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

Jonathan Köhler*, Michael Grubb**, David Popp*** and Ottmar Edenhofer†

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

*   Tyndall Centre and Faculty of Economics, University of Cambridge, Sidgwick Avenue, Cambridge CB3 9DE, U.K., E-Mail: J.Kohler@econ.cam.ac.uk.

**   Imperial College and Faculty of Economics, University of Cambridge, Cambridge, E-Mail: michael.grubb@imperial.ac.uk.

***   Department of Public Administration, Center for Policy Research, The Maxwell School, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244-1020. E-mail: dcpopp@maxwell.syr.edu.

†   Potsdam Institute for Climate Impact Research, P.O. Box 60 12 03, Germany, E-mail: edenhofer@pik-potsdam.de.

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

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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 at-

tract 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 Schum-

peterian 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
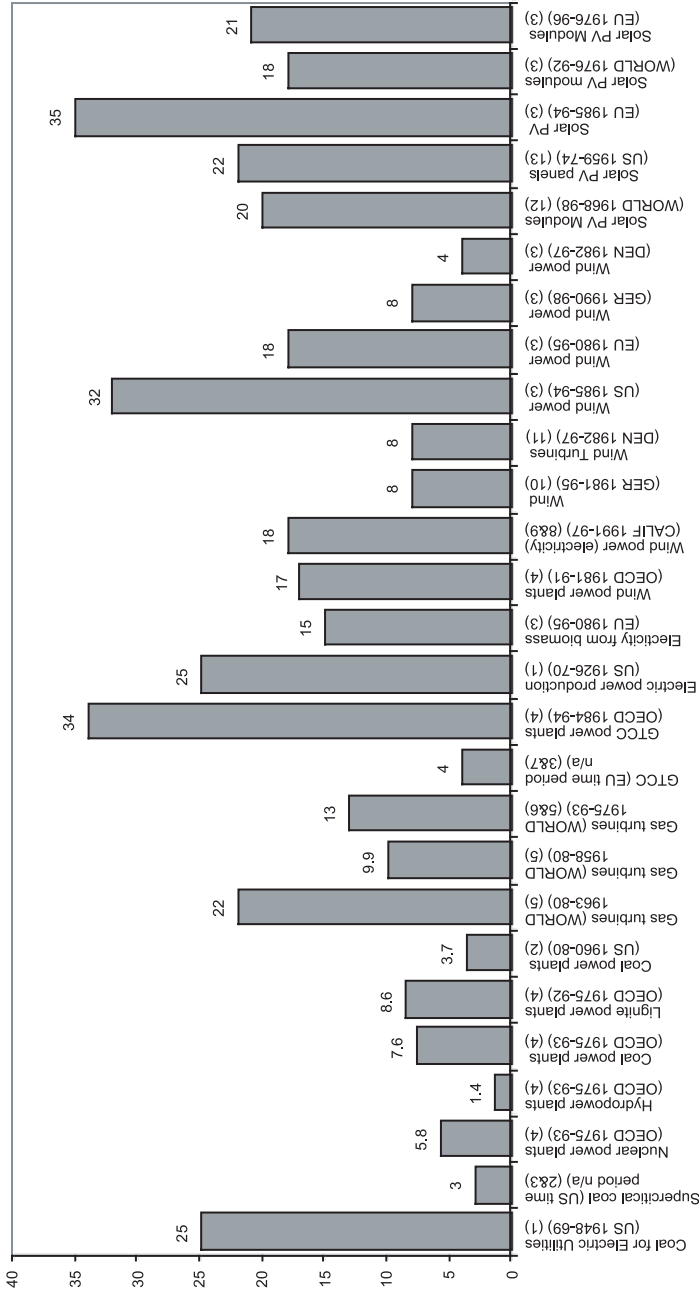
The data suggest some broad yet useful patterns. For many energy technologies, learning rates appear higher in earlier stages. Thus early coal development (US 1948-1969) showed rapid learning in contrast to later evidence (US 1960-1980). Gas turbine data also suggest some evidence of learning depreciation (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?
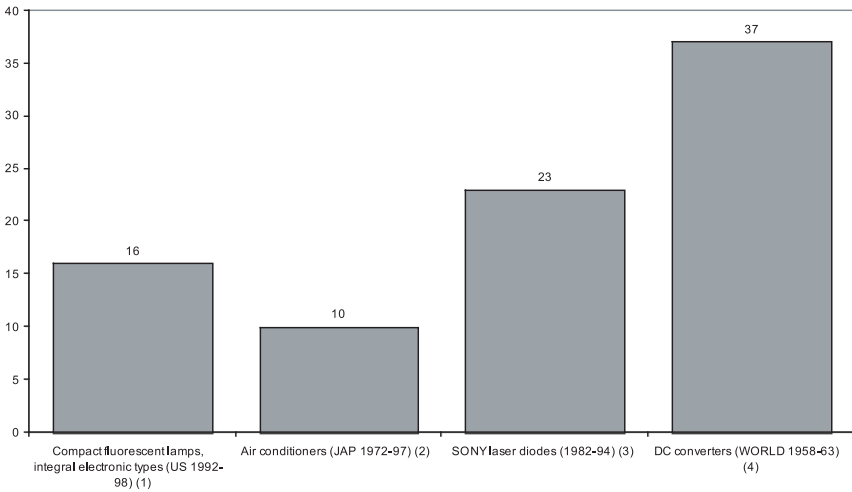
Figure 2. Learning Rates in Liquid Fuels
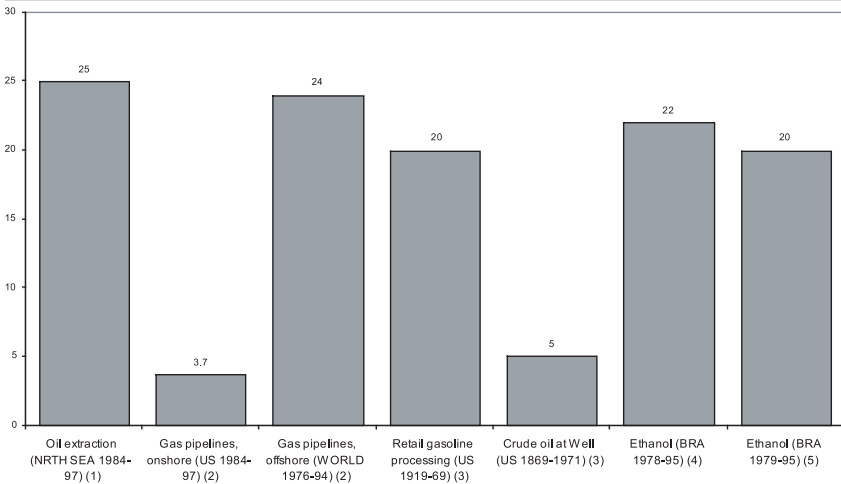
Sources: Adapted from McDonald & Schrattenholzer 2001
(1) Blackwood (1997); (2) Zhao (1999); (3) Fisher (1974); (4) IEA (2000); (5) Goldemberg (1996)

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 ef-

ficiency. 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 par-

ticular technology. The GET-LFL and MESSAGE-MACRO models have spill-overs 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 invest-ment is more detrimental to the economy compared with other types of invest-ments 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 con-sider 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 mod-els 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 invest-ment 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 exog-enous improvement rate. MIND, however, has a fixed TFP. In energy system mod-els, 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 MES-SAGE-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/ Dy-namic-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 imple-

mentation 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

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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?

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