-series of varying quality and reliability across regions and sectors. It contains information about the historic changes by region and sector in emissions, energy use, energy prices and taxes, input-output coefficients, and industries' output, trade, investment and employment. This is supplemented by data on macroeconomic behavior from the IMF and the World Bank. These data are used to estimate a set of econometric equations using cointegration techniques proposed originally by Engel and Granger (1987) and discussed by Abadir (2004) as appropriate for post-Keynesian modeling of non-clearing markets in which a long-run solution is not necessarily in equilibrium. E3MG requires as inputs dynamic profiles of population, energy supplies, baseline GDP, government expenditures, tax and interest and exchange rates; and it derives outputs of carbon dioxide and other greenhouse gas emissions, SO_2 emissions, energy use and GDP and its expenditure and industrial components.

The emphasis in the modeling for this paper is on two sets of estimated demand equations as in equation (1) above: aggregate energy demand by 19 fuel users and 20 regions and exports of goods and services by 41 industries and 20 regions. These sets of equations have been estimated by instrumental variables in a co-integrating general-to-specific framework, assuming a long-run relationship that can be projected over the next 100 years. Each sector in each region is assumed to follow a different pattern of behavior within an overall theoretical structure, implying that the representative agent assumption[12] is invalid.

Two sets of critical parameters, one from each set of equations are shown in Figures 1 and 2 as probability plots (see Barker and De Ramon, 2006, for an explanation of the tests and graphics) of the short- and long-run responses of energy demand to relative prices, and the long-run responses of export demand to the technological progress indicator for Annex I and non-Annex I regions. There are in principle 380 parameter estimates for energy and 820 for exports, and the estimated ones are shown with bubbles representing their standard

11. The database was constructed, and the equations estimated, by teams in Cambridge Econometrics headed by Rachel Beaven and Sebastian De-Ramon, including Dijon Antony, Ole Lofsnaes, Michele Pacillo and Hector Pollitt.

12. The assumption of the representative agent, commonly adopted in equilibrium models, is that the behaviour of an economic group is adequately represented by that of a group, each of whose members have the identical characteristics of the average of the group.

Figure 1. Probability Plots for Short- and Long-run Response of Fuel Use to Relative Price

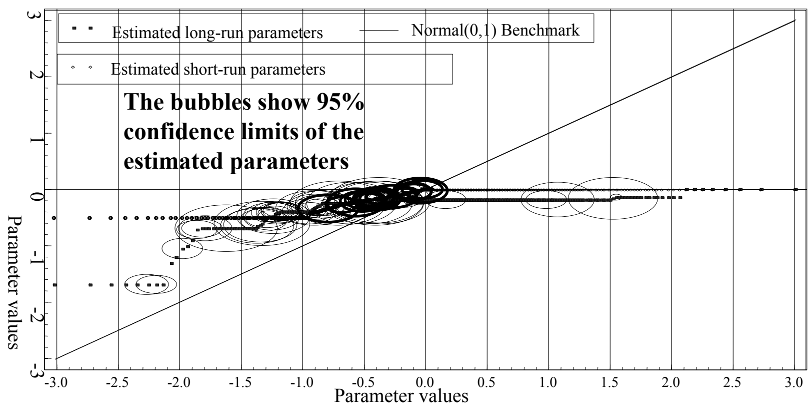
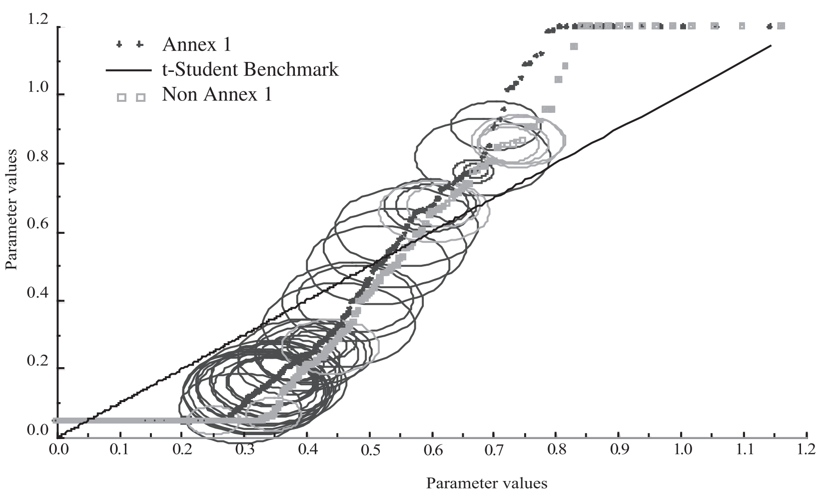


Figure 2. Probability Plots for Annex I and Non-annex I Long-run Responses of Exports to the Technological Progress Indicator



errors. If a parameter is significantly different from a unique estimate using the whole dataset, then the bubble will intersect with the 45 degree line, showing the expected values of the average assuming normality. Both plots show a number of departures from the benchmark t-Student distribution. Figure 1 shows that the short-run responses are small compared with the long-run ones, which have a maximum of -1.8; Figure 2 shows that the long-run responses for Annex I regions are more reliable (many more bubbles shown), more concentrated (most of them near the origin) and lower (clustered around 0.2) than those for non-Annex I regions, which is not a surprise, given the quality of the data for the latter regions.

For the ETM, a database was developed by Anderson and Winne (2004), using learning rates reported in McDonald and Schrattenholzer (2001). Regional differences in the costs of fuels were taken into account and the model was fitted to IEA data on electricity capacity and generation by region and technology. However it should be noted that for many technologies, no past data on capacities exist, so the projections rely on assumed initial shares.

The Common POLES-IMAGE (CPI) baseline has been derived from the IMAGE IPCC SRES A1B and B2 baselines. CPI assumes continued globalization, medium technology, continued development, and strong dependence on fossil fuels. Population follows the UN medium projections for 2030 and the UN long-term medium projection between 2030 and 2100. Further details may be found in Criqui et al. (2003). This baseline is used for the population assumptions of E3MG and projections are made for government expenditures and per capita household consumption for each region assuming the average growth rate will slow after 2050. With other components of GDP endogenous in the model, GDP (in $ at year 1995 prices and market exchange rates) is calculated. Economic growth is near the historic average at 2.3%pa 2000-2100, with higher rates to 2050 and lower rates thereafter. The assumption that baseline growth with ITC is given makes it clear that the model is essentially explaining relative effects, and that the effects on the relative level of GDP and the relative costs of carbon of GHG reductions or of removing ITC may be more reliable than the absolute numbers of GDP and carbon costs in the baseline.

The solution process is complicated. There are three baseline solutions, each yielding closely similar results. The first is the calibrated solution of the model, in which consumers' expenditures are exogenous. A second endogenous, but calibrated, solution is derived by including equations explaining these expenditures, and calculating and storing the residuals between the equation solution and the exogenous values. A third endogenous un-calibrated solution then solves the equations with the residuals and so reproduces the calibrated solution. This endogenous solution includes, for each sector and region: sectoral output, employment, energy use and prices and emissions. It is the basis for two baseline sets of CO_2 emissions, one in which E3MG and ETM allow for endogenous technological change, and another in which they do not. In these baseline solutions technological change still occurs and is modeled as a projection of the estimated effects and through learning by doing.

