The Transition to Endogenous Technical Change in Climate-Economy Models.

Draft – accepted for publication in the Energy Journal IMCP special edition, subject to minor revisions

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Abstract

1. INTRODUCTION

The increasing importance of climate change as a policy issue has led to considerable international efforts to develop policies that will control or reduce GHG emissions. This debate is being transformed. All parties to the debate, both political and academic, agree that the widespread implementation of new, low carbon and energy saving technologies will be crucial to climate change mitigation. This fits in well with recent policy statements and the Joint Implementation (JI) and Clean Development Mechanism (CDM) introduced in the Kyoto protocol. There are two reasons why technology is important for climate change analysis. Firstly, the application of technology has caused the anthropogenic contribution to climate change, while both coal and oil were part of processes of transformations of economies and societies. Secondly, a change to a low carbon society will require widespread development and mass deployment of new, low carbon technologies.

Energy economic modelling of climate policy also has to reflect the main aspects of the climate change problem. A timescale of the order of 100 years is necessary, because changes in CO_2 concentrations, which change the climate through the Greenhouse Gas effect, exert this influence over a time period of 50-100 years or more. This happens because CO_2 is an inert gas, which remains in the atmosphere on a timescale of 50-100 years. Therefore, 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. This suggests that models must include processes of economic change in the long run.

The industrial revolution of the 19^{th} century was founded on burning coal at rates never before attempted. It was used for home heating, steam engines in factories and on railways and later for electric power generation. In the 20^{th} century, the new technologies were based on burning oil: cars, industrial chemicals and later air transport have led to continuing increases in GHG emissions. Motor vehicles and aviation are still diffusing through the world, providing the most serious challenge for policy to reduce the rate of climate change. In order to avoid rates of climate change that will cause major changes to the climate and ecosystems, reductions in emissions of 60% + from the industrialised world (relative to current emissions levels) will be necessary. Even more important, countries that are becoming major world economies – China, India and Brazil are well known examples – will have to follow a different technological path, if GHG emissions are not to increase, let alone decrease. Therefore, addressing climate change requires a change in the structure of economic activity and in technologies used by society. Technology policy also has the potential to overcome some of the objections to climate change mitigation. Hence, modelling technologies is particularly important for the economic analysis of climate change mitigation.

There have been considerable developments in macroeconomics and energy economics, both theoretical and empirical, on the theme of technological change in recent years. These have been in the new macroeconomic endogenous growth literature and the application of the learning curve management literature to the energy sector. Following these developments, there has been a transition in the climate energy literature, such that endogenous technical change (ETC)[1] is now a feature of all leading models. The international model comparison project (IMCP) is a first attempt at comparing approaches to incorporating ETC and ITC into climate-economy models, and demonstrates the range of methods/ideas in use. Although there is a wide variety of formulations of ETC, there is a common intuition underlying these models, that knowledge capital and its growth is a fundamental driver of technical progress.

The purpose of this paper is to assess this transition in modelling technical change in climate-economy models, using the models in the international model comparison project (IMCP) as a representative cross-section of ETC climate economy models. The ETC approaches used in the IMCP are reported in the other papers in this issue, while Edenhofer et al. (this issue) discuss the results obtained for a range of stabilisation targets. Edenhofer et al. (table 1) also contains a summary of the ETC features in the IMCP models. Section 2 describes the advances in understanding of the economics of technical change made in the endogenous growth (top down) and the bottom up, energy sector literatures and examines the empirical evidence. Technical change happens in a world of imperfect competition and spillovers, bringing new theoretical and empirical challenges. Section 3 assesses the state of the art as represented by the IMCP models and shows that the consequence of the new literatures is that increasing returns are a major feature of the IMCP models. There are two main concepts employed, knowledge capital and learning curves. These incorporate a common theme: 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 bottom-up literature is quite cohesive: it has adopted 1 factor learning curves and is moving to 2 factor learning curves. The top down literature is more diverse in its theoretical treatment. The models represent a 2nd best world, opening the possibility of improved economic performance from well designed climate policy. There are other important considerations: the specification of the baseline, the

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[1] ETC, where technical progress is dependent upon variables and processes within the model, leads to possibilites 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.

specification of floor costs for backstop technologies, the representation of the policy process and calibration/estimation of model parameters. Section 4 assesses the strengths and weaknesses of the various approaches when applied to ETC in climate mitigation economics; CGE models face particular difficulties. Section 5 concludes and proposes that the understanding of technology transfer and knowledge spillovers is an important direction for future research, together with examining the implications of changes in the structure of demand for the endogenous growth literature.

2. ADVANCES IN THE THEORY AND MEASUREMENT OF TECHNICAL CHANGE

The changes in the climate economy literature have been most heavily influenced by two literatures: 1) the new endogenous growth theory, with its introduction of knowledge as a capital stock determining productivity 2) the learning curve literature, describing the reductions in unit cost with increases in production in firms and sectors. The critical change is that both of these introduce increasing returns to scale in knowledge, with an explicit treatment of processes of technical change i.e. ETC. This takes modelling into a 2nd best world of imperfect competition as a result of spillovers. This section considers the theoretical and empirical contributions of the endogenous growth and learning curves literatures, to show how the adoption of ETC implies significant innovation in modelling. The endogenous growth literature has changed thinking about the macroeconomics of growth, although the empirical evidence for these models is mixed. In contrast, the learning curve literature arose from an observation of a learning curve, but has relatively weak theoretical underpinnings. 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. Section 3 then proceeds to discuss how these ideas have been applied in climate economy models.

This new emphasis on ETC implies increased attention to the innovation literature. The innovation literature has developed a sophisticated understanding of the economics of technical change. For economic analysis, technical change presents difficult challenges. Technology is partially a public good, but of a complex sort. Technology includes physical goods, but is equally knowledge – of practices, scientific understanding and also supporting institutions – both educational and markets. It is nonrival: once the technology is developed, use of the technology by an agent does not preclude other agents using the same technology. Knowledge, as represented in specifications and patents, can be communicated almost costlessly. The limitations are that the recipients must have the capability to apply the information and that part of any technology is tacit knowledge. Therefore, technology is partly nonexcludeable. Furthermore, technical change is characterised by non-linearities and increasing returns to scale: knowledge spillovers, learning by researching and by doing, diffusion processes, heterogeneity among firms and discontinuities in technology pathways. Finally, uncertainty is pervasive. These features of technical change lead to various forms of market failure, which provide a considerable challenge for economic analysis of GHG mitigation. The positive externalities of spillovers mean that, without policy intervention, private industry can be expected to underinvest in R&D. Policy tools such as patents and government investment in R&D address underinvestment, either by increasing private benefits of knowledge through improved appropriability (e.g. patents) or by substituting government resources for underprovided private resources (e.g. government R&D). Another area of increasing policy interest is international technology diffusion. This is seen as being a major determinant of economic growth in many countries, but the survey of Keller (2004) shows that there are many factors here, including the ability of receiver countries to ‘absorb’ new knowledge. These ideas provide the basis for a constructive critique of the state of the art in climate economy models in section 4.

