Endogenous technological change in climate-energy-economic models: An inventory of key uncertainties

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Abstract

This article gives an overview of uncertainties related to endogenous technological change as observed in IAMs of global warming, both for bottom-up and top-down climate-energy-economic models. A classification is formulated by which uncertainties can be evaluated, and through which one can distinguish between modelling, methodological and parameter uncertainties. We emphasise that the analysis of uncertainties in IAM exercises of global warming is essential for both scientific and policy-related reasons. At present, proper analyses of the sensitivity and robustness characteristics of modelling results are often neglected. Our main conclusion, and recommendation, is that in future IAM analyses of climate change, both for the benefit of scientists and public policy decision makers, the presence of different kinds of major uncertainties should be appropriately recognised, classified, quantified and reported.

1. Introduction

Integrated assessment models (IAMs), that combine natural scientific with social scientific (economic) modelling techniques to come to a trans-disciplinary analysis of complex policy issues, are used in a number of different areas. One domain that has received particular attention from integrated assessment modellers since about the last decade of the 20th century is that of global warming. Because of their multi-disciplinary character, it proves especially useful to use IAMs for addressing problems related to climate change. However useful IAMs might be for both our scientific understanding of the compound facets of climate change and for policy making related to the implementation of mechanisms and/or institutions designed to mitigate excessive greenhouse gas emissions, results obtained from different IAMs vary widely. This leaves for scientists a difficulty of interpretation, and for policy makers an intricacy of implementation. At present, a need exists for a better understanding of the origins of the discrepancies between different IAM exercises, both for scientific purposes and to serve decision making in public policy.

Kann and Weyant (2000) suggest that the disparities in results arising between different modelling exercises can be ascribed to a few dominant factors[1]:

- Different underlying assumptions about processes exogenous to the model (1).
- Different assumptions about endogenous processes and their internal dynamics (2).
- Differences in value judgements (3).
- Different approaches for simplifying the model for computational purposes (4).

While in generic terms appreciating the merits of this categorisation for the origins of the differences encountered in findings obtained with diverse IAMs, for the purpose of this paper we propose a somewhat modified classification. Our proposal encompasses (1) to (4), but is able to capture topics beyond these items:

- Different underlying assumptions about processes exogenous and endogenous to the model, as well as different assumptions about whether certain processes should be considered either exogenous or endogenous in the first place (I).
- Different approaches for simplifying the model structure for computational purposes, or for enriching it with descriptive detail for reasons of reality reflection (II).
- Differences in assumptions concerning the values of modelling parameters, as well as concerning the start- and/or end-values of modelling variables (III).

In this alternative grouping, (1) and (2) are combined to form (I), the latter being extended with the observation that certain modelling dynamics, considered as exogenous in some models, can be treated as endogenous in others, and vice-versa. Differences of the kind in this category lead to what we refer to as *modelling uncertainties* in the interpretation and application of scientific findings with IAMs of global warming. Point (II) basically repeats (3), but explicitly adds that with any integrated assessment model a compromise needs to be made between simplification (for analysis convenience, as well as to meet limited available computing power) and diversification (to render the model as realistic as possible, and hence to allow deriving findings that are as concrete as feasible for policy implementation). Differences of this nature lead to *methodological uncertainties* in the lessons one can derive

[1] Other interesting classification schemes have been proposed, among which those of van der Sluijs (1997) and van Asselt (2000).

from IAMs. Item (3) is a specific case of (III), the latter not merely referring to parameters and variables related to value judgements, such as the value of human life (for certain IAMs of global warming), but also to those regarding e.g. population growth, labour force, technological development, carbon intensity, energy consumption and material savings. Differences in assumptions of this kind lead to *parameter uncertainties* in IAM analysis results.

This article attempts to illustrate this categorisation with an example, related to the modelling of endogenous technological change (ETC), through learning curves, in IAMs of climate change. In section 2, an overview is given of the most important uncertainties in the modelling of the learning type of ETC in IAMs of global warming. These uncertainties are grouped according to the above classification. Section 3 expands on this, and describes the dichotomy in modelling ETC via either learning-by-doing or R&D. Section 4 describes the relevance of uncertainties related to ETC for policy making. Section 5 concludes and provides some recommendations.