The emission scenarios are also subject to exogenously defined dates at which countries together impose permit and carbon tax schemes. By default the permit scheme covers the energy sectors only (electricity supply, the fossil fuel and energy-intensive sectors covering metals, chemicals, mineral products and ore extraction) while carbon taxes at the same rates are imposed on the non-energy sectors. The rates start from small values in 2011 and are assumed to escalate in real terms until 2050, then stay constant in real terms until 2100. 50% of the permits are allocated freely to the energy users on the basis of their past emissions (grandfathering) and the rest are auctioned (this rule is adopted to prevent excessive profits in the energy sectors from the sale of permits under conditions in which the industries have market power).[13] The carbon tax revenues are assumed to be recycled in each region independently. The auction revenues are used along with the revenues from carbon taxes to reduce indirect taxes in general (such as the USA's sales taxes or the EU's VAT) as the instrument to help maintain macroeconomic price stability.

5. RESULTS

The results obtained use policies (carbon taxes and/or carbon permit trading) to induce technological change in sectoral energy use in general and electricity generation and motor vehicles to achieve stabilization levels of 450, 500 and 550 ppmv CO_2 by 2100. Table 1 shows the tax levels and trading prices necessary to achieve these targets and Figure 3 shows the resulting CO_2 emissions pathways.

Table 1. Global Carbon Tax Rates and CO_2 Permit Prices[14] ($(1995)/tC)

	With no ITC				With ITC			
Scenario	**2020**	**2030**	**2040**	**2050-2100**	**2020**	**2030**	**2040**	**2050-2100**
550ppmv	37	74	110	147	16	32	49	65
500ppmv	59	119	178	238	27	54	81	108
450ppmv	184	368	551	735	108	216	324	432

Source: E3MG2.1sp2

13. Barker and Rosendahl (2000) in a study of ancillary benefits of GHG mitigation in the EU find that free allocation of permits leads to large profits in the energy industries, compared to the baseline, and that profits can be maintained in the long run if only 50% of the permits are allocated freely (p. 21). Goulder has also addressed this issue, using a general equilibrium approach. A recent paper concludes: "Under a wide range of parameter values, profits can be maintained in both "upstream" (fossil-fuel-supplying) and "downstream" (fossil-fuel-using) industries by freely allocating less (and sometimes considerably less) than 50 percent of pollution permits." (Goulder et al. forthcoming, p 4).

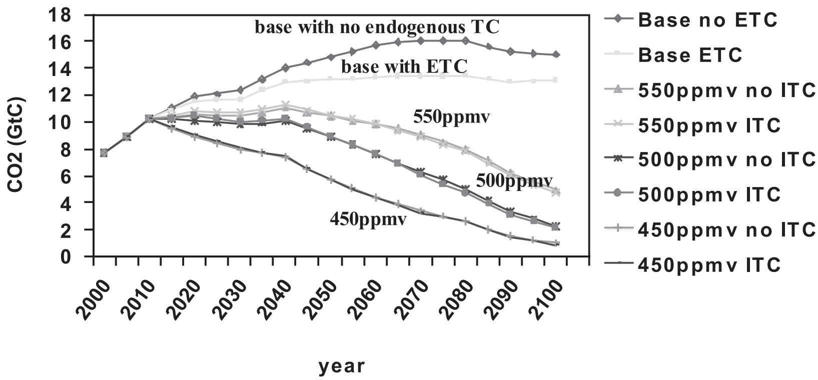
14. These and other reported results are uncertain. A major exercise is planned to assess the uncertainties in the projections, but was not possible for this paper. However the projections are expected to become less reliable the further they are in the future.

There are four features worth mentioning about the rates. First the rates with ITC are about half those without. Second, there are the modest levels required for the 550ppmv target with ITC, with rates starting at $1.6/tC in 2011 and rising to $16tC by 2020. These rates are sufficient to increase energy efficiency appreciably and shift the electricity system to a mixture of low-carbon options including renewables, coal and gas with sequestration, and nuclear depending on region and local conditions. Third, the rates for the 500ppmv target are not quite double those for the 550ppmv target. The increase is a sufficient incentive to cause the conversion from gasoline to electric vehicles largely over the years to 2050. The modeling of the conversion is highly non-linear, since it requires a system change, and the permit/tax rates required are very uncertain. As the transport sector decarbonises, it requires more electricity, and this further accelerates the move to low-carbon technologies in the electricity sector. Third, the 450ppmv target is much more difficult to achieve. Rates with ITC start at $11/tC in 2011 and rise to $108tC by 2020 and $432 by 2050. The easier, lower cost options for reducing emissions have been exhausted, and the extra growth stimulated by the higher investment is also encouraging the demand for energy in general.

Figure 3 shows the emission pathways, both with and without induced technological change. The baseline with no ETC or ITC is substantially higher than that with ETC and, since there are no tax changes, no ITC. The striking feature of the stabilized scenarios is that the treatment of technological change makes very little difference to the use of carbon. Taking the system as a whole, the effects of technological change as modeled are simultaneously to reduce energy demand directly through improvements in efficiency but increase economic growth and so increase energy demand indirectly, offsetting the effects of the improvements in energy efficiency. This relates to the "rebound effect" found in studies of energy efficiency (Herring, 2004; Frondel, 2004) in which the expected reductions in energy use do not occur because the extra real income provided by the improvement in efficiency leads to more energy use. At the global, long-run scale, technology drives energy efficiency, but it also, more significantly, drives economic growth and offsets the efficiency gains so that energy use and CO_2 emissions remain high. The scenarios show that these can be curtailed by increases in real carbon prices.

Both energy and carbon intensities fall after 2010, with energy intensities falling earlier, partly because low-carbon transportation requires a longer time to develop but mainly because technological change affects energy use in general, rather than carbon use in particular. The carbon taxes and permits also have their main effect on energy use rather than CO_2 because of the difficulties of substituting away from carbon outside the power sector. In power generation, fossil fuel shares fall and renewable shares rise in both the base and the scenarios. The higher real costs of carbon in the scenarios have their main effect in accelerating this shift. Within the renewable group, there is a wide diversity of technologies adopted, depending on local conditions and niche markets.

Figure 3. Global CO_2 Emission Pathways and Endogenous Technological Change



Source: E3MG2.0sp1r1, model solutions annually to 2020 and every 10 years to 2100.

Table 2. Global GDP Projections in the Scenarios

		$(1995) trillion		Difference from base %	%pa	
Scenario	**2000**	**2050**	**2100**	**2100**	**2000-2050**	**2050-2100**
Baselines:						
no ITC	33.2	133.5	289.2		2.8	1.6
ITC	33.2	141.9	330.1		3.0	1.7
550ppmv:						
no ITC	33.2	134.8	292.5	1.11	2.8	1.6
ITC	33.2	143.3	334.2	1.15	3.0	1.7
500ppmv:						
no ITC	33.2	135.9	294.8	1.85	2.9	1.6
ITC	33.2	144.1	336.4	1.75	3.0	1.7
450ppmv:						
no ITC	33.2	166.2	298.6	3.09	3.3	1.2
ITC	33.2	180.6	342.0	3.37	3.4	1.3

Source: E3MG2.1sp2

Table 2 shows the outcomes for GDP, also with and without induced technological change. The effects of including endogenous technological change in the baseline are apparent, with appreciable effects on global economic growth as employment shifts more rapidly from traditional to modern sectors, especially in developing countries. This is not a surprise. Technological change is led by improvements e.g. in the use of machinery and information technology, which allow long-run growth to proceed by restructuring and saving on scarce resources such as labor and energy. The growth itself ultimately comes from the demand by consumers for goods and services, through increasing returns exploiting technological and marketing innovations. The growth rates are hardly affected by decarbonisation of the global economy, partly because energy demand and supply is very small in relation to the rest of the economy, around 3-4% of value added. These results appear to confirm those of Gritsevskyi and Nakicenovic (2000) using the MESSAGE model which suggest that a decarbonised economy may not cost any more than a carbonised one and that there is a large diversity across alternative energy technology strategies.