2.1 The endogenous growth literature

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 studied US data on economic growth and his econometric analysis showed that there was an increase in productivity that was unexplained by the main economic variables. He then argued that the unexplained element of growth was due to technological progress. This became known as the ‘Solow residual’ - the residual part of the regression was taken to be technological change. The next major step was to explain technological change. The recent endogenous growth literature has been built on the concept of knowledge capital, starting with Romer (1986, 1990). Aghion and Howitt (1998) is an extensive survey of the field. Romer (1986) rediscovered the ‘Y=AK’ endogenous growth model, in which production is dependent on knowledge, a function of capital in Romer (1986). 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 a fixed cost element in an intermediate goods sector. This extra form of increasing returns then generates a model of oligopolistic competition. The stock of knowledge is usually treated in a similar way to physical capital: it is assumed to be dependent on cumulated R&D expenditures. Thus these models incorporated ETC. Grossman and Helpman (jl of ec persp 1994?) also emphasise international interdependence through trade, introducing yet another form of spillover. These developments revitalised the economic literature on growth, leading to insights for business cycles, sustainable development, international income distribution and a renewed awareness of the fundamental role of industrial innovation in macroeconomic growth (Aghion and Howitt, 1998). Aghion and Howitt (1998) also develop these ideas to incorporate ‘Schumpeterian’ growth – the idea that firms search in an uncertain world for innovations that qualitatively improve the production technology, making previous technologies obsolete – Schumpeter’s idea of ‘creative destruction’. These ideas have not yet been applied to climate economy models.

2.1.1 Empirical assessments of the endogenous growth models

The empirical evidence for these imperfect competition endogenous growth models is mixed. For ETC, there were several critiques of the Schumpeterian innovations models. Aghion and Howitt (1998) discuss several of these critiques. Growth accounting studies, in particular for East Asian countries, found 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 growth. Jones (1995) argues that this is due to decreasing returns to scale in knowledge generation. 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 that growth rates are converging, in line with the results of Solow-Swan growth models and argue that this is incompatible with the Schumpeterian growth models. This view is supported by Evans (1996?). Technical change, however, remained exogenous. Temple (1999) is highly critical of the Mankiw, Romer and Weil (1992) finding 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. Temple points out that they assume that investment rates are exogenous to the level of income and uncorrelated with efficiency. Also, their measure of schooling ignores primary schooling and hence 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 multicountry framework. This enables them to find results which are consistent with the evidence from growth accounting, scale effects and cross-country growth, while delivering some testable hypotheses. These are: 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, entry of new firms and flow of new products and negatively correlated with exit and the rate of capital obsolescence. While Schumpeterian models give ambiguous predictions on the relation between competition and growth, there is evidence that there is a significant correlation between these variables. However, they also discuss a fundamental problem – the data from national accounts is collected in a way which assumes that knowledge is fixed and common. There are, they argue, no commonly accepted empirical measures for the fundamental concepts in the new theories – the stock of technological knowledge, the stock of human capital, resource cost of knowledge acquisition, the rate of innovation and the obsolescence of knowledge. Hence, it is difficult to test the Schumpeterian theories.

Temple (1999?) surveys empirical research on macroeconomic growth across countries. It is a much criticised literature, partly due to methodological problems with the econometrics and he argues for panel analysis, rather than time series methods. It is not known whether there is convergence in growth rates, gives a range of estimates of convergence rates of 0-30% a year. Coe and Helpman (1995?) find large effects of foreign R&D on domestic total factor productivity (TFP), while 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. There is mixed evidence for convergence of efficiency in OECD manufacturing in the 1970s and 1980s, suggesting convergence in growth rates comes from services. Here is some evidence of decreasing income dispersion between countries linked through trade, which might reflect technology transfer through trade. More encouragingly, there is a robust correlation between investment rates and growth. The strongest econometric result is that returns to physical capital are diminishing, in accordance with the Solow-Swan model. For developing countries, investment in equipment, possibly incorporating technology transfer, is important in determining growth in developing countries, less so in OECD countries. 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. Temple (1999) argues that macroeconomic data is too aggregated to address the issues of interest, such as schooling quality or health. There is widespread agreement that human capital accumulation is not a sufficient condition for growth. The question is then – under what circumstances is human capital accumulation beneficial?

R&D has an important role, 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 and, given the difficulties in measuring knowledge and ideas, may be impossible to resolve. Temple points out that 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 microceonomic and the macroeconomic evidence. Thus the literature remains open. The macroeconomic empirical analysis 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 is probably more fruitful.

To summarise, the theoretical endogenous growth literature has emphasised the role of knowledge capital spillovers in technical change and hence economic growth. The criticisms of this idea in the empirical literature have serious limitations and the empirical argument is made difficult by the difficulties in measuring knowledge or human capital and their contribution to innovation in a meaningful way at the aggregate level. The overall conclusion is that knowledge capital is fundamental to increases in productivity, but empirical analysis is possibly most productive at the microeconomic level. It is to this we turn next.

2.2 The microeconomics evidence on technical change - learning curves and prices

Many climate economy models incorporate knowledge indirectly through learning or experience curves, which relate investment or R&D expenditures to cost reductions. The reason for this is the strong empirical literature on the existence of learning curves in industry. Here, we shall briefly review the learning curve literature in industry in general and then its application to energy technologies in the context of climate change mitigation. The incorporation of experience curves into modelling creates great complexity and can greatly change not only numerical results, but also qualitative aspects of conclusions drawn from economic modelling. Notably, experience curve analysis suggests a far richer set of futures to be possible and introduces strong path dependence: the costs of future technologies and systems will be intimately bound up with the investments made in earlier decades. For this reason, their use, and their empirical basis, needs careful examination. Argote and Epple (1990) survey the literature in manufacturing. This literature starts with Wright (1936) for aircraft production in the 1930s and learning curves have been found both in manufacturing and service sectors. Rapping (1965) looked at shipbuilding. Recent contributions to this literature consider the learning processes that lead to learning curves (Thornton and Thompson, 2001 for shipbuilding) and extend the idea to production processes (Jaber and Guiffrida, 2004) for reductions in defects and current industries) and new industries such as semiconductors (Hatch and Mowery, 1998). As Argote and Epple (1990) emphasise, there is considerable variability in learning, not only between industries, but also across different plants in the same company. This also holds across countries: Keller (2004) discusses international technology diffusion and its varying effects on growth in different countries. 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%. 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.

