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A Critical Assessment of Energy-economy-climate Models for Policy Analysis

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Abstract

Energy-economy-climate models are used extensively in the policy debate to address issues on energy planning and climate mitigation scenarios. We present an overview of types of models commonly used in policy processes, and we analyze some of the main mechanisms in these models. For example, parameterization of aspects such as technology diffusion and intangible and transaction costs may have great importance for the results and the dynamics of the model. We also find that model comparison papers tend to offer little qualitative insight into the effect of different model approaches and mechanisms. Finally, an extensive sensitivity analysis and a skilled modeling team are of key importance for the usefulness of these kinds of models as policy input.

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1. Introduction

Climate policy discussions involve complicated inter-linkages between the climate system, the energy system, the economic system, political processes and issues of fairness and justice. Furthermore, addressing climate change involves actions that span and have consequences over several decades and centuries. For these reasons, among others, energy-economic models have been used for climate policy studies.

However, the use of models for studies of energy and environmental issues is not new. Groundbreaking steps related to this area of research were taken in the early seventies with the publication of The Limits to Growth, Meadows, Meadows, Randers and Behrens (1972),

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including the reactions to this study, and attempts to analyze the turmoil of the first oil crises. Novel theoretical research included articles by Dasgupta and Heal (1974), Solow (1974), Stiglitz (1974), and Salant (1976), while innovative numerical approaches to energy, resource, and environmental economic analysis were taken by Meadows et al. (1972), Nordhaus (1973), Nordhaus (1979), and Manne (1976). Although various models have been developed and improved during the last decades, much of the underlying theory behind these models and their conceptual modeling approach can be traced back to the 70's or even earlier.

The study of interactions between the energy system, society and the climate system, is very complex and involves linkages that are not well known, especially those concerning socio-economic interactions that take place several decades into the future. Considering this level of complexity, one must interpret the results of models with care and be aware of the limitations of such models and their results. Rather than generating foresights the models should be seen as tools for generating insights and offering plausible pictures on how the future may develop in internally consistent way. These pictures of the future could be generated for different sets of assumptions on important driving factors such as climate policies, resources, technology progress, etc. In that way, qualitative insight may be generated on how these parameters and different policy alternatives interact.

The aim of this paper is to present an overview of different types of models commonly used in policy processes, and to analyze some of the main mechanisms in these models and how they affect the results.

The paper is structured as follows, in section two we provide a framework for the kinds of questions energy-economy-climate models usually address, and a general characterization of these models. In section three, we assess how aspects such as diffusion and technology learning are modeled and how that may affect model results. Finally, in section four, we discuss the problems of choosing the "right" model.

2. Use and characterization of energy-economy-climate models

2.1. Utilization of energy-economy-climate models

Energy-economy-climate models are used to answer several different types of questions concerning how economy, technology and climate targets interact. Below we list some of the most common types of questions addressed by energy system models in a climate policy context:

a) Cost of climate stabilization (primarily the cost pertinent to the energy system): The models are used to estimate the cost, or the cost difference compared to a business-as-usual scenario, for the world or a region to reach a certain emission level or climate target.

b) Feasibility. Related to cost estimates are assessments on whether it is feasible to reach certain climate targets (primarily emissions, concentration or radiative forcing targets, as temperature targets are often assessed in a separate modeling step). In these cases assumptions on technology availability and diffusion rates are crucial.

c) Burden sharing and timing: If the world strives to meet a climate target or an emissions target, questions arise on who will mitigate how much and when and who will pay for the mitigation. For this purpose different fairness principles may be used and then evaluated by regionalized energy-economy-climate models.

d) Role of technologies: Energy system models may be used to evaluate the potential role of certain technologies in a climate constrained future.

e) Exploring the future and baseline scenario construction. Models may be used to explore possible futures and how these futures may depend on aspects such as population growth, urbanization, economic development, resource constraints and technological development.