Table 2 also shows the extent to which higher growth is induced by the extra investment as a result of the increases in real carbon prices. At 550ppmv, the overall effects are very small, with the growth rates unchanged. When the stabilization targets are more demanding, the extra investment required leads to a small increase in the growth rate before 2050, and GDP is about 3-4% higher by 2100.

Table 3. Sensitivity Tests on Inclusion of ITC in E3MG

	Base		**450ppmv**	
	CCO2	**GDP**	**CCO2**	**GDP**
Effects of ITC as % difference from non-ITC base by 2100:				
sectoral energy equations	-9.4	0.1	-0.9	-0.8
sectoral export equations	3.2	13.6	0.7	12.3
ETM	-1.6	0.4	0.1	2.7
Total	-8.0	14.1	-0.1	14.5

Source: E3MG2.1sp2
Note: CCO2 is accumulated global CO_2 emissions to 2100.

The sensitivity[15] of the results to the inclusion of endogenous technological change (ETC) in the different sets of equations in the model is reported in Table 3. Starting with a solution without ITC, the model has then been run with the ITC effects included in the sectoral energy equations, and the differences calculated for accumulated CO_2 (CCO_2) and GDP for 2100: the main effect is to reduce CO_2 emissions in the base by 9.4%, while the small emissions in the 450ppmv stabilized scenario are almost unchanged. The effects of ITC in the export equations are to increase CO_2 by 3.2% in the base, and GDP by over 10% in both scenarios. The effect of the ITC in the ETM is to reduce emissions slightly in the base, but increase GDP by 2.7% in the 450ppmv scenario. The extra investment induced by the switch to low-carbon technologies then leads to higher exports and hence higher world growth.

15. A sensitivity analysis of E3MG parameters in principle requires repeated re-estimation of parameters under different assumptions, with associated projections. This major exercise was not possible for this paper.

6. CONCLUSIONS

Under a set of plausible assumptions, economic growth has been made endogenous in a large-scale econometric model, with sets of export and energy demand equations estimated on 20-region annual data 1971-2001. General technological progress at the macroeconomic level has been measured by indicators chosen as accumulated gross fixed investment enhanced by R&D expenditures, and its effects estimated by inclusion of the indicators in these equations. However, improvements in energy efficiency are offset in their effects on emissions by the effects of higher growth in exports, incomes and therefore the demand for energy. This phenomenon is a global, macroeconomic counterpart to the rebound effect found in microeconomic studies of energy policies. The main conclusion is that general technological change alone seems unlikely to lead to decarbonisation.

Specific technological progress has been included in the model by a bottom-up representation of technologies using energy in the electricity and vehicle industries, with learning curves and responses to real energy prices. When technological change is induced by allowing the technologies to respond to increase in the costs of carbon through costs of permits and taxes, the outcome is a wave of extra investment, initiated in the electricity and vehicle industries, but diffusing rapidly to all investing and other industries in all regions. The extra investment raises economic growth, with demands being stimulated by higher incomes and supplies made available by economies of scale and specialization as well as a more rapid shift of employment from traditional to modern sectors in developing countries. At the 450ppmv stabilizations level, the permit price and the carbon tax rates are much higher than at the 500ppmv and 550ppmv levels, but the increase in economic growth is only slightly higher.

The conclusions are conditional on model uncertainties and assumptions, and on specific fiscal polices. Macroeconomic inflation stability is assumed by the recycling of permit-auction and tax revenues through reductions in indirect taxes, e.g. VAT, holding consumer inflation at baseline values. In effect indirect taxation is shifted towards products in proportion to their carbon intensity. Energy-industry profits are assumed to remain at baseline values by half the permits being freely allocated. The long-run public sector finances are assumed to be kept in balance by the increases in tax revenues from the higher growth. Under these conditions, if policies raise real carbon prices, then the extra investment from the induced technological change is expected to lead to slightly more economic growth.

ACKNOWLEDGEMENTS

E3MG has been developed by the UK Tyndall Centre for Climate Change Research, funded by the UK Research Councils. The large-scale version 2 used in this paper could not have been developed without substantial contributions from Cambridge Econometrics Ltd in the forms of some data provision and of

procedures for data management and estimation, which were undertaken by teams headed by Rachel Beaven and Sebastian De-Ramon, and including Dijon Antony, Ole Lofsnaes, Michele Pacillo and Hector Pollitt. The authors are very grateful for these contributions.

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Endogenous Structural Change and Climate Targets Modeling Experiments with Imaclim-R

Renaud Crassous, Jean-Charles Hourcade, Olivier Sassi

This paper envisages endogenous technical change that results from the interplay between the economic growth engine, consumption, technology and localization patterns. We perform numerical simulations with the recursive dynamic general equilibrium model Imaclim-R to study how modeling induced technical change affects costs of CO_2 stabilization. Imaclim-R incorporates innovative specifications about final consumption of transportation and energy to represent critical stylized facts such as rebound effects and demand induction by infrastructures and equipments. Doing so brings to light how induced technical change may not only lower stabilization costs thanks to pure technological progress, but also trigger induction of final demand—effects critical to both the level of the carbon tax and the costs of policy given a specific stabilization target. Finally, we study the sensitivity of total stabilization costs to various parameters including both technical assumptions as accelerated turnover of equipments and non-energy choices as alternative infrastructure policies.

1. INTRODUCTION

This paper revisits the comparison between autonomous (ATC) and endogenous (ETC) models of technical change from a specific premise: in a model where policy signals induce the rate of technical change (through both learning by doing and investments in R&D), the behavior of households' consumption must necessarily be taken into account.

This premise is one made in the context of a wider discussion on how to endogenize structural changes in economic growth models. The notion that the rate and direction of technical progress (in terms of aggregate factor intensity) depend not only on the efficiency of physical capital but also on the structure of final households' demand has been put forward by Solow (1990). Economic

The Energy Journal, Endogenous Technological Change and the Economics of Atmospheric Stabilisation Special Issue.

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history has also demonstrated the importance of the interplay between these two parameters (Wright, 1990). In this paper, parameters such as product differentiation (Barro and Sala-i-Martin, 1998) in non energy related goods and services are not endogenized, and we assume static private and public preferences for end-use services. Nonetheless we attempt to contribute to the discussion of endogenous structural changes by explicitly addressing the interplay between the endogenous growth engine, decarbonization policies and transportation dynamics as a critical component of final demand. More specifically, we attempt to capture the rebound effects on gasoline demand triggered by efficiency gains of vehicles as well as the mobility needs induced by infrastructure choices for given consumer preferences. In this way, we attempt to extend the concept of ETC to the interplay between innovation, infrastructure and energy consumption (Hourcade, 1993).

To disentangle the many facets of the ETC vs. ATC debate, we conduct numerical experiments assuming: i) the absence of carbon free gasoline as a backstop by the end of the century; ii) no "negative costs potentials" and no carbon sequestration; iii) a linear carbon tax profile (hence sub-optimal in all simulations); iv) no possibility of early retirement of capital stocks. The results from such exercise magnifies effects of the key factors at play (at the expense of high GDP losses for meeting tight GHG concentration targets as 450 ppm in some policy scenarios)[1], with the advantage of delivering some novel insights on the policy variables capable of minimizing costs of such ambitious targets.

This paper is structured as follows. Section two describes the rationale of the Imaclim-R framework and how it describes induced technical change mechanisms (ITC). Section three presents the baseline scenario. In section four, we explain why assuming that the same overall potentials of technical change that may or may not be policy-induced leads to very different costs assessments of stabilization scenarios. We pay particular focus to the demand induction in transportation as well as to the crowding-out effect of investments. Sensitivity tests are performed in the fifth section to illuminate the underlying mechanisms concerning both induced technical change and broader structural change, with a specific focus on the control of mobility.