2. Endogenous technological change and uncertainties

Endogenous technological change has been introduced in IAMs of global warming since about the mid-1990s. A common way to endogenise technological change in these models is through so-called ‘learning-by-doing’, that is, through experience (learning) curves. This concept involves a learning rate that is defined as the percentage reduction in unit capital or investment costs with each successive doubling of cumulative installed capacity. Examples of ‘bottom-up’ (systems engineering) energy models that have explored this approach are MESSAGE (Messner, 1997), MARKAL (Seebregts *et al*., 2000), and ERIS (Kypreos *et al*., 2000). More recently, also ‘top-down’ (macro-economic) energy models have been expanded to represent endogenous technological change, through R&D or learning curves, such as the models by Goulder and Mathai (1998), Goulder and Schneider (1999) or DEMETER (van der Zwaan *et al*., 2002). With learning curves, like with the modelling of R&D, one avoids that technological change is simulated as some exogenously assumed process, or as a coefficient in the production function, e.g. as an autonomous energy efficiency improvement.

We focus on two energy models, MARKAL and DEMETER, for making an inventory of key uncertainties that dominate the learning-by-doing mechanism in IAMs of climate change. Given their different character, especially these two models lend themselves well for an analysis of uncertainties vis-à-vis IAM results. Irrespective of the modelling differences between MARKAL and DEMETER, it proves that the nature and origins of the modelling uncertainties affecting them are often rather similar. Also differences occur, however, largely as a result of the methodological differences between bottom-up and top-down modelling exercises with experience curves.

The MARKAL family of models has contributed to energy-environmental planning since the early 1980s (see, for example, Seebregts *et al*., 2001). MARKAL started as a linear programming (LP) application focusing strictly on the integrated assessment of energy systems. It was followed by a non-linear programming (NLP) formulation that combines the bottom-up technology approach with characteristics of top-down macro-economic models. In recent years, the family of MARKAL models was enlarged with features to model material flows, to employ stochastic programming (SP), to allow coupling with a partial equilibrium model (via price-elastic energy demands), and to model endogenous technological learning using mixed integer programming (MIP) techniques.

The DEMETER model (van der Zwaan *et al*., 2002) has been developed to investigate the endogenisation of technological change through learning curves in the top-down modelling of climate-energy interactions. DEMETER can be used to analyse the optimal timing and macro-economic costs of carbon emission reductions that mitigate the global average atmospheric temperature increase. DEMETER simulates two competing energy sources, fossil-fuelled and non-fossil-fuelled. Technological change is represented endogenously through learning curves, and a positive demand exists for the relatively expensive non-fossil-fuelled energy source. An extensive sensitivity exercise has recently been performed (Gerlagh and van der Zwaan, 2002) in relation to the timing and costs of greenhouse gas emission reductions.

2.1. Modelling uncertainties

Both MARKAL and DEMETER exercises demonstrate that it makes a difference whether technological change is modelled in an endogenous or exogenous way. In recent experiments with modelling endogenous technological learning for a West-European MARKAL model, different energy technologies are assigned to belong to certain clusters of related technologies (Seebregts *et al.*, 2000). Model runs have been executed by setting progress ratios to 1 (that is, a learning rate of 0), which mimics the situation without endogenous learning (exogenous learning). This implies that in that case no learning is achieved in the investment costs of key technologies. The only (exogenous) learning that occurs is in those cost parts of the energy technologies in the respective clusters that are unrelated to key technologies. A comparison of the cases with and without endogenous learning shows that the effect of simulating induced technology progress may be large[2].

It is shown that differences between endogenous and exogenous technological change emerge, from about 2020 onwards, regarding the deployment of most energy technologies. In a business-as-usual scenario (BAU), significantly larger shares of e.g. gasifiers, gas turbines, and wind turbine technologies are obtained in the case of endogenous technological learning, in comparison to the case in which technological learning is simulated exogenously. In a scenario in which the maximum allowed emissions of CO_2 are constrained, even much higher shares of wind turbine technologies are realised when ETC is accounted for, than when ETC is not simulated. Especially the combined simulation of ETC and the application of CO_2 reduction policies accelerates the deployment of carbon-free technologies, such as wind energy, over the first decades of the 21st century.