The answers to these questions depend critically on, among other things, the time span one utilizes in the modeling. Four different time perspectives are of interest for discussion:

a) Years: If one considers system development over only a few years, no large changes in the energy system emerge since most of the capital stock remains intact. For this time perspective it may be possible to make sensible predictions. Econometric based models and Computable General Equilibrium (CGE) models with short term substitution elasticities between different production factors may be applied to such questions, while energy system models are often less useful, see for instance Barker, Ekins and Foxon (2007) and Kasahara, et al (2007). The strength of energy system models is that they capture capital turnover and technical change in the energy system, which is a process too slow to have any significant impact over a time perspective of only a few years. CGE models capture the change in the economy when it moves toward a new equilibrium given a change in, for example, tax schedules.

b) Decades: For many questions connected to emission targets and policy planning, a time span over one or a few decades may be considered, see for instance Capros, Mantzos, Vouyoukas and Peprellis (1999) and Amann et al (2011). For these time horizons the investigation of what role different technologies can play in meeting certain emissions targets becomes interesting, along with their associated costs and what impact climate policies may have on the economic structure of a country, region or on the global level. Detailed predictions are not possible. However, for example, one can with energy system models illustrate possible energy system development within several scenarios given different climate policies. For insights into how the general economy may be restructured given changes in policies, CGE models are typically suited for this time perspective. However, in scenarios with substantial reductions in emissions a relatively detailed model of the energy system must be designed so that possibilities for change in energy technologies and fuels are reflected. Furthermore, to predict the costs and feasibility of reaching certain climate targets, the representation of inertia and diffusion of new technologies in the energy system is essential. The applicability of CGE models depends on how large the required changes in the energy system must be to achieve relevant policy goals and if the model can account for the expansion of new energy technologies (i.e., if the CGE model is a hybrid CGE/energy system model or not). CGE models are typically based on a social accounting matrix calibrated to a year in the recent past. If the scenario studied carries the economic system too far from the conditions prevailing in the year for which the social accounting matrix was based on and if the model does not include the possibility of new technologies (which standard version CGE models often do not) the results tend to become less relevant for scenarios aiming for, for example, large cuts in GHG emissions.

c) Half a century. In climate policy discussions, benchmark emissions for 2050 are often discussed and used as targets in national and international planning. On this time scale, bottom-up energy system models are typically more useful than CGE models, for reasons detailed above. By 2050 the capital stock of the prevailing energy system will likely have been replaced, and large scale restructuring of the energy system is theoretically possible, see for instance Odenberger and Jonsson (2010) and Höglund-Isakssona et al (2012).

d) Century: A 100-year perspective is often considered in the discussion on climate stabilization, see for instance Russ and Criqui (2007) and Edenhofer et al. (2010) and Calvin et al (2010). Within this time horizon the whole energy system may be replaced two or three times, and certain subsectors, like vehicles, even more. With this long time span the costs and feasibility of different technologies are inherently uncertain, and new energy technologies that are today not considered in these types of models may have been developed. Predictions are not possible. Rather, the aim with energy system models in this context is to get a qualitative and internally consistent picture of energy system development, as represented by different scenarios, and how it connects to climate change targets. One may also obtain an understanding of what role different known technologies can play in meeting emissions targets.

In the present paper, we focus on the time horizons of decades to centuries, as this is of primary interest for policy issues related to climate change and a restructuring of the energy system.

2.2. Model characteristics

Different models have varying characteristics that are important to take into account when interpreting results, and for understanding what questions the models are suitable to analyze.

2.2.1. Optimization and time horizons

Many energy-economic models are optimization or market equilibrium models. In the optimization models the system cost is minimized, or welfare maximized, whereas in the market equilibrium models price and quantities equilibrates. Under many conditions the optimization models and market equilibrium models give identical results and it is primarily the implementation of the model that differ between them. These models may be used with various implementations of the time dynamics. The optimization/equilibrium may be found in each time step without knowledge about the future, through myopic optimization (a recursive dynamic model). Here you find models such as the global energy system model POLES (European Commission, 2010; Kitous, Criqui, Bellevrat and Chateau, 2010), the European energy system model PRIMES (Capros et al., 1999) and the global energy and land-use model MiniCam (Clarke et al., 2007). The optimization may also be done with foresight, for instance the global energy system models MERGE (Richels and Blanford, 2008), MESSAGE (Messner and Strubegger, 1995), and GET (Azar, Lindgren and Andersson, 2003). Foresight mean that the model considers all future events such as prices and carbon constraints in the optimization. There are also models with limited foresight. In limited foresight models the model optimizes over a time frame of some decades, i.e. the foresight is perfect, but only over a limited period of time. Even though the foresight is limited to a few decades the model may be used to analyze the development over longer time horizon (Hedenus, Azar and Lindgren, 2006; Keppo and Strubegger, 2009).