2. THE Imaclim-R MODELING FRAMEWORK[2]

2.1 Structure of the Model

Imaclim-R is a multi-sector multi-region recursive growth model projecting, on a yearly basis, the world economy up to 2100. It is run for five regions

1. Note, however, that some of the assumptions retained for these simulations are far from being implausible. For example, the assumption of cheap carbon-free gasoline by the middle of the 21st century would dampen effects of some of the mechanims at play, which may in turn have a critical role in the absence of this optimistic assumption.

2. An extensive description of the model is available on line at http://www.centre-cired.fr/forum/article359.html.

(the four SRES regions—OECD90, REF, ASIA, ALM[3]—from which we set apart the OPEC region), 10 economic sectors (coal, crude oil, natural gas, oil products, electricity, construction, composite good, air transport, sea transport, terrestrial transport) and two transport modes auto-produced by households (personal vehicles and non-motorized transportation).

The model uses a recursive dynamic framework[4] where economic pathways are represented through a sequence of static general equilibria, linked by dynamic equations (Figure 1). These successive equilibria are computed under the constraints imposed by the availability of production factors and inter-sectoral technical relations at each point in time. The outcome is a set of values (output levels, price structure and investment) sent to dynamic equations which represent population dynamics, fossil fuel resource depletion and technical change. Technical change encompasses overall labor productivity and technical coefficients and results in a new production frontier used to compute the subsequent equilibrium. In an ATC framework, the new parameters of this new production frontier come from exogenous trends, whereas under ETC assumptions, they come systematically from endogenous relations between cumulated investments and technical progress.

This approach was developed in an effort to address four interrelated challenges:

i) to incorporate some of factors that drive economic growth, rather than defining growth rates through entirely exogenous assumptions;
ii) to utilise in a consistent manner, bottom-up expertise about technical change;
iii) to allow for the description of imperfect foresight (about future relative prices, final demand and profitability) and of possible decision routines[5] in infrastructure sectors;
iv) to capture possible transition costs towards long run equilibria, transition costs that may result from the interplay between non perfect foresight and the inertia of technical systems.

The framework also allows us to a) represent baseline scenarios which can have a non-optimal use of production factors (structural unemployment, excess capacity or capacity shortages[6]) and b) to account for the fact that economies adapt to climate targets within the constraints imposed by past decisions, includ-

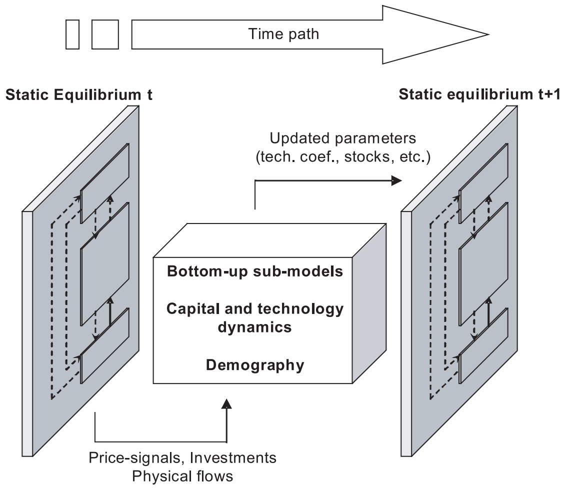
3. See (IPCC, SRES, 2000) or http://www.grida.no/climate/ipcc/emission/149.htm for a full description of regions.

4. Similar to the option followed by EPPA (Paltsev et al., 2005 for the last version) or SGM (Edmonds et al., 1993) for instance.

5. The notion of decision routines encompasses here, seemingly non optimal choices due to the influence of institutional contexts and/or the incorporation of non economic objectives (equity, security) in public decisions.

6. Picturing non-optimal baselines and policies is important in the context of developing countries since underdevelopment is the product of institutional and market failures (for that reason current work at CIRED aims to include public indebtedness in long-term simulations). It is also important for developed countries; for example the 4% GDP loss predicted in some studies as a cost of Kyoto target for the US relied specifically on the assumption of non-optimal responses (IPCC, TAR, WGIII).

Figure 1. The Recursive Dynamic Framework of Imaclim-R



ing transaction costs of changing domestic social contracts. The model incorporates mechanisms driving the economy back to stabilized trajectories which are reached if steady long term signals are given to the agents (carbon and oil prices) and when the influence of inertia progressively recedes.

In this modeling system, all flows are tracked at each point in time, by a double accounting in both money metric values and in physical quantities, the two being linked by relative prices[7]. This hybrid accounting is used to by-pass difficulties linked to the representation of capital in usual production functions: at a given point, the model accounts for the available *physical* capacities of production and describes the financial flows serving to replace and expand them (see 2.2. herebelow). It is worth noting that, in addition to facilitating the tracking of the sources of GHG emissions and of the dipping into fossil fuel resources, this methodology facilitates a transparent incorporation through *physical* technical coefficients of bottom-up information regarding (i) the technical saturations of efficiency gains in energy and transportation equipments at a given time horizon and (ii) how the technical characteristics of energy (and transportation) systems react to relative price variations.

2.2 Static Equilibrium Under a Given Production Frontier

Each *static equilibrium* is Walrasian in nature: it is characterized by annual flows of goods and money and a set of relative prices as they result from supply and demand behaviors, investment decisions, private and public income bud-

7. The flows of the five energy goods are expressed in Mtoe; final consumption of transportation is indexed in terms of passenger-kilometers; housing area is tracked in terms of square-meters built.

get constraints and clearance conditions for international and national markets. The calibration of the static equilibrium at the benchmark year (1997) is based on data from the following sources: social accounting matrices form the GTAP Database Version 5 (Dimaranan and McDougall, 2002); IEA/OECD physical database for energy (IEA, 2000; 2001), and data from Schäfer and Victor (2000) and the *World Road Statistics database* for transportation (International Road Federation, 2001). The following is assumed for the current:

(i) *Producers* are constrained by fixed capacities *Cap* (the depreciated sum of previous vintages) and the technical characteristics of the equipment stock that result from past decisions. This comes to a putty-clay assumption. Hence, the variables of the model are prices p, wages w and utilization rate (UR) linked to the level of output. Average production costs thus derive from fixed input-output coefficients IC_j, a fixed labor intensity l, and a static diminishing return factor Ω^{UR} which is function of a flexible capacity utilization rate. A constant mark-up π is added to the mean cost[8]. For primary energy sectors, the mark-up increases in function of cumulated production, as to capture the scarcity rent on the long-run.

$$p = \sum_j p_j^{IC} \bullet IC_j + (\Omega^{UR} \bullet w) \bullet l + \pi \bullet p \tag{1}$$

$$\text{with } UR = \frac{Q}{Cap} \tag{2}$$

Equation (1) in fact represents the *inverse supply curve* of each sector, since it shows how the representative producer decides its level of ouput Q ($Q<Cap$) in function of all prices and wages. The desired level of ouput in each sector implies a labor demand $l \bullet Q$. The difference between total labor demand across all sectors and the current labor force[9] is unemployment. The level of unemployement has an impact on real wages through regional wage curves: wages tend to infinity as unemployment disappears and they tend to zero as unemployment rate tends to one. The calibration of these wage curves rests on Blanchflower and Oswald (1995).

(ii) *Consumers' final demand* is derived by solving the utility maximization problem for a representative consumer:

$$Max\ \mathrm{U} = \prod_{\substack{\text{goods i} \\ \text{(composite, construction)}}} (C_i - bn_i) \bullet \tag{3}$$

$$(S_{\text{housing}} - bn_{\text{housing}})^{\xi_{\text{housing}}} \bullet (S_{\text{mobility}} - bn_{\text{mobility}})^{\xi_{\text{mobility}}}$$

$$\text{with } S_{mobility} = CES(pkm_{air}, pkm_{public}, pkm_{cars}, pkm_{non\text{-}motorized}) \tag{4}$$

8. Such a constant markup corresponds to a profit-maximizing decision of producers when the diminishing return factor follows an exponential function of utilization rate.