Also in terms of CO_2 reduction costs, the impact of including ETC on the formulation of policies to reduce CO_2 emissions is apparent. Both the marginal costs of CO_2 reduction and the difference in the total discounted system costs between the BAU and CO_2 reduction scenarios are, from about 2020, lower when ETC is simulated. The inclusion of endogenous learning also leads to earlier action than with exogenous technological change. In the former case the necessary investments in non-carbon energy alternatives are made earlier than in the latter case. The benefits of early investments then appear in later periods.

In DEMETER, the effect of including endogenous technological progress in an optimal timing simulation of the abatement of greenhouse gases (CO_2) is analysed, as well as its impact on the optimal path of required taxes and subsidies over time. Calculations with DEMETER confirm that including endogenous innovation implies earlier emission reduction to meet atmospheric carbon concentration constraints. Thus, the inclusion of endogenous technological progress implies that earlier investments in the carbon-free technology are warranted, than traditional models without ETC suggest. The effect is stronger than suggested in the literature (van der Zwaan *et al.*, 2002).

With ETC, optimal carbon tax levels, reducing fossil energy use, are lower than usually advocated. In fact, they are lower during the entire simulation period, in comparison

[2] With other bottom-up models, like MESSAGE and ERIS (Kram *et al.*, 2000), similar exercises have been performed.

to the case without endogenous learning. The reason is that endogenous learning implies earlier investments in non-fossil energy, which lead to a reduction in energy production costs and the price of the corresponding technology in the longer run. In the presence of endogenous learning, it also proves useful to apply subsidies to new energy resources, since these stimulate the learning process. The optimal subsidies are allowed to gradually decline, as the non-fossil technology becomes cheaper, following the non-carbon investments earlier in time.

In terms of climate policy making, DEMETER suggests that whether or not to account for endogenous technological change matters considerably. If a maximum allowed temperature increase of 2°C (relative to the pre-industrial level) is the aim, it might be optimal, in the endogenous case, to let global CO_2 emissions increase to levels not exceeding approximately 10 GtC. This maximum could be reached by about 2030, but emissions should decrease steadily thereafter. In the exogenous case (like in most conventional top-down models), however, emissions may increase to levels exceeding considerably 10 GtC, and only by 2050 they need to fall below this threshold. The optimal policy in DEMETER for this temperature increase stabilisation value should initially focus on the support of carbon-free technologies, possibly via subsidies, and perhaps less on the levying of taxes on the use of carbon fuels. Although numerical results of highly stylised models with ETC such as DEMETER could be judged debatable, they suggest that subsidies for investments in non-carbon renewables, such as solar, biomass and wind, may play a decisive role.

2.2. Methodological uncertainties

Whereas with the MARKAL and DEMETER models roughly the same findings are obtained regarding certain modelling uncertainties (with both models one finds that whether to represent technological change endogenously or not matters decisively), the fact that these models simulate climate-energy-economy interactions in a fundamentally different way leaves the modeller and decision maker with a number of methodological uncertainties. The way in which the global economy is described, or the detail with which energy production is simulated, varies a lot between these two (types of) models. This has important consequences for the extent to which policy lessons can be derived from the respective modelling results. Whereas a bottom-up model like MARKAL can be instrumental in deriving the potential of and required circumstances for the development of specified (renewable) energy technologies, a top-down model is more apt to derive how certain generic (renewable) energy policies interact with the economy at large.

From recent MARKAL analyses, it is found that the number of technologies that are allowed to learn endogenously, as well as the way these technologies learn (that is, within clusters of technologies or individually), matters significantly. It is shown that this number and way are of significant importance to the nature of the solutions that are calculated with the model. They determine to a considerable extent which technologies are expected to be important sources of energy supply by the middle, or second half, of the 21st century. In a similar way, it is relevant whether the model meets criteria of completeness, that is, the extent to which it includes all relevant technologies, both conventional and novel ones. Also the regional specification, that is, the geographical refinement, influences the modelling results considerably.