The optimization time horizon has some important implications. One may argue that it is unreasonable that the planner would anticipate the future as is assumed in a model with foresight. However, a model with foresight has on the other hand the possibility of presenting a prescriptive image. Thus, if we know the climate constraint and energy price or energy resources, or at least have a probability distribution of them, the model can find the energy system solution that is most cost-effective given the assumptions and constraints at hand. Climate models may be linked to models using either myopic or perfect foresight. In the case

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of perfect (or at least limited) foresight, the climate model can be completely integrated (endogenized), which enables the model to adapt in advance to future climate targets. The targets can be expressed in terms of greenhouse gas (GHG) concentrations, radiative forcing or global average surface temperature (Blanford, Richels and Rutherford, 2009). On the other hand, myopic models are in general run with a GHG tax or with annual emissions constraints, and the emissions path generated can be tested ex post if it is compatible with the climate target at hand by using an exogenous simple climate model (for example MAGICC).

In myopic optimization models (or recursive dynamic models) the market agents do not have any foresight or expectations of what happens beyond the time period the agents are in. This is also a highly idealized representation of real world decision making. Still, how well a model represents reality may be as dependent on the choice of parameters and other features in the model as the length of the foresight. New model approaches in which optimization and simulation are combined with agent-based modeling are under development, and some models of that type already exist, see, e.g., (Sassi et al, 2010).

In addition to the rational expectations and the myopic approaches discussed above, one may use an approach called System Dynamics, as used in the model TIMER (van Vuuren, Stehfest den Elzen, van Vliet and Isaac, 2010). There is no rational forward looking behavior in the model but the agents the model try to simulate are assumed using heuristic forecasting approaches for prices and other relevant variables when determining if an investment will be made or not. These heuristics are based on limited empirical data on how companies and consumers actually behave, and thus many parameters critical for the heuristically forecasting methods are based on expert estimates.

2.2.2. Partial market and full market models

Another important distinction can be made between partial market and general market models. In cases where the models are based on optimization approaches, the model type is often termed partial and general equilibrium models. In partial market (partial equilibrium) models (for instance the models MESSAGE, GET, Mini-CAM) the effect of price changes, resource base, policy instruments, etc., are studied within a part of the economy, often in the energy system and in some cases the land use system. In a general equilibrium model, e.g. GEM-E3 (van Regemorter, 2004), the effects to other sectors are also considered; i.e., how increased energy prices may affect the service sector, labor market, etc., and in the end, GDP growth. There are also hybrid models, such as MERGE (Manne and Richels, 1992; Magné et al., 2010), E3MG (Barker, Scrieciu and Foxon 2008; Barker et al, 2006) and MESSAGE-MACRO (Messner and Schrattenholzer, 2000) where a soft link is established between the energy system MESSAGE and a macro-economic model.

2.2.3. Bottom-up and top-down

Most energy system models are bottom-up models, which mean that there is an explicit and relatively detailed representation of the energy system and in some cases other systems. In top-down models, production functions are used instead of detailed technological representation. These functions may either be calibrated with data from bottom-up models or through empirical data (McFarland, Reilly and Herzog, 2006). There exists extensive literature on the comparative advantages of selecting top-down or bottom-up approaches, see e.g. van Vuuren et al (2009).Some models combine a detailed bottom-up energy system with marginal abatement cost curves in other sectors, see for instance MESSAGE (Rao and Riahi, 2006).

2.2.4. Demand elasticity and technology evolution

Most bottom-up models have a relatively detailed representation of the supply side of the energy system. However, the extent that the demand side is represented varies. The response on the demand side may be represented by a demand function where the demand typically is reduced as energy prices increase, and vice versa. In this case behavioral changes (driving less, lower indoor temperatures), structural changes (more service based economy, relocation of housing) and technical changes (energy efficiency measures, better insulation) are lumped together. In other cases some important end-use technologies are represented, such as passive housing or heat pumps for local heating, electric/hybrid cars, energy efficient industrial processes, etc. In some cases a combination of the two methods is used, see European Commission (2010) and Russ et al (2009).

As many models span over long periods of time, technological evolution becomes a pressing issue. One may distinguish between endogenous or exogenous technological change. If technology evolution is represented exogenously, cost and performance change over time according to a pre-set schedule. In models with endogenous learning, performance and costs are improved as a result of investments. Thus, as agents in the system invest in a certain technology, the cost of this technology decreases; however if no investments are made, no or little improvement occurs. This will be discussed in greater detail in the next section.