9. Regional active population follows exogenous trends (ONU 2004 medium fertility variant, available at http://esa.un.org/unpp/index.asp?panel=2) and incorporate fixed migration flows. These parameters are kept constant between the baseline and policy scenarios.

In equation (3), C_i holds for consumed quantities of composite and construction, S_i holds for services provided by energy and mobility, *bn* corresponds to the basic needs of final consumers for final goods and services and *pkm* represents the physical consumption of each mode of transportation accounted in terms of passenger-kilometers.

Note first that energy does not directly enter the utility function; it contributes to welfare through the services it fuels. The demand for these services is driven by private housing and transportation equipments. Energy consumption is then dependent upon the efficiency coefficients characterizing the existing stock of end-use equipments. Second, transportation modes are nested in a single index of mobility defined by equation (4). To account for preferences and spatial heterogeneity of their availability, the different modes of transport are assumed to be imperfect substitutes.

Equation (3) is maximized subject to income and time constraints. Income, defined by equation (5) equates the sum of savings *S*, the energy bill (induced by unitary needs α^{Ei} for residential end-use, and for private transportation α^{cars}) and expenditure on other goods and services (including public transportation). In this equation, $stock^{m2}$ accounts for the stock of housing. Savings follow an exogenous saving rate. The time constraint *Tdisp* (6) is derived from empirical findings (Zahavi and Talvitie, 1980) and represents average daily travel time of a household. For a given travel mode *j*, the marginal consumption of time per kilometer τ_j is inversely correlated to the congestion which, for a given mobility demand, depends on the availability and efficiency of infrastructure and equipment.

$$Income = S + \sum_{\substack{\text{non-energy}\\ \text{non-transport goods i}}} \mathrm{p_i} \bullet \mathrm{C_i} + \Big(\sum_{\text{energies Ei}} p_{Ei} \bullet \alpha_{Ei}^{housing} \bullet stock^{m^2} \Big) \tag{5}$$

$$+ \big(p_{public} \bullet pkm_{public} + p_{air} \bullet pkm_{air} + \sum_{\text{fuels Fi}} (pkm_{cars} \bullet \alpha_{Fi}^{cars})\big)$$

$$Tdisp = \sum_{\text{modes Ti}} \int_0^{\mathrm{pkm_{Tj}}} \tau_j(u)du \tag{6}$$

Ultimately modal shares and mobility demand that result from utility maximization depend on both travel costs and travel time productivity of the various modes (average km traveled per unit of time). Through this channel, the quantity and cost efficiency of infrastructure stocks and the energy efficiency of vehicles have an impact on mobility demand, as well as the trade-off between mobility and other goods and services.

(iii) *Investment allocation* across regions and sectors is governed by the expectations of future profits. Parts of the regional savings are reinvested domestically, the rest being redirected to an international capital pool, which in turn re-allocates them to regions according to the sectors' profitability. Allocation of investments does not, however, equalize the marginal productivity of new investments because investors account for idiosyncratic country-risk[10]. Future profits are imperfectly foreseen, as decision-makers interpret the current economic signals as the best available information about present and future economic conditions. Sub-sector allocations of

10. 'Country risks' represents the aggregate relative economic attractiveness of regions.

investments across technologies are treated in the dynamic equations.

(iv) The equilibrium clears *international markets* for goods and capital. A conventional 'Armington' specification (Armington, 1969) is adopted for non energy goods though energy goods are considered to be homogenous commodities. Their trade rests on specific market shares and real physical account of quantities[11]. Capital and trade balances compensate each other, through variations of all regional prices[12].

The existence of short term constraints on the physical capital and technical coefficients implies that market clearing is made through modifications to relative prices and sectoral level of output. The equilibrium is thus second best and allows for capacity shortages, overcapacity and unemployment. The new relative prices impact on profitability rates and investment allocation. Inside each region, investments are converted into new productive capacities through a regional β-matrix[13], which allows for calculating the price of a new unit of production capacity for each sector. The over or under-employment of factors of production can thus be released across time thanks to these investments and related incorporated technical change.

2.3 From Static Equilibria to Growth Dynamics

As pictured in Figure 1, dynamic equations encompass both the evolution of the production frontier and movement along this frontier (i/o coefficients, installed capacities, public infrastructures, labor force) and of the constraints impinging upon the consumers program (income, end-use equipments). They capture the joint effect of the macroeconomic growth engine and technical changes on the supply and demand-side.

The *growth engine* is composed of exogenous demographic trends and labor productivity changes (the labor intensity l in equation (1), and is fueled by regional saving rates and by investments allocation across sectors. Even though they do not affect long-run growth rates, such as in the Solowian models, short term adjustments condition output growth on the short and medium term. Productivity can be assumed either to follow an exogenous trend (w/o ITC) or to be driven by cumulated investment in the composite good sector (with ITC), accounting for an investment externality on all other sectors. In both cases the parameters are calibrated on historic trajectories (Maddison, 1995) and the 'best guess' of long-term trends (Oliveira-Martins et al., 2005). In addition, the β-matrix values are increased to account for the part of productivity gains that comes from capital deepening[14].

11. Armington specifications do not allow the summing of physical quantities that are imported and produced domestically, since they are supposed to be different kind of goods.

12. The variation of regional price index can be interpreted as implicit flexible exchange rates.

13. With $\beta_{i,j}$ the physical amount of good i that is necessary to build in sector j the capacity to produce one physical unit of good j.

14. The link beween labor productivity gains and capital deepening is calibrated on historical data gathered by (Maddison, 1995).

Technical change at a sector level (intermediate or end-use efficiency gains, costs of new technologies and substitutions between energy sources) are driven by the interplay between changes in relative prices and cumulated investments. Relative prices operate in the same way in both versions of the model by affecting choices of both firms and consumers in purchasing new equipment (the resulting new values of their energy and mobility demand being captured in the *following* static equilibrium). The calculation of the production frontier is based on a putty-clay assumption which implies that technologies are embodied in the equipment stocks resulting from the cumulated investment vintages. In the 'w/o ITC' version, the diffusion of autonomous technical change is thus constrained by the pace of replacement of capital. This creates short run inertia, which is considered realistic for energy, transportation and heavy industry sectors. With ITC, this pace is also binding with the difference that 'learning-by-doing' and R&D mechanisms are also positively correlated to cumulated investments. It is thus possible to accelerate the efficiency gains in energy and composite sectors (7) and the decrease of investments costs of carbon-free techniques (8). In addition, changes in energy prices induce efficiency gains in private cars, end-use equipments and in the composite sector.

Imaclim-R, in some sense, describes such mechanisms through 'reaction functions', for example, through reduced forms of bottom-up information. It computes the evolution of coefficients of the technical input-output matrix, end-use efficiencies (7) and β-matrixes coefficients (8) in function of historical investments, as well as variations of relative prices:

- endogenous variations of energy efficiency of production capacities and equipments:

$$\text{Energy Efficiency}^{(t)} = f\,(\sum_{\tau=t_0}^{t} \textit{Investments},\ \Delta p^{(t)}_{energy}) \quad f'_{\Sigma I} > 0, f'_{\Delta I} > 0 \qquad (7)$$

- endogenous variations of investments costs for carbon saving equipments (learning by doing and R&D):

$$\beta^{(t+1)}_{i,j,k} = g\,(\sum_{\tau=t_0}^{t} \textit{Investments}^{(\tau)}_{k,j}) \qquad g'_{\Sigma I} < 0 \qquad (8)$$

for any low carbon energy *j* in country *k* and any investment good *i*.