With DEMETER, on the other hand, whether only the non-carbon technology or both the non-carbon and carbon technologies learn endogenously, is found to be hardly of any influence on the modelling results. However, the fact that DEMETER simulates only two technologies, carbon and carbon-free, is a fundamental difference with MARKAL, where hundreds of technologies can be analysed at once. The former cannot be expected to be usefully employed for deriving energy-specific policy lessons, whereas it is an appropriate tool for assessing e.g. the role of energy expenditures in the future evolution of the economy at large, and of consumption opportunities herein. The latter incorporates little feedback with economic behaviour in general terms, but lends itself adequately to evaluate certain specified energy technology potentials.

2.3. Parameter uncertainties

From recent MARKAL experiments it followed that the technology progress ratio and market penetration constraints (expressed as the maximum allowed annual growth rates for installed capacity) are important parameters for deriving policy-relevant lessons. Therefore, estimates of their values prove to be major sources for (parameter) uncertainties. The uncertainty ranges for progress ratios observed in the literature are rather large. For example, for wind energy progress ratios range typically from 0.86 to 0.94, and for solar energy this range is considerably broader. The choice for the value of the progress ratio determines to a significant extent the nature of the modelling outcome. Especially for emerging technologies like solar PV and fuel cells, progress ratios are important, and their values affect largely the modelling solutions, e.g. regarding their future potential. For these still rather new and innovative technologies, start-off conditions, such as initial cumulative capacity and initial cost, are also sensitive parameters that considerably influence modelling results. Like progress ratios, these parameters are subject to significant uncertainties.

In bottom-up technology assessments and prospective studies, a number of potential sources of parameter uncertainties specifically related to endogenous learning have been characterised (Kram *et al*., 2000). First, statistics matter (that is, historical data), on which the estimation for the required parameters is based, in particular time series about cost figures and cumulative capacities. One needs to derive initial cost and capacity values, as well as progress ratios, from historical data, possibly supported by expert judgement. But historical data are known to often display errors, interruptions and gaps, or show unexplainable jumps or missing data sets. They can also have been obtained through different measurement techniques, possibly leading to discrepancies in internal consistency. Second, it is often difficult to give realistic estimates for current energy technology prices. The origin can be the differences that are encountered in this respect between countries, manufacturers, types and brands. Third, some models involve estimates or guesses, exogenous to the model, of future energy production costs or maximum cumulative installed capacities at a certain future point in time. Both the estimation of long-term electricity production prices and ultimate market potential at the end of the modelling time horizon can result in significant modelling uncertainties.

Besides these specific ‘learning’ uncertainties, other uncertainties (with perhaps more impact) are present in bottom-up energy models. The most pronounced and often mentioned sources of uncertainty are energy demand, fuel resources and fuel prices, various technology characteristics (such as availability, efficiency, component costs) and discount rates (for the latter, see Portney and Weyant, 1999). Traditionally, such uncertainties are handled by considering different scenarios and sensitivity analyses. A perfect foresight energy system model like MARKAL is capable of addressing certain classes of uncertainties more explicitly, such as those related to CO_2 constraints. For example, the stochastic version of MARKAL can come up with so-called ‘hedging’ strategies, i.e. development paths for the near term energy system with minimal regret in relation to more uncertain long-term time horizons (see e.g. ETSAP, 1999).

Most of these observations on parameter uncertainties also apply to top-down models such as DEMETER (Gerlagh and van der Zwaan, 2002). It is demonstrated, through a sensitivity analysis, that the main results produced with DEMETER, as well as the patterns of the derived dynamic energy transformation paths, are robust against changes in the values assumed for most economic and technological parameters. Still, regarding a few of these parameters, the results prove to be sensitive to the particular values used. The numerical results on the costs and timing of emission reductions appear most sensitive to the parameters that characterise the learning curve of the non-fossil-fuel energy source, on the one hand, and the substitution possibilities between this energy source and the fossil-fuel energy source, on the other hand.