With the development of climate change as a major policy issue, attention turned to the power generation sector as one of the major sources of GHGs. Nuclear and fossil fuel power plants were already a part of the learning curve literature (Zimmerman, 1982; Joskow and Rose, 1985). This analysis has also been applied extensively to renewable technologies, to justify policies to support renewables. The idea is that, although fossil fuel technologies are currently cheaper and are also on a learning curve, renewables will eventually become competitive. This is because they are much less mature technologies and therefore have greater potential for cost reductions through learning. Gritsevskyi and Nakićenović (2000) provide an example of this argument and indeed, current wind power is only 10-20% more expensive than conventional generation (Junginger, Faaij and Turkenburg, 2005). As in other industries, learning rates vary IEA (2000), McDonald and Schrattenholzer (2001) survey the results obtained for learning rates.

As part of the IMCP, the empirical literature on quantifying experience curves in energy-related technologies was surveyed. A summary of results is presented in Figures 1 – 3. The great majority of published learning rate estimates relate to electricity generation technologies. As illustrated in Fig.1, the estimates associated with different technologies and time periods span a very wide range, from about 3% up to over 35% cost reductions associated with a doubling of volumes. 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 FGD costs are not separated), and for *price-based* learning rates in some periods reflecting aspects of market behaviour.

The data do suggest some broad patterns. In many technologies, learning rates appear to be higher in earlier than later 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) - learning rates are often more rapid in early stages of development relative to later. 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) and IEA (2000) survey the evidence for energy technologies, showing that a reduction of 20% in production cost per capacity doubling is a typical learning rate for energy generation technologies, with the exception of nuclear power.

This learning rate literature has led some to use a general "rule of thumb" for learning rates of 20%. Whilst this is not an unreasonable representation of the observed rates for many of the electric technologies, the evidence on the decline of learning rates over time suggests it may err on the high side if treated generically across electric technologies as a constant in long-run modelling exercises. Indeed, the application of such learning rates has led to such big cost reductions that some studies have artificially imposed a "floor price" to prevent technologies like wind energy from becoming absurdly cheap. Amongst the non-electric supply technologies (liquid fuels) - 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 versus 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 generally, but particularly so within electronics based technologies (diodes and DC converters).

Interpreting experience curves and learning rates.

The fact that the magnitude of learning rates seem to depend to a large extent on both the technology and the choice of data points/time period, with low R^2 values in many of the studies, 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. What exactly to experience curves tell us, and how robust is their use in models? Learning may come from R&D undertaken to develop new products and develop new markets or from learning by doing – 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 an indirect one in the sense that both are plotted over time, and many other things happen over that time. We distinguish three major issues to be disentangled:

The role of direct R&D. First in general there is direct R&D expenditure, by both governments and companies. How much of the learning is attributable to this? This is the area most explored, in the form of "two factor" experience curves, where cost reductions result from both R&D expenditures and capital investment. Unfortunately additional problems are introduced by this decomposition. The results can be quite unstable. In addition, it is legitimate to ask how much the increased R&D expenditure itself reflected the greater market scale (and hence overall level of finance flowing into the sector), and whether the greater market scale and associated feedbacks made the R&D more productive, by focusing it on solving problems emerging in market application. Thus, R&D expenditure, market scale and R&D productivity may themselves be interrelated.

The role of time and cross-sectoral spillovers. Second, how much of the learning is due to time alone and would have occurred in the absence of any increased deployment? A specific aspect of this is that time allows technologies to exploit developments in other sectors. For example, the huge improvement in offshore oil reservoir mapping in the 1980s and 1990s drew initially on advances in medical 3-dimensional scanning techniques, with the later evolution more specifically in relation to oil.

The direction of causality. The final important issue around experience curves is the question of what drives what? Whilst it is entirely reasonable to assume that greater market scale leads to cost reductions, it is equally true that cost reductions would be expected to lead to greater market scale. Indeed X[] demonstrate that models with purely exogenous technologies can generate the appearance of experience effects.

These three categories of caveats indicate that applying data on experience curves is not simple and has the potential to lead to an exaggeration of the effects. The strongest reason for applying learning rates in long-run modelling is not that the issues are fully understood, but on the contrary, that they need further exploration acknowledging that the evidence for *some* degree of experience-based cost reduction is overwhelming. We do not know the appropriate 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.

While there are many studies that examine the relationship between experience and prices, there is less empirical work on the relationship between prices and technical change. Much of this work makes use of patents or R&D spending as proxies for technical change. Examples include Popp (2002), who regresses energy patents on energy prices and other control variables. He calculates a 0.35 elasticity of energy patents with respect to energy prices. Popp also 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, they are not able to estimate a price elasticity between research and energy prices. In addition, 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).

2.3 Insights from the innovation literature – the prevalence of spillovers

Weyant and Olavson (1999) briefly review the literature on technology. Schmookler (1966) argued for market pull factors, where major innovations create new markets and developing new products is relatively easy; the challenge to entrepreneurs is assessing market needs. In contrast, Rosenberg (1976) emphasised 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/experience 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 also a major theme of the energy technology literature. 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, spillovers across industries are rarely represented. A 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 that each region has individual costs of the different technologies. This is not the same as different prices in different regions, although the two forms of imperfect competition are related. Weyant and Olavson (1999) distinguish between intra- or intersectoral and local or international spillovers, reflecting Archibugi and Michie (1997). They may be embodied – reducing input costs or resource requirements - or disembodied - knowledge spillovers are the application of ideas from one production process in another. Spillovers occur in many directions: up and down a value chain for a single product, between firms in an industry, between firms in different industries and where there is international trade and foreign direct investment (FDI), across countries. Since spillovers are not only a geographical phenomenon, they are knowledge as a partly public good. Thus it is relationships between different agents in production that determine the direction and intensity of 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) find that the social returns are higher than the private returns to R&D. Typical findings are that the private rates of return are about 4 times higher than social rates of return. They are difficult to model as processes, because they depend on the diffusion of knowledge, rather than sales in markets or even patents. They may reduce the incentives for R&D, because they reduce appropriability, while the positive externality means that the socially optimal level of R&D is greater than the sum of firms' private R&D. Hence there is a theoretical argument for policies to support R&D. This is reflected in current policy debates about supporting new technologies such as renewables that are currently not competitive in the main markets. There is however a problem: the long history of expensive and inefficient government programmes to support e.g. supersonic aircraft and nuclear power has left policymakers unwilling to 'pick winners'.

Freeman and Soete (1997), in their discussion of the history of the industrial organisation of R&D emphasise that innovation is characterised by uncertainty. Firms' strategies for innovation are about trying to manage this uncertainty. Firm innovation behaviour is dependent upon 'competencies' in R&D, manufacturing and marketing. The heterogeneity between firms is important – firms in the same sector respond differently to the same market conditions – due to differing capabilities. 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. Also at the macroeconomic scale, clusters of innovations can be identified, which follow a diffusion pattern through sectors and economies, if the innovations are to be adopted on a large scale. They show that the processes of technical change are fundamentally dynamic. Weyant and Olavson (1999) also stress heterogeneity and discontinuity in technology development. Freeman and Soete (1997), following Schumpeter (1939), emphasise competition among heterogeneous technologies in the early stages of new technologies. This requires modelling of switching processes to new technologies – non-linear dependence on relative prices of fossil fuel vs. new low carbon technologies.