Such functions are calibrated on (i) explicit views of technical potentials in the form of asymptotes on energy efficiencies and on the shares of given energy carriers in end-use demand and energy supply, and (ii) on results from bottom-up models. They incorporate technical asymptotes translating expert judgments about the ultimate potential of each technical bundle. In the base case experiment of this exercise we used the following estimates[15]: in the *electric* sector, the technical asymptotes for energy efficiency are set at 0.5 for coal-based technologies, 0.6 for oil and gas technologies (these figures do not reflect the potential efficiency gains from cogeneration); the carbon content of energy mix is likely to fall to zero. With ITC, the rate of decrease of the price of non-carbon energies doubles when investment in those technologies is multiplied by four with respect to the reference case. In the *composite* sector, the rate of global energy efficiency improvement doubles if the energy prices increases by 60%, and the energy mix can be decarbonized up to 100% by 2100. For the residential consumption of energy, maximum efficiency gains are -2% per year. For transportation, the maximum average efficiency of cars and trucks in 2100 is set at 25% of today's best available techniques.

2.4 Stabilization of CO_2 Concentrations

To date Imaclim-R does not include a climate model, thus we use the total carbon budget over the century as a proxy for the stabilization level[16]. We have checked *ex post* that the emissions trajectories we derived from these carbon budget are consistent with expected stabilization, using the carbon cycle and climate module developed at CIRED (Ambrosi et al., 2003).

3. THE REFERENCE SCENARIO: SLOW CATCHING-UP, CARBON INTENSIVE DEVELOPMENT PATTERNS[17]

Imaclim-R is not designed to follow an *ex-ante* scenario but rather to produce its own reference scenario from a set of upstream assumptions regarding labor productivity growth, demography or international trade. To try and calibrate it on the CPI baseline would require a cumbersome process of selecting one *ad hoc* set of parameters.

As in a Solowian model, real GDP growth follow similar trends as the potential growth of each region (sum of input assumptions of productivity and population growth), the functioning of the world markets (goods, energy, capital) accounting for differences. The ASIA and REF regions, after a sustained high economic growth in the first part of the century (above 4%), converge to growth rates on the same order of magnitude as OECD (down to 1% in 2100), whereas the economic growth rate re-accelerates in ALM after 2070 because the catching up of most African countries is delayed by comparison with ASIA. At the end of the century the trend towards some form of steady growth is interrupted due to the sharp increase of oil prices: the transition costs to this shock explain why the real

15. The estimates we used reproduce orders of magnitude from experts judgments (IEA Investment Oultook, 2003) and from output of the POLES energy model.

16. Since in the 550 ppm scenarios stabilization would occur after 2100, the budget over the 21st century is only a necessary condition for stabilization.

17. An extensive presentation of the baseline scenario is given in a previous version of this paper and in numerical appendixes available on http://www.centre-cired.fr/forum/article358.html

GDP growth of all regions, with the exception of OPEC, become lower than the sum of input assumptions regarding productivity and population.

This reference case generates 25 GtC of emissions in 2100 and a cumulated 1677 GtC carbon release over the century. This results from three main components to be borne in mind when analyzing the costs of stabilization scenarios.

a) The *increase of households final consumption* shows a significant but modest and regionally heterogeneous catching up between 2000 and 2100: (i) the mean annual growth rate of per capita consumption of composite goods is 1.37% in OECD, 1.87 % in ASIA, 2.67 % for REF, 1.25 % for ALM and 1.63 % for OPEC[18]; (ii) per capita housing space is multiplied by 2.5 in OECD, 4 in ASIA, 6 in REF; (iii) per capita total mobility doubles in OECD, triples in ASIA and quadruples in REF. The growth of the traffic rests on different modal breakdowns across regions: in non-OECD countries mobility growth is mainly due to an increasing access to motorized mobility (public modes followed by private cars when welfare increases), while OECD experiences a shift to air transport.

b) The *decoupling between economic growth and energy demand* ranges between 0.66% to 0.98% per year depending on regions. For OECD, this decoupling comes mostly from the increasing share of services in the composite good (-0.76% per year against -0.12% for energy efficiency after 2050) while for ASIA, ALM and OPEC it comes primarily from energy efficiency gains (-0.5% over the century). This translates the fact that, in these regions the 'dematerialization' of the economy takes place only in the second part of the century.

c) *The aggregate carbon content of the energy supply* increases slightly in the first half of the century since the electricity supply rests mostly on coal and gas, fuel for transportation is still dominantly produced from conventional and non conventional oil. In the second half of the century fossil fuel prices start rising more significantly, with'peak oil' between 2080 and 2090[19]. This triggers more significant penetration of non-fossil energy at the end of the century. Thus part of the potential of decarbonization is already included in the baseline, but this a minor part.

4. POLICY SCENARIOS: WHY DOES ITC MAKE A DIFFERENCE?

Unequivocally, running Imaclim-R with or without ITC has impact on the dynamic component of the model. One precondition for comparing these two different treatments is to guarantee that they describe identical no-policy baselines and the same degree of pessimism or optimism regarding technical change potentials. For the 'w/o ITC' simulations we switched off all the 'ITC' components

18. Mean growth rates of developing countries over the century masks high growth rates during its first half and a generalized slowdown in the second half, due to both a downward convergence of labor productivity growth to a 2% per year and the ageing of population, especially in Asia.

19. This derives from the cost assessment of conventional and non conventional oil resources provided by the Institut Français du Pétrole. Geopolitical tensions triggered by the geographical polarization of oil resources may induce upward pressure on oil prices before 2080, but such events have not been incorporated in the baseline of this exercice .

and we calibrated exogenous technical change coefficients to reproduce the same trends of technical change as in the 'with ITC' baseline. This treatment encompasses all kinds of technical change: general trend of labor productivity, energy mix, energy efficiency on supply and demand sides, and costs of equipment for non-fossil sources of electricity.

Table 1 summarizes the costs assessment of meeting various CO_2 concentration targets for OECD and non-OECD regions with a policy based on a carbon tax which increases linearly from 2005 to 2100[20], and the product of which is recycled first by lowering preexisting taxes on labor and second with lump-sum transfers to households. In our central case, meeting a 550 ppm target requires a 115 \$/tC and 384 \$/tC carbon tax in 2100 with ITC and without ITC respectively. The 450 ppm target requires 365 \$/tC and 1166 \$/tC carbon prices with ITC and without ITC respectively.

Table 1. Costs of CO_2 Stabilization Targets Under Various Technical Change Assumptions[21]

	with ITC		**without ITC**	
	550 pm	**450 ppm**	**550 ppm**	**450 ppm**
Tax profile	+ 1.5\$/ton of C/year	+ 3.8 \$/ton of C/year	+ 4 \$/ton of C/year	+12.15\$/ton of C/year
Carbon price in 2100	115 \$ per ton of C	365 \$ per ton of C	384 \$ per ton of C	1166 \$ per ton of C
OECD losses in Composite consumption	-0.9 %	-3.7 %	-4.6 %	-10.1 %
Non-OECD losses in composite consumption[22]	-2.0 %	-5.6 %	-5.6 %	-13.2 %

These tax levels cause significant consumption losses, far higher without ITC, than those of the post-SRES IPCC scenarios (IPCC, 2001). This is only in part due to conservative assumptions behind our central case; these assumptions are supported by the consideration of limits to large scale deployment of bio-fuels, concerns about nuclear energy, and the inhibition of investments by uncertainty about the ultimate performance of alternative technological routes. The sensitivity analysis conducted in Section 5 discusses these assumptions and shows out how they interact with the more fundamental mechanisms explained herebelow and which governs the differences in the cost assessments delivered with or without ITC.