The sensitivity of the results of DEMETER to the learning rate is most relevant for this paper. This sensitivity is understandable, since it determines the intensity of the mechanism that promotes accelerated price decreases. A low learning rate of e.g. 10% substantially increases the costs of a climate change stabilisation programme, in comparison to the costs calculated for a central parameter value of the learning rate (typically 20%). A low learning rate also implies a delay of the transition towards the non-fossil-fuel energy source, and hence a delay of emission reductions. A high learning rate, of e.g. 30%, implies that the transition towards the non-fossil-fuel energy source is accelerated. Climate control costs are then reduced compared to the case in which the learning rate is relatively low. With a high learning rate, it becomes optimal to set in motion the transition as soon as possible: already in 2020 the non-fossil-fuel energy source should reach a share of above 40% of total energy supply. Also, carbon emissions should decrease starting today, whereas with a central value of the learning rate they are allowed to increase first, and decrease only in a few decades from now.

A number of other technology-related parameters have been subjected to an extensive sensitivity analysis in DEMETER, providing further useful insight. The long-term production costs for the non-fossil-fuel energy source defines the floor of the learning curve, that is, the production costs that apply when learning opportunities have been fully exhausted. The long-term production cost parameter has substantial impact on the cumulative costs required to reach the temperature ceiling. In the short and medium term, however, changes in this parameter have only a minor effect on the costs and timing of emission reductions.

3. Learning-by-doing versus learning by R&D

So far, we have basically ignored that at least two major ways can be distinguished to endogenise technological change in IAMs of climate change (and in economic models at large). The first is through simulating learning curves, the second through modelling a decision variable regarding investments in research and development (R&D). In bottom-up models, learning-by-doing has been included for nearly a decade now, whereas the R&D path of endogenising technological change has so far been largely ignored. Recently, attempts have been made in this direction, through splitting investment costs into a learning and non-learning part, and implementing two-factor learning curves that explicitly account for R&D. In top-down models, the R&D option has been explored already significantly longer. There, on the contrary, the learning-by-doing alternative is more recent. The fact that at least two major options exist for implementing ETC leads to another important source for methodological uncertainties[3].

In terms of including endogenous technological change in top-down models, much of the focus has so far been on the effect of R&D expenditures, rather than on learning-by-doing. Nordhaus (1999) incorporated “induced innovation” in an up-dated version of his globally aggregated DICE model, called R&DICE. In the DICE model, capital and labour can

[3] A special section, additional to section 2.2, is dedicated to this matter, since the distinction between different forms of ETC is considered important.

substitute for carbon energy. The economic mechanism at work is that increases in the price of carbon energy, relative to other production inputs, induce users to purchase more fuel-efficient equipment or employ less energy-intensive products. In the R&DICE model, on the other hand, the use of carbon energy is controlled by what Nordhaus calls induced technological change. A rise in the price of carbon energy induces firms to develop new processes and products that are less carbon-intensive than existing products. Goulder and Schneider (1999) investigate the impact of including induced technological progress in the form of expanded R&D efforts. The basis behind their modelling of R&D is that carbon taxes might lead to increased R&D involving a reduced reliance on conventional fuels. These additional R&D expenditures might, in turn, lead to technological progress. They investigate to what extent increased climate R&D efforts might 'crowd out' R&D by non-energy sectors and carbon-based energy sectors. Goulder and Mathai (1998) incorporate induced technological progress in both ways: first, as a function of the stock of R&D expenditures, and second, in the form of learning-by-doing, with the stock of knowledge being a function of the level of abatement. Whereas these authors seem to have different opinions about the extent to which accounting for ETC in the form of R&D affects the deriving of policy-relevant modelling results, they seem to agree that whether to include it or not in top-down models matters. Goulder and Mathai (1998) notably find that it matters whether to endogenise technological change via learning-by-doing or through R&D[4].

4. Policy making and technological uncertainties

The uncertainties that exist in the modelling of energy technologies in IAMs, as depicted above, have major consequences for the policy lessons that can be derived from them. When interpreting modelling results from IAMs, e.g. to design instruments that can implement climate change objectives, it is important to understand how policy lessons may be affected by the uncertainties inherent to the modelling of e.g. learning-by-doing. Depending on the nature of key uncertainties, and approaches to deal with them quantitatively, energy-economic models can come up with very different future energy systems, energy technology perspectives, and impacts of energy or climate change policy measures. Therefore, a systematic analysis and careful consideration of technological uncertainties has major policy relevance.