Both Freeman and Soete (1997) and Weyant and Olavson (1999) emphasise the importance of path dependence, leading to inertia in the technology system. Following Rosenberg, technological change can only be understood as a sequence of events, as the path cannot be constructed by only considering the initial conditions. A corollary of this is technological lock-in (David, 1985) – the processes by which a particular technology establishes dominance include changing institutions, infrastructures and even cultures. A new competing technology then has institutional and cultural barriers to overcome, as well as any initial cost disadvantage. Therefore, an inferior technology may remain dominant. This can be thought of as a form of temporal spillover. Howells (2005, ch3.) shows that for both civil aircraft in the 1903s and wind turbines, an initial wide variety of technologies and competing approaches to innovation led to success for a small group of manufacturers through a series of incremental developments from which a defining product – the DC3 aircraft in the 1930s and Danish wind turbines in the 1980s emerged and led the way to mass adoption. This then is a 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.

Modern economies are subject to a continuing process of globalisation. Archibugie and Michie (1997, ch.1) consider that 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 globalisation tend to magnify the success or lack of success of national industries. For modelling, this implies that models need to differentiate between different economic regions, while incorporating international processes of technology diffusion and knowledge transfer or spillovers. Keller (2004) surveys this literature. He finds that technology diffusion is important for most countries, but the effects are country specific, requiring microeconomic analysis and disaggregated data. Both trade and FDI are important, although the literature is mixed about the strength of the effects and he is cautious about policy messages.

2.4 The state of the art in the economics of technical change

What are the conclusions of these literatures for climate-economy modelling? Technical change comes through the development of knowledge and human capital. There are positive spillovers in knowledge, such that innovation is characterised by increasing returns and imperfect competition. The learning curve literature provides empirical evidence of rates of cost reduction, 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 are still not clear. This suggests that it is necessary to consider the microeconomics of innovation. The different literatures on innovation open up a very complex picture of multiple factors influencing innovation and technical change, with pervasive market failures. Innovation is characterised by uncertainty in new discoveries, the need to consider new markets and the partly non-rival and non-excludable nature of knowledge about technologies. There is heterogeneity in firms' innovation behaviour and in national systems of innovation. The next section considers how these insights have been incorporated into climate-economy models, using the IMCP models as a representative cross section of the state of the art.

3. ETC IN THE NEW CLIMATE ECONOMY MODELS

How have these recent insights about the economics of technology been incorporated in the climate economy modelling literature? The response has been dramatic: there has been a transition in climate energy modelling, such that ETC is now a feature of all leading models. There are several recent surveys, reflecting the increasing interest in this area. Azar and Dowlatabadi (1999) discuss technology diffusion, demand pull in technology development, and learning curve models. They further argue that policy results and prescriptions are dependent on technical change assumptions made in modelling work. Grübler, Nakiƒenoviƒ and Victor (1999a,b) describe the breakthrough made in the energy sector modelling literature in which learning curves were applied to energy and climate policy analysis. Goulder (200? Pew centre) and Jaffe, Newell and Stavins (2000) also review the application of ETC in the climate economy literature. Grubb, Köhler and Anderson (2002) include a survey of the approaches to modelling ETC in climate energy models and the policy implications of ETC. There are also various combinations as well as the incorporation of both macroeconomic and energy system models in climate policy IAMs. Most recently, Clarke and Weyant (2004?) have an extensive discussion of the issues of induced technological change in the climate economy literature. One conclusion of these reviews is that the representation of technical change matters. Economic analyses have produced widely differing estimates of the economic implications of policies. Barker, Köhler and Villena (2002) show that the differences are due to different theories and structures used by the different modelling teams. Grubb, Köhler and Anderson (2002) show that ETC can give very different results compared to models with autonomous technical change. Positive spillovers may dominate leakage effects, costs of stabilisation may be relatively small and early policy action gives higher overall welfare than delaying action.

The IMCP is a first attempt at comparing approaches to incorporating ETC into climate-economy models and demonstrates the range of methods/ideas in use. There are two main concepts employed, knowledge capital and learning curves, reflecting the endogenous growth and learning curve literatures. This section argues that the consequence of the new literatures discussed above is that imperfect competition due to spillovers is the major innovation in the climate economy literature and is represented by the IMCP models. The IMCP models are all intended to provide insights into climate policy and economics and they are all global, long term models. (See Edenhofer et al. table 1 for a summary of the features of IMCP models; the other papers in this issue report the ETC features of the individual models in detail.) There is regional disaggregation in most models, apart from MIND, DEMETER, GET, ENTICE. The modelling includes some specific representation of the energy sector, generation or end use or both, but with differing levels of detail and abstraction. Almost all models include one or more backstop or low carbon technologies. Some models also consider energy use in the transport sector. They provide results on GWP or energy system costs and, as a minimum, CO_2 emissions. Several models include all the main GHGs. AIM is a CGE, DEMETER is a dynamic general equilibrium model, IMACLIM-R is a dynamic recursive growth model and FEEM-RICE and ENTICE are endogenous growth IAMs. DNE21+ and GET-LFL are energy system models. There are several hybrid models, where features of macroeconomic models and energy system models are combined. These are MIND, MESSAGE-MACRO and E3MG.

3.1 Production structures and vintages

The macroeconomic models and integrated assessment models usually have technical change incorporated in a generalised way. There may be a single production sector (DICE, RICE, AIM, WIAGEM), but most models have a number of different sectors for each region allowing for heterogeneity between sectors' use of energy. Multisectoral models offer the possibility of distinguishing technological progress in different areas of the economy as well as between different countries. Technical change is then specified either through R&D expenditures determining improvements in energy intensity, or through learning curves. Total factor productivity is generally exogenous in CGEs and the optimal growth models. Technological progress implies that a model with ETC (or, indeed, exogenous technological change) has different installed capital vintages. The common way of dealing with this is to specify an average productivity and specify how the average productivity improves with ETC, getting around the requirement for explicit representation of different vintages. Models with a production function which allows substitution in all time periods have a putty-putty vintage structure. DEMETER, IMACLIM-R and E3MG have explicit putty-clay vintage capital structures. In IMACLIM-R, vintages in electricity production and end use are modelled through changes in mean input-output coefficients determined by investment. MIND has a clay-clay vintage capital structure for renewables and CCS technologies.