20. A 'benevolent planner' should impose a specific tax profile under each specification. We used an identical profile in both cases in order to concentrate on the differences in the economic mechanisms at work with and w/o ITC.

21. We report consumptions losses discounted with a 5% rate to be consistent with the figures reported in the synthesis report of this journal issue.

22. These figures encompass losses in OPEC and REF regions due to lower oil and gas exports.

4.1 Lower Carbon Prices with ITC Despite Demand Induction

In all simulations, the carbon tax triggers a move towards low carbon intensive production and consumption and the tax levels for a given target are determined by the substitution possibilities on both the demand and supply sides at each point in time. The difference in results with and without ITC lies in the dynamics of these substitution possibilities. *Without ITC*, substitution possibilities are moved forward by the autonomous progress coefficients of carbon saving techniques and by the turnover of capital equipment which limits the pace of penetration of these techniques. The tighter the targets, the higher required carbon price in order to foster larger substitutions. This hampers sectors' profitability, lowers economic growth, and triggers a vicious circle: reducing the replacement rate of equipment in turn slows down the penetration of lower costs carbon saving techniques. *With ITC,* this mechanism is in part offset: the higher the taxes, the quicker the decrease of costs of carbon saving techniques and the higher the pace of their incorporation in the equipment stock. Thus, for a given carbon tax profile, the difference in carbon intensity between capital stocks with and without ITC is quickly substantial.

However, this dominant mechanism masks more complex dynamics at play in the transportation sector. Unsurprisingly, during the first half of the century, accelerated *induced* efficiency gains in vehicles limit the increase of emissions from transportation to 63% with ITC instead of 70% without ITC in a 550 ppm scenario for a 2.5 times lower carbon tax. But with ITC, a countertendency exists which is fully revealed after 2050: the availability of more efficient infrastructures and the lower user cost of private vehicles induce a higher mobility of demand. In the OECD the induced energy efficiency gains partially offset the burden of the tax and households reallocate part of their budget to air travel. In non-OECD regions, these gains mainly facilitate the access to motorized private mobility. After 2050, energy efficiency of vehicles reaches an asymptote and the countertendency prevails: in both the 450 and 550 ppm scenarios demand for gazoline still increases with ITC (+23% for 550 ppm) while it decreases in scenarios without ITC (-7% for 550 ppm).

The lesson is that, under 'with ITC' scenarios, the relative cost of mobility increases far less over the first decades than the price of the gasoline because of induced efficiency gains.

4.2 From Carbon Taxes to Variations of Economic Growth

Aggregate costs of stabilization targets with or without ITC differ in a way which is globally consistent with the carbon prices profiles of each scenario: 1.1 % decrease of the discounted sum of households' consumption of composite goods (a proxy for welfare losses) with ITC against 4.8 % without ITC for a 550 ppm target. However a deeper scrutiny reveals a more complex picture: in both scenarios, losses are higher in non-OECD countries (2.0% and 5.6% against 0.9% and 4.6%) despite a consistent carbon tax in both regions. For a carbon tax 2.66 times lower with ITC than without ITC, consumption losses are divided by 5.1

in OECD countries, and by 2.8 in developing countries. These results can be explained by the interplay between two main mechanisms.

First, at any static equilibrium, a carbon tax lowers the purchasing power of households; it causes a decrease of the demand for composite goods and this mechanism is higher in low income countries. However, the impact of a given tax level is lower with ITC than without ITC because ITC triggers higher energy efficiency gains in end-use equipments (residential and vehicles) and a lower carbon content of energy production[23]. The same observations hold for variations of the share of energy costs in total composite production costs.

Second, carbon saving investments may crowd out investments in the composite goods (Smulders, 2003). Without ITC, this only slows down the pace of turnover of equipment and the extension of capacities. With ITC, the overall productivity is also affected. This effect is higher for non-OECD regions: for 450 ppm the annual labor productivity growth falls from 1.2 to 1.16% per year and 1.92 to 1.86% per year for OECD and non OECD respectively. But this slowdown is only responsible for a very minor part of total discounted consumption losses (0.3% and 0.6% respectively). Finally lower gains in non-OECD countries are also due to the decrease of their exports of oil and gas.

5. IS TECHNOLOGICAL OPTIMISM ENOUGH TO LOWER COSTS?

In the simulations above the costs of reaching a stabilization target are contingent upon the transitional tensions in energy markets provoked by the carbon tax. It now matters to check to what extent such tensions are sensitive only to changes in the available set of techniques in the energy sector or also to broader structural changes induced by climate policies.

5.1 Sensitivivity Tests on Technological Assumptions

Three sensitivity tests were conducted on the following *technological* parameters: (i) induced energy efficiency gains; (ii) the pace of decrease of the cost of carbon free technologies in the electric sector; (iii) the lifetime of production capacities in the electric sector. We present the results only for the 550 ppm stabilization scenario 'with ITC'.

One unsurprising result is that 20% larger energy efficiency gains in the composite sector cut down 16.3 % and 17.1 % of consumption losses for OECD and non-OECD respectively. Less intuitive is the result that increasing the pace of learning in carbon-free technologies by 20% only reduces consumption losses by 7% and 4.7% in these regions. Cheaper carbon-free technologies foster a faster penetration of these techniques and thus reduce the tax impact on electricity prices

23. The rise of oil prices due to resources scarcity is postponed compared with the baseline; this counterbalances the impact of the tax on households energy bill, and even leads to a gain in 2100 for a 550 ppm target with ITC.

and the crowding-out effect, but the gain from this more optimistic assumption is inhibited by the pace of replacement of production capacities.

A good indicator of this inertia effect is the carbon content of the composite goods displayed in Table 2 for various stabilization targets. Although the carbon content of new equipments start declining as soon as 2005 and is drastically cut down in 2100 (between 80% and 95% for 550 ppm with ITC), the average carbon content of the production of the composite good is still very high in 2050. At that date the equipment stock is still composed of equipments build in 2020 (for the electric sector). This generates an obvious environmental irreversibility: given the cumulated carbon release in the first periods, the abatement requirements to meet the carbon targets have to increase sharply by the second part of the century.

Table 2. Variations in the Carbon Content of Composite Goods (w.r.t. the Reference Scenario)

Scenarios	2050	2100
550 ppm with ITC (tax =1.5)	-29%	-56%
450 ppm with ITC (tax =3.8)	-47%	-78%
550 ppm without ITC (tax =4)	-33%	-61%
450 ppm without ITC (tax =12.15)	-51%	-83%

The impact of this barrier is demonstrated by reducing the lifetime of capacities in the electric sector by 20%: this allows for 10.0% and 6.7% reductions of the consumption losses in OECD and non-OECD respectively. Thanks to lower inertia, equipments purchased in the first decades of the century (most of them installed in the DCs) are retired more quickly when carbon prices go up, thus reducing the environmental irreversibility effect.

Finally the joint effect of technological optimism and lower inertia allows fot cutting by 24.5% and 22% total consumption losses for OECD and non-OECD respectively.

5.2 Beyond Carbon Price Only Policies: A Broader View of Structural Change

The slowness in curbing carbon emissions is far more impressive in the transportation sector since, in the absence of a carbon free backstop substitute but with significant efficiency improvements, neither for the 550 ppm nor for the 450 ppm target does the assumption of ITC lead to reductions in emissions from transportation. This is typically the type of induced structural change that Imaclim-R is designed to reveal.

Regarding issues related to freight dynamics, the above simulations considered that the transportation content of the composite good was sensitive to the transportation prices. However the development of freight ultimately depends on the localization patterns, themselves depending on a multiplicity of other factors such as international wages discrepancies, industrial specialization and trade-offs between supply security and minimizing stocks through 'just in time' production.