It goes beyond the scope of this paper to describe in large extent how modelling uncertainties should be dealt with in terms of policy making. It is probably impossible to be exhaustive in this matter. Still, we give some directions for future action regarding those uncertainties governing endogenous technological change in IAMs of global warming. First, it is imperative for energy modellers, in particular those involved in IAM development, to not just report single modelling results on e.g. emissions, costs, taxes and subsidies related to climate change, but to complement all of their communicated findings with estimates of the ranges within which these findings can be expected to vary. At present, elaborate sensitivity assessments with respect to the uncertainties that are inherent in energy-economic modelling are often omitted. To make proper scientific sense, however, robustness analyses ought not to be avoided.

Second, it is important for decision makers in public policy to realise that the results of IAM exercises should never be interpreted in an absolute way, but should be expected to constitute merely specific findings amongst a bandwidth of possible outcomes. The mere richness in modelling outcomes, and the large ranges over which IAM results can vary, justifies this observation. Policy makers are in a good position to complement the quantitative results of energy-economic modellers with their own, equally essential, qualitative

[4] Ongoing EU research, e.g. in the SAPIENT project, seems to confirm this finding.

judgements on the standards that energy systems should meet in the future, and on how to get there.

Finally, further development of experience curves, and the approach to implement these in energy-economic models, for the strategic assessment of energy policy and research programmes, is important (IEA, 2000). Efforts to materialise local applications of clean technologies and initiatives promoting global learning of energy technologies are crucial for an accelerated development and deployment of renewables and other clean energy technologies. A transition towards such technologies constitutes a cornerstone for developing a path towards sustainable energy futures. Extended analyses of learning effects and learning-by-doing in energy-economic models can illuminate this transition path.

5. Conclusions and recommendations

The above assessment of (technological) uncertainties regarding IAMs of global warming has given us the opportunity to compare two basically different types of climate-energy-economic models: bottom-up versus top-down. Both types of modelling possess drawbacks, and each of them is beneficial regarding certain, specifically formulated, purposes. Bottom-up models should mostly be seen as constituting an appropriate tool to provide detailed energy technology assessments, while top-down models are fit to analyse, from a global perspective, the interaction between the economy, energy use and atmospheric temperature in broad terms, without being able to derive technology-specific lessons.

With respect to the endogenisation of technological change, this article has confirmed that these two modelling approaches share certain sources of *modelling uncertainties*. Both approaches find that it matters, in much the same way, whether technological change is represented endogenously or not, as we confirmed for the case of learning-by-doing. The fact that two intrinsically different kinds of models, or two different ways to endogenise technological change, can be used to derive climate-related policies suggests that *methodological uncertainties* may be significant. Indeed, the two approaches' usefulness proves to be in rather different fields. It is believed that scope exists to further bridge these two modelling worlds, beyond the incorporation, for each of them, of technological learning curves. We think that these two different modelling types should be brought closer together, since attempts to do so may reduce some of the methodology-related uncertainties of the integrated assessment of climate change. The above analysis may be instrumental herein. As for *parameter uncertainties*, what is relevant in the end, is an appreciation of the fact that parameter choices may have an important effect on modelling results. Determining the overall uncertainty in model outcomes, and the robustness of the conclusions with respect to individual uncertainties, constitutes an aspect of integrated assessment modelling that is indispensable.

The analysis of uncertainties in IAM exercises of global warming, essential both for scientific and policy-related reasons, can take various forms: Monte Carlo analysis, bandwidth determination, probability likelihood assessments, to name just a few. On which uncertainty analysis to choose, on how to quantify uncertainties, and by which means to report them, much further future studies can, and should, be dedicated. That no silver bullet or optimal representation to address uncertainties is available today does not provide an excuse to avoid uncertainty or sensitivity analyses altogether. While more refined technology uncertainty assessment techniques in the field of IAM studies of climate change are required, for the moment the classification presented in this article could function as a guideline for scientists and policy makers the like.

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