3.2 Methods of incorporating ETC

Rather than using the usual top-down/bottom-up distinction to classify models, we concentrate here on the features of ETC in the models, to make clear the relationships to the literatures discussed above. There are 5 concepts used in modelling ETC in the IMCP models:

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. Learning curves
4. Spillovers, from knowledge capital or in learning curves
5. Crowding out

Energy technologies and backstops

In comparison with general economic models that incorporate technical change, climate-economy models have several particular features. 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 the Kaya identity shows, changes in emissions may take place through carbon intensity of energy production and/or energy intensity in industrial 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. This backstop price may vary. A backstop technology in this context is an energy supply technology that does not depend on inherently finite resource inputs. These are the renewables, dependent on wind, solar, tidal, geothermal resources etc. While fossil fuels can be assumed to (eventually) become increasingly subject to scarcity costs, giving rise to Hotelling's law, the resource costs of renewables are zero. There has, as yet, been no attempt to specify property rights on these natural processes, in contrast to underground resources. Backstop technologies are usually assumed to have higher costs than the cheapest fossil fuel technologies, but are subject to learning. Therefore, they represent the possibility of a switch away from fossil fuel energy, given incentives to invest that make renewables competitive. If their learning rates are higher than fossil fuel technologies, the switch will be permanent.

All the IMCP models with a macroeconomic component allow for a reduction in energy intensity in production. The CGE and endogenous growth models, including IMACLIM-R, through their production functions allow for factor substitution, dependent on the relative prices of fossil fuel and other resources compared to labour, capital and sometimes materials. This enables ITC to be modelled through policies to change relative factor prices, typically taxes on energy use 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 equations are dependent on energy prices, such that similar policies can be modelled. It includes indicators of technological progress in the form of accumulated investment and R&D, such that extra investment in new technologies induces energy saving. The 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 learning curves for energy efficiency technologies. GET-LFL has a learning curve for energy conversion and FEEM-RICE has ETC in abatement. AIM, FEEM-RICE and ENTICE all have some form of reduction in energy intensity through Human Capital/Knowledge stocks, endogenised through an R&D variable.

There is a wide range in the level of detail of energy technologies in the different models. The GET and MESSAGE models have considerable technological detail, with learning applied to clusters covering all technologies. This is typical for current energy systems models. In contrast, the DNE21+ energy system model has many technologies, but a more limited application of learning for three low carbon technologies. The hybrid model E3MG has some technological detail, also with learning curves for each technology. The macroeconomic models have less detail. The FEEM-RICE and ENTICE 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, DNE21+, GET, MERGE, MIND, MESSAGE and E3MG models. DEMETER 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 is a similar concept 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. CCS technologies are treated in an unusually detailed way, with DEMETER includes generic fossil and non-fossil energy technologies are modelled, with CCS for fossil energy.

Knowledge capital and R&D

Various climate-economy models use a knowledge variable to calculate cost reductions/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 or both. They are equivalent to a learning curve, because they parameterise productivity increases from R&D (learning by searching in a 2 factor learning curve) and investment in capital (learning by doing in a 2 factor learning curve), but do not necessarily use the same learning rate formulation. The treatment as a stock variable introduces the 'learning rate' implicitly through the parameterisation 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. However, in the climate-economy literature, human capital is not modelled explicitly. Most top-down models have R&D variables and a knowledge capital stock. AIM has energy saving capital. In FEEM-RICE, a stock of cumulated abatement combines with a generalised stock of 'energy knowledge' to generate an index of technical change, leading to increased carbon energy efficiency. R&D spending on energy adds to the energy knowledge stock. ENTICE 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.

Learning curves

These are the most commonly used form of ETC. All the IMCP models have some form of cost reduction or productivity increase from cumulated investment. Since learning curves are the most common feature of ETC in climate energy modelling, it is also useful to be precise about their meaning. There is a difference between learning by searching or researching and learning by doing. Several energy sector models, including MESSAGE, have 2 factor learning curves where production cost reductions are dependent on both R&D expenditures and physical capital or installation expenditures. There is a further distinction between learning from cumulated investment and learning by producing/using. The FEEM-RICE model has a similar concept: a stock of cumulated abatement combines with a generalised stock of 'energy knowledge' to generate an index of technical change, leading to increased carbon energy efficiency. R&D spending on energy adds to the energy knowledge stock.

An important assumption in a learning curve is that of floor costs. The conventional learning curve is a declining exponential. Therefore, 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, therefore, the process of switching to the new technologies will tend to a set of stable values of technology shares. These relative shares will not be dependent on learning rates, but will be determined by the relative floor price assumptions (as well as availability for non-backstop technologies). Thus, in the long run, a static equilibrium solution may emerge, even in these non-linear dynamic models.

Several limitations of learning curves can be readily identified, as discussed in section 2 above. Should learning curves be applied to individual or aggregated technologies? There is a need to disaggregate learning curves into engineering elements e.g. for wind turbines – blade size, gearboxes, mast/installation, connections to grid. Of the IMCP models, this is only undertaken in GET-LFL and to a certain extent MESSAGE.

Spillovers

All of the models also include spillovers of some form, either explicitly or implicitly. Models incorporating learning curves will include spillovers if the curve is made dependent on e.g. investment cumulated over different regions. Several models have 'global' learning, where the sum of all regions' investments is incorporated in a single learning curve for a particular technology. The GET and MESSAGE models also have spillovers within clusters of technologies. If spillovers are included in the technical change specification, the positive externality will mean that ITC from policy has a bigger effect. However, it also means 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 modelled is the importance of crowding out. R&D inputs are specialised. Thus, their supply is inelastic (see, for example, Goolsbee, 1998). Therefore, at least some new energy R&D efforts are likely to come at the expense of other R&D efforts. Moreover, because R&D in general has higher social rates of return than other investments, the loss of $1 of R&D investment elsewhere in the economy has a bigger impact on the economy than the loss of $1 of other types of investment. For example, if the social rate of return is four times higher for R&D than for other investments, as is often found in empirical studies, giving up a dollar of other R&D activity has the same effect as giving up four dollars of other investment. Popp (2004) shows that assumptions about the magnitude of crowding out have significant effects on the potential welfare gains from ITC. For example, because most learning by doing models do not consider R&D, they do not consider this type of 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. Another important area for policy: how can the uncertainty associated with investment decisions be reduced to attract finance? This has been a particular problem for renewables, where secure and continuing policy support is necessary to convince investors that there will be returns on what are expensive technologies compared to CCGT power stations. Other investment factors are also critical, in particular the availability of resources and security of supply. Countries with large coal resources in particular still tend to build coal fired power stations in preference to other technologies.

The endogenous growth IAMs make explicit assumptions about crowding out of R&D in the general economy from R&D in the energy sector. FEEM-RICE uses the ENTICE assumptions, where new energy R&D crowds out 50% of other R&D. More generally, macroeconomic models with investment decisions between different sectors will generate crowding out effects, although these will not be as strong as crowding out effects from lost R&D. Given ETC in the investment sectors, this will have an ongoing impact, generating path dependency in the economy, as is described in Crassous et al. for IMACLIM-R (this issue).