No analysis is currently available about how carbon policies might modify these parameters. Let us however assume that they may offset the impact of higher transportation prices, so that the 'freight content' of production remains constant: in this case the losses for 550 ppm with ITC pass from 1.1% to 3%. This reveals a key mechanism: even though the share of transportation in total costs is low, keeping constant the corresponding i/o coefficients causes a very high increase in mitigation costs, since, once exhausted the bulk of carbon-saving potentials in transportation, constraining emissions mechanically constrains economic growth[24].

Regarding mobility, Imaclim-R induces additional demand through the development of infrastructures which increases the time- and cost-efficiency of transportation. In our central case, decisions to build new infrastructures rest on the same rationale as for any other production capacities: when infrastructures approach saturation, their expected profitability is enhanced. Investments are triggered to expand the network, which in turn reinforces the modal shares of road and air transportation[25].

In the real world however, infrastructure decisions are, under forms that vary in function of their institutional context, a case of private-public partnership in which local authorities give authorizations and subsidies and impose constraints on pricing and project specifics. Public authorities, with interests other than energy and climate goals, also influence *indirectly* transportation investments through urban and land-use policies that affect real estate pricing and loan practices and ultimately the localization choices of households[26]. This may lead to transportation policies driven by the combination of many public concerns and supported by a wider set of policy instruments than carbon prices. We illustrate them in an aggregated way through a decision routine of limiting investments in road infrastructures at a maximum ceiling. This has a significant impact: for a 550 ppm target under ITC, the required level of the yearly tax increment is $1.2 per ton of carbon with the alternative complementary infrastructure policy instead of $1.5 with 'carbon price only' policy[27]. This results in a 2.4% total discounted composite consumption gain instead of a -1.1% loss.

This demonstrates the interest of a) accounting for induced changes in households' demand as one the driver of overall structural change b) not letting the sole carbon price the charge of curbing down emissions from transportation. To go beyond this preliminary exercise would imply to incorporate analysis developed in the field of urban economics (Fujita, 1991) about lifestyles and localization patterns, and to describe better interactions between land-use patterns and the price of real estate.

24. This illustrates the interest of an extended dialogue where top-down analysis helps detecting issues which are still underworked by sector-based analysis.

25. A *ex post* check on transportation trends show that we produce trends with the same order of magnitude as scenarios of (WBCSD, 2004) and (Schäffer et Victor, 2000).

26. In France the evolution of average prices of fuels since 1960 does not statistically present a significant upward trend, whereas the price of real estate were multiplied by a factor 3.

27. In the 450 ppm case, the tax increment falls from $3.8 down to $3.0

6. CONCLUSION

Advocates of modeling technical change as induced by economic signals (Grubb, 1997) argue that, by taking into account the acceleration of the penetration of new techniques, models using this approach yield a more realistic representation of costs of mitigation policies. It is not the intention of this paper to establish what is realistic and what is not. Rather, it demonstrates that adopting an endogenous framework generates additional complexities that blur the univocal view of ITC causing lower policy costs.

First, we confirm this overall intuition: climate policies imply an increased energy bill which hampers sector profitability and constrains household budgets. Both parameters are reduced more quickly with induced technical change.

Second, sensitivity tests corroborate the critical role of the interplay between the carbon tax, the pace of technical progress on low-carbon technologies and the pace of turnover of equipments. The role of inertia is magnified in our simulations: (i) the carbon taxes start low and do not exert a strong incentive to decarbonization in the first decades; (ii) imperfect foresight of investors about future tax profiles makes them continue to build equipment stocks with non-optimal carbon intensity. This confirms that a major way of reducing stabilization costs is to launch credible signals to stabilize the expectations of decision-makers and to adopt an optimal time profile of carbon prices under ITC (benefits of accelerated technical change *vs.* costs of accelerated scrapping of capital stock).

Third, the role of inertia is aggravated by the rebound effect of energy efficiency in the transportation sector and by the induction of mobility demand that offsets part of the efficiency gains. Infrastructures built in the first decades of the century will induce carbon intensive consumption patterns. This is all the more critical in developing countries which will build the bulk of these infrastructures in the following decades; there is a danger of a lock-in on carbon intensive development patterns that is hard to unlock overnight (Lecocq et al., 1998).

Fourth, the assumption of *induced* technical change makes the policy context far more complex; it forces to diversify policy signals in order to change some key parameters of the economic growth engine. Beyond the role of R&D policies, it shows the importance of infrastructure policies, of policies affecting the pace of capital stock turnover and of the prices of the real estates.

Finally, within the limits of our modeling framework, we hope to have demonstrated the interest and the possibility of modeling technical change not only as 'pure' efficiency gains on carbon saving techniques but also as a process of induction of consumption pattern and structural change.

ACKNOWLEDGEMENTS

The authors are indebted to Jonathan Khoeler, Misato Sato, Ottmar Edenhofer and Michael Grubb for their helpful collaboration on this paper and the two referees for their constructive comments. The development of the

Imaclim-R model results from a collective effort at CIRED to develop a recursive version of the Imaclim-S model (Ghersi et al., 2003). It benefited from the sound contribution of Philippe Ambrosi, Vincent Gitz and Meriem Hamdi-Cherief.

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IMCP Participant Acknowledgements

This project rests fundamentally on the contributions of the individual modelling teams, and the resulting papers each illustrate interesting and diverse insights above and beyond those that could be realistically captured in any overall synthesis. First and foremost we thus thank all the modelling teams who chose to devote time to this project, and their continuing commitment to it through the long and difficult process of review and revision. All the teams funded their own participation, thus in addition to the project sponsors acknowledged in the Introduction, we are indebted to the diverse funders around the world for the long-term investments they have made in accumulating the "knowledge capital" in the field of energy and technology modelling, upon which this entire project ultimately rests.

I would like to express my thanks to Mary Jean Burer, who helped establishment of the Steering Committee and contributed extensive review work on innovation and experience curves, and to fellow members of the Steering Committee that helped to design and support the programme, in particular:

- Tom Kram and his colleague Detlef van Vurren at RIVM, who hosted the first consultative meeting in Utrecht and assisted with data and discussion particularly around the CPI reference scenario;
- Jean-Charles Hourcade, who helped to bring diverse parties together, hosted the subsequent scoping meeting and give critical advice throughout;
- Jean-Pascale van Ypersele and his colleague Ben Matthews, who contributed early thoughts on the choices around stabilisation goals;
- Claudia Kemfert, who made many key contributions in the initiation and design of the project and the range of participation, and who with colleagues at DIW hosted the second full workshop.

Above all thanks go to the core Editorial team, namely:

- Jonathan Kohler, who together with Lucy Butler hosted the first full workshop at Cambridge and went on to manage the review process with Lucy and subsequently Misato Sato and Jim Cust, who also worked hard to improve the papers in the final stages of submission;
- Carlo Carraro, who contributed quality throughout and hosted the marathon Sunday session of the Steering Committee at which the principal selections and review procedures were established;

- Ottmar Edenhofer and his colleague Kai Lessman, who sustained the daunting task of collecting and analysing the model results and quizzing contributing teams until full details of analyses were apparent, and John Schellnhuber and PIK for enabling them to devote so much time to the task

On behalf of the full Steering Committee, we are all also much indebted to the reviewers of the papers who gave time freely to improving the quality of their peers' work, in this case under significant time pressure from the coordinators, and to David Williams and his colleagues at *The Energy Journal* for their prompt and efficient handling of the papers through to production of this final volume. Though every effort has been made to catch errors arising in the preparation of these papers, some may have crept though. The editors take full responsibility for any such errors arising.

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ISSN 0195-6574

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