What remains exogenous?

The CGEs and the dynamic GE models include general technical change as improvements in total factor productivity, assumed as an exogenous improvement rate. MIND has a fixed TFP. In the energy system models energy demand and GDP is exogenous. Several models have an AEEI for various energy technologies – WIAGEM, AIM, MERGE, DNE21+, while MIND and MESSAGE assume exogenous technical progress in resource extraction. Several models combine ETC in the energy sector with an exogenous element of technical progress e.g. MERGE, ENTICE. Finally, a critical behavioural 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

The IMCP models of ETC incorporate a common theme: 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. This leads to imperfect competition from spillovers and market failures. There are two main formulations of this common idea, learning curves and knowledge capital. A 2 factor learning 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 1 factor learning curves and is moving to 2 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 incorporating the theoretical features of ETC and what is their empirical base?

Success!

All the IMCP models have succeeded in reflecting the recent literatures; they all incorporate a learning process that has increasing returns. They also all have spillovers, usually through assumptions of common learning across the different regions. However, there is a wide range of detailed implementations, with some models having wide ranging ETC that is fundamental to the model structure and others having very restricted applications. We consider the different types of models in the IMCP in turn and then turn to some 'practical' modelling issues that have been illuminated by the IMCP.

Optimal growth models

The optimal growth models have been relatively successful in incorporating knowledge capital, because they have adopted the theoretical structures used in the endogenous growth literature. Issues around imperfect competition and increasing returns to scale have already been extensively discussed in the general literature, and the IMCP models have been able to adapt these ideas. FEEM-RICE, and ENTICE have both extended Nordhaus' (1994) DICE framework to include knowledge capital and crowding out in the energy sector. FEEM-RICE includes learning by researching and learning by doing. A stock of cumulated abatement combines with a generalised stock of 'energy knowledge' to generate an index of technical change, leading to increased carbon energy efficiency. R&D spending on energy adds to the energy knowledge stock. ENTICE has knowledge accumulation from R&D in energy efficiency and the backstop technology. The MIND model includes ETC for both labour and energy productivity, from learning by doing (with R&D investments as decision variables). 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. There is a clay-clay vintage capital structure for renewables and CCS technologies, with learning by doing from cumulative installed capital. The more problematic area of these models is their empirical base. The models are all calibrated to data, but the functional forms and their parameterisations do not have a strong econometric evidence base. This issue is discussed further below. This also reflects the more general literature and the problems of measurement of knowledge, as discussed above in section 2. The consequence of these difficulties is that there are a wide range of functional implementations, partly also because there are many detailed issues of the energy sector that can be included and these models start from an aggregated model and then expand their detail in some aspects of the energy sector. There are a wide range of possible choices about what to include, 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 was an extension of the previous literature. The strength of these models is their extensive technological detail. This enables the wealth of empirical information to be represented in the model structure. However, problems arise because these models usually calculate a dynamic optimum using linear programming methods, the minimum total cost of the energy sector over the time frame of the model. The non-convexities of knowledge spillovers and learning curves can lead to local maxima and therefore multiple equilibria. The most sophisticated method used to solve such problems in this literature is the Mixed Integer Programming method adopted for the MESSAGE model. In the MERGE-ETL model (reference?), 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 by limiting the implementation of learning. It only has learning by doing for three specific technologies, while having 8 energy sources and 4 energy carriers in 77 world regions. Therefore, the impact of the new technologies on the overall energy system will be restricted. DNE21+ solves the optimisation problem iteratively. An initial estimate is used for the learning variables, the time series values determined and these are then used as input into the next iteration, until differences between subsequent runs are small. This method is less computationally intensive than the Mixed Integer Programming (MIP) method used in MESSAGE. This issue is discussed further in the context of CGEs below.

Dynamic General Equilibrium models

The experience of the IMCP has shown that this class of models face considerable difficulties in incorporating ETC in a meaningful way. Linear programming methods, as frequently used in CGE models, are best suited to solving problems with a single maximum. In many of these models, this is 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 with generate local minima and maxima and can easily destabilise the model, such that finding a solution depends critically on the parameter values used. If the model is "tuned" such that it solves to give plausible results, then the question of how these values relate to data becomes very important. 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, the AIM model incorporates energy efficiency i.e. productivity improving capital, along with an AEEI, so that the structure of the model is only slightly changed, given that the model optimises allowing for (previously exogenous) productivity improvements over time. The WIAGEM model (reference?) also uses a restricted implementation. The more successful implementations of ETC tackle the problem head on, by changing their theoretical structure to include detailed dynamic functions. DEMETER and IMACLIM-R have taken this approach, which involves considerable theoretical development.

Dynamic Simulation Models

One way of dealing with the problem of optimisation with multiple optima is not to optimize. The E3MG macroeconometric model represents this approach in the IMCP. A strength of this model is that it is based on time series estimation and therefore has a strong connection to historical data. This is also a limitation, in that the timescales of climate economy models mean that there will be considerable changes in production structures. Such changes are incorporated, but cannot be estimated. Also, the econometric methodology implies to backward looking investment functions as dependent on previous demand and investment trends. This does not represent the details of investment decision making well and a forward looking, cost minimising decision has been implemented for energy generation. As with other top down models, the model has been implemented as a hybrid model, where the treatment of the energy sector is expanded compared to the other sectors.

There are other important considerations that apply to all models in a model comparison project. To make the results at all comparable, a common policy target and a common the specification of the baseline should be adopted as far as possible. Another significant area of variation is the assumed decision making process. There is also the question of calibration/estimation of model parameters. To what extent do the models use common data and how are they calibrated?

Baseline and scenarios definition; main factors affecting technical change in the baseline.

All climate-economy models depend for their insights on modelling the impact of policy changes away from a baseline; results are normally reported as changes in economic performance from a baseline, given changes in emissions (either an optimal profile or an arbitrary constraint). This limits the range of possible outcomes and hence the very large uncertainties in such modelling. It is therefore vital to properly specify the baseline and be clear about the assumptions that lead to the baseline. The aim of the IMCP project is to illustrate the impact of ETC on estimates of mitigation costs and technology pathways. As explained in the results synthesis paper (Edenhofer et al., this issue), policies to stabilise CO2 concentrations are compared with a common baseline – the CPI baseline (ref?). Several issues arise. The baseline growth (and population growth) will combine with assumptions about energy and carbon intensity to determine baseline emissions. Given a series of arbitrary stabilisation scenarios i.e. constraints on emissions, the economic impact of meeting the constraint will be higher if the baseline incorporates high emissions. In particular, for the IMCP, all the models include some form of ETC in their structure, so the technological pathways defined in the baseline will also have ITC, unless the baseline does not have any implicit policies that operate through the ETC mechanisms of the model. Therefore, the IMCP results come through increases in technical change that is induced by the policies imposed on the models. If the baseline already includes a high degree of technical change, there will be little possibility of ITC in the stabilisation scenarios.

Therefore, the ITC from the policies cannot be assessed without a specification of ETC and any ITC that is (implicitly) included in the baseline. All the IMCP models incorporate some level of investment in the baseline. Models with a learning curve will therefore have ETC from these investment paths in the baseline. Also, the level of emissions in the baseline will determine the difficulty of achieving the stabilisation targets and hence the results for stabilisation scenarios (Edenhofer et al., this issue). Of the IMCP models, GET and DEMETER have a high level of technological progress in the baseline and therefore have limited possibilities for improvements in technology through policy acting on the energy sector alone. Another question in matching scenario definitions is whether abatement/mitigation efforts are included as a control variable as in Goulder and Schneider (1999). In the IMCP, as with many exercises, the mitigation is exogenously assumed by choosing stabilisation levels and specifying a notional emissions pathway for CO_2. However, the endogenous growth models derived from DICE, FEEM-RICE and ENTICE, have emissions dependent on growth. This means that they cannot match any arbitrary emissions pathway. This is also true of other models, because they all model capital stock changes through investment. The structure of the investment function then determines the feasible rates of change in the production and energy systems, together with any exogenous technical change assumptions. There is another important feature of the modelling approach of the IMCP. The imposition of stabilisation scenarios through emissions constraints means that the models are representing a second best world. This is in addition to the many features of the models that imply imperfect competition, even given the GE structure of some of the models. This implies that the economic impact of stabilisation policy may be positive and this is indeed the case for some of the models, FEEM-RICE and E3MG in particular.

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 of these approaches have major problems in the long run, where economic structures can be expected to change to a large degree. 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 there is no historical data. An additional source of information is engineering estimates of performance of new technologies (Anderson and Winne, 2004), which are very uncertain for technologies still in development, but are better than nothing. As discussed in section 2 above, another set of variables presenting particular problems are knowledge/human capital variables. Knowledge capital, like utility, is an abstract concept which has to be inferred through proxy variables – usually R&D expenditures and patent applications numbers in the technology and economics literatures.

Decision making processes in the models

Climate energy models also differ in their representation of the policy process. Dynamic optimisation models (both CGE and optimal growth) typically assume a single decision maker, a social planner who maximises a social welfare function based on a utility function, but typically given an arbitrary emissions constraint. An alternative approach is that of the simulation models, where an optimum is not calculated, but the economic pathway is simulated forwards, given a climate policy. This can then identify the different economic impacts of different policy portfolios, but cannot claim to have found a Pareto maximising solution. Consequently, the decision structure of the model will have an impact on whether climate policy may improve or worsen economic performance.

What is still missing?

Compared to the understanding of the economics of technical change, what is still missing in these models? 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

Firstly, and indeed fundamentally, the IMCP models are all deterministic. There is little in the literature, Grübler A., N. Nakiƒenoviƒ and D.G. Victor (1999b) being one of the few stochastic analyses using an energy sector model. The only stochastic IAM in the literature is the PAGE2002 model, which has not yet 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.

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 the models that differentiate between alternative technologies assume that new technologies are adopted on a small scale, even though they are more expensive. This then 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 that are observed in practice.

The models are more 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 further limitation of all the IMCP models is that they do not represent the processes of knowledge transfer, except through implicit assumptions about spillovers, through the application of common learning assumed to apply to more than one region. Therefore, it is not possible for these models to examine questions of under what conditions will knowledge development and transfer take place, or what the factors are that enable successful knowledge development and transfer.

Heterogeneous agents

The R&D activities in the models are introduced mainly using aggregate data. Hence, the insights given by allowing for heterogeneous agents are not captured. This is, of course, partly inevitable, given the very large scale of model necessary to address a global, long term issue such as climate change mitigation. The problem is that this heterogeneity, when combined with non-linear dynamics, can give rise to very different model behaviours compared to a representative agent CGE with decreasing returns to scale.

To summarize, in spite of all these limitations, the IMCP models do provide a representative cross-section of the state of the art in climate economy modelling. They have adopted the two main approaches to modelling technical change in the broader literature – knowledge capital in endogenous growth models and learning curves. The success of the climate economy models in incorporating increasing returns and imperfect competition through knowledge spillovers is mixed. Recursive CGE models based on linear programming solutions face particular difficulties. Dynamic CGEs with a changed theoretical structure have been more successful. The optimal growth models are successful, because they adopt the theory of the new endogenous growth literature. Dynamic simulation models that already incorporate increasing returns and do not optimise are also successful. The bottom-up models, which are based on cost minimisation, face similar problems to CGEs in including increasing returns, but have found various ways of overcoming the difficulties.

While Edenhofer et al. (this issue) consider the IMCP results in depth, a comment on the results generated using these new models is appropriate. Because of the wide range of results from top down models and the limited detail, it is difficult to draw firm conclusions from these models. The bottom-up studies, in contrast, do have some common findings, which also apply to top down models with learning by doing. All of these models include learning curves as a mechanism for technical progress, so that the energy technology portfolio changes in favour of those technologies with the highest learning rates and abatement costs decline significantly with the incorporation of ITC.

5. METHODOLOGICAL ADVANCES IN THE IMCP MODELS: AN OVERALL EVALUATION

Modelling technical change is particularly important for the economic analysis of climate change mitigation. 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 (ETC) is now a feature of all leading models. The international model comparison project (IMCP) is demonstrates the range of methods/ideas in use.

There are two main concepts employed, 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 top-down literature is diverse in its theoretical treatment, partly because the empirical evidence on the impact of ETC variables on economic growth is mixed.

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. Because learning curves are founded on empirical observation, the empirical support for the learning curve models is strong. Therefore, the bottom-up literature is quite cohesive: it has adopted 1 factor learning curves and is moving to 2 factor learning curves. The models represent a 2nd best world of imperfect competition from knowledge spillovers, opening the possibility of improved economic performance from well designed climate policy.

The success of the climate economy models in incorporating increasing returns and imperfect competition through knowledge spillovers is also mixed. Recursive CGE models based on linear programming solutions face particular difficulties. Dynamic CGEs with a changed theoretical structure have been more successful. The optimal growth models are successful, because they adopt the theory of the new endogenous growth literature. Dynamic simulation models that already incorporate increasing returns and do not optimise are also successful. The bottom-up models, which are based on cost minimisation, face similar problems to CGEs in including increasing returns, but have found various ways of overcoming the difficulties.

There are several routes for further research which can be identified. There is a need to disaggregate learning curves into engineering elements, to 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. As emphasised by work in the Schumpeterian tradition of disruptive new technologies, whether and how to incorporate uncertainty and the vital role of heterogeneous agents are issues requiring further conceptual work.

Finally, what can the climate economy literature contribute to the rest of the literatures on technical change and growth? One point[2] is that the endogenous growth models do not consider changes in the structure of demand. Reduction in energy demand through efficiency measures is a common feature of the energy literature and the methodologies used could possibly be applied in the endogenous growth models.

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

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Figure 1. Learning rates in electricity production technologies

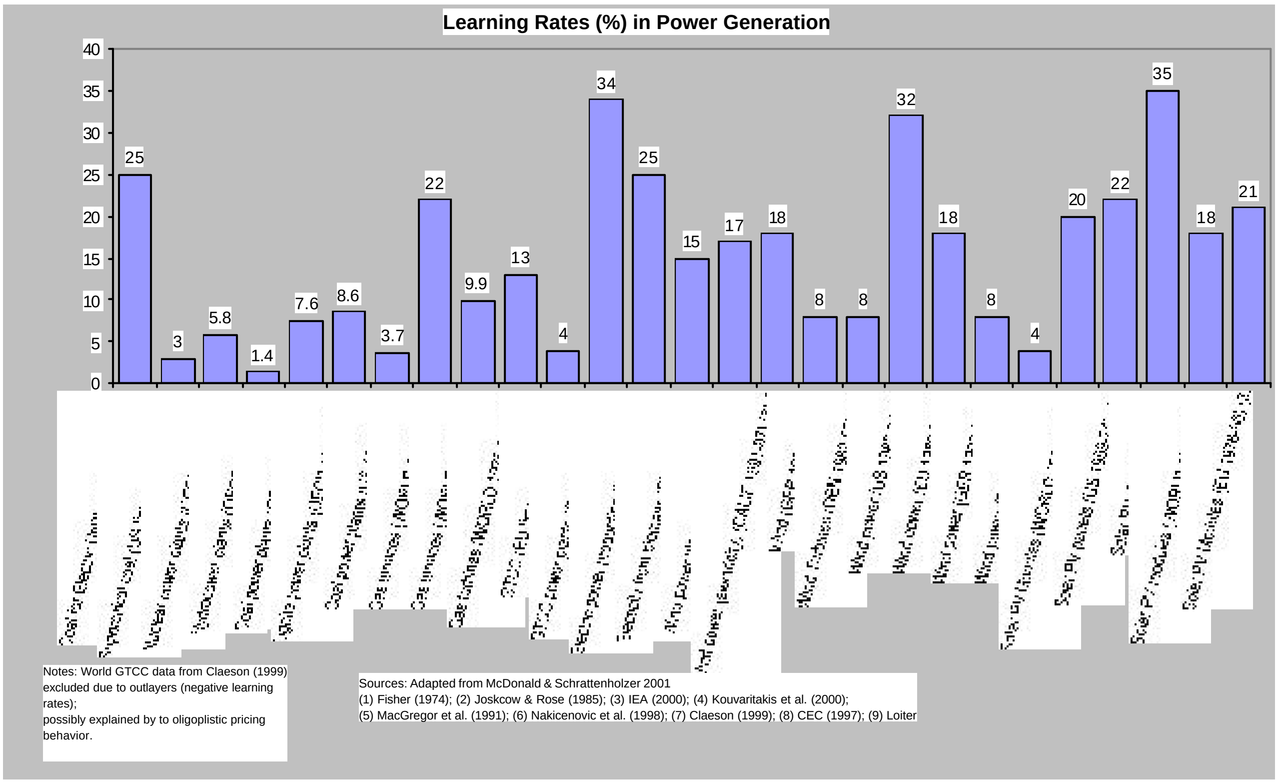

Figure 2 Learning rates in liquid fuels

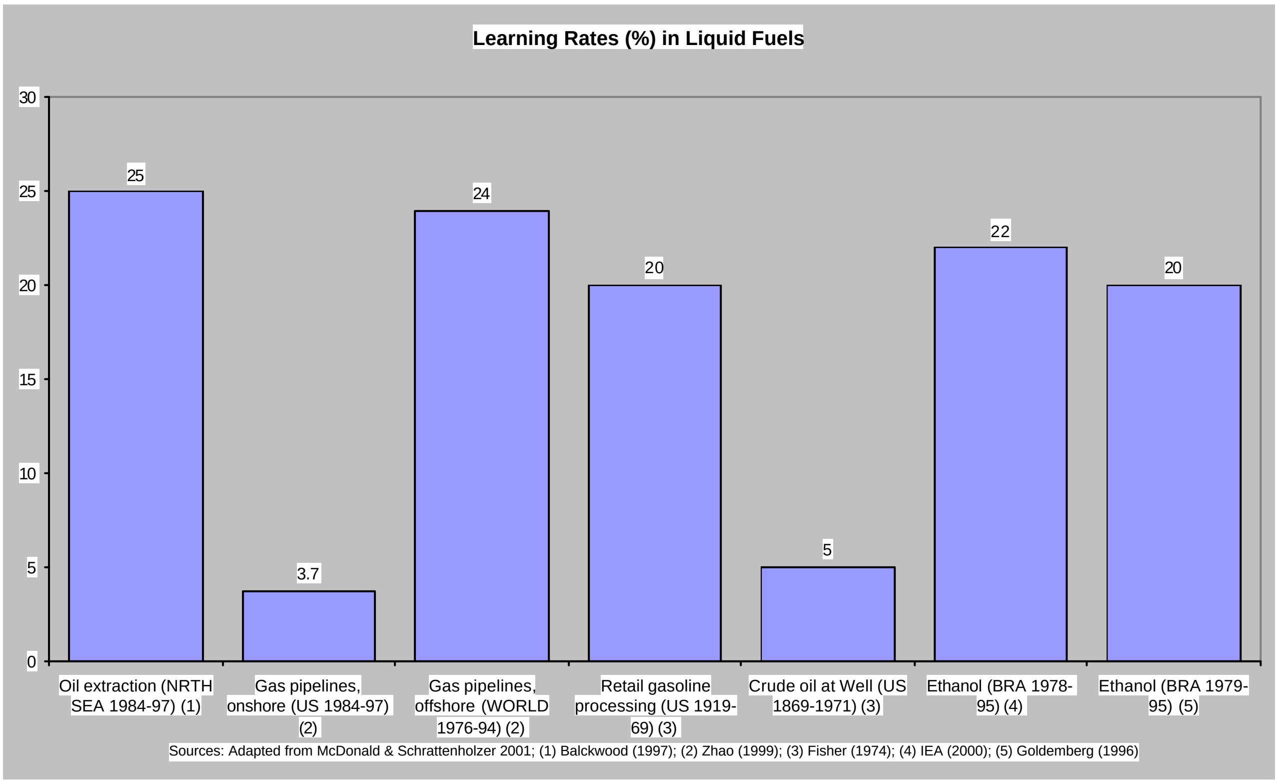

Figure 3. Learning rates in energy end-use-related technologies