Another important part of technology evolution in models is related to restrictions on technology growth rates. Technology diffusion becomes especially important if stringent climate targets should be reached within a short time frame; in these cases fast diffusion of new technologies are essential. Some models restrain the diffusion of a new technology by a certain percentage per year, an expansion rate constraint. The parameterization of these constraints is typically based on rough estimates based on historical growth rates of other technologies. In an optimization model, without constraints, investment is solely made in the cheapest technology. In reality, investments are usually made in a diversity of technologies. To represent this, a distribution function (e.g. multinomial logit function) can be used to allocate the investment among technologies based on their relative prices, see for example the TIMER model (van Vuuren, Vries, Eickhout and Kram, 2004). Depending on the parameterization, this makes the model results more diverse than would otherwise have been the case in a linear programming type optimization model. These distribution functions also implicitly constrain the diffusion of new technologies.

3. Critical issues and analysis of model results

3.1. Transaction costs, diffusion and learning

Most models take a cost-effectiveness approach, which means that the cheapest mitigation options are used first, and thereafter increasingly expensive ones are employed. This perspective, e is well-founded in economic theory. The cost of a technology is most often characterized by capital costs, fuel costs and operation and maintenance costs. These are the most important costs when comparing large scale facilities such as power plants. Hence, under these conditions the cost effectiveness principle works well in engineering based abatement cost analysis. Energy efficient appliances (such as refrigerators, low energy light, etc.) are often found to be cost-effective from this perspective also. Still, in many cases, people tend not to invest as much in them despite their cost-effectiveness as described by a standard engineering based cost analysis. Economists have tried to explain this by pointing at other types of costs that are often omitted in these engineering based analyses. Transaction costs such as costs of seeking and processing information about new products are typically not included. Further, there may be risks associated with early adoption of a new technology

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as well as other hidden costs such as, for example, installation costs. Hence, the actual full cost will in general be larger than the engineering cost estimate. Finally, people tend not always to make the most cost-effective choice but act within “bounded rationality”. In any case, if end-use appliances are introduced in a simulation model these costs and behavioral aspects, in addition to engineering costs, must be somehow considered. In other cases energy efficiency measures may be undertaken at a rate that has not been preceded in history.

The global bottom-up model POLES does represent end-use technologies and finds that half of the emissions reduction until 2030 consists of energy efficiency measures (Russ et al., 2009). This may be an indication that the transaction costs and intangible costs involved in energy efficiency measures are underestimated. Especially if the aim is to present simulation scenarios, rather than exploring scenarios for cost-effective potentials.

Besides transaction costs and hidden costs, another factor, diffusion rates, may limit the diffusion of new cost-effective technologies. We discussed in section 2.2.4 different ways of handling diffusion in models. Distribution functions are a possible way of modeling a limited diffusion of new technologies and introducing heterogeneity in the system. A problem exists in calibrating the equations.

Endogenous learning, the decrease in technological performance (primarily measured in costs) as a result of investments in the model, is introduced in some of the models. Thus if large investments are made in wind power, the cost of wind power also decreases. This is rather realistic; however, the importance of introducing endogenous learning depends on other features of a model. The most used alternative to endogenous learning is exogenous learning, where costs decrease over time to a certain cost level. This long-term cost level can either be determined by engineering estimates or by extrapolation of learning curves. In a model with perfect foresight, the choice between endogenous and exogenous learning is of little importance for the technology mix and emissions targets in the long run. With endogenous learning one may see small shifts towards a larger share of technologies with a large learning potential at an earlier date than with a model with exogenous learning, although this difference depends much on the assumptions on diffusion rates. Of major importance for model outcomes are the long-term cost level estimates of technologies. However, these do not depend on the choice between endogenous and exogenous learning (Hedenus et al 2006). In myopic models, or models with limited foresight, how one deals with endogenous learning is of central importance. In such a model investments in new technologies do not appear for the reason that investments in the short-term leads to cost reductions in the long-term. In such models with no or limited foresight if and how technology policies are implemented in the models becomes central, hence one can study the effect of policies that induce investments.

Potential problems may emerge when distribution functions are combined with endogenous learning. In Edenhofer et al (2010), both wind power and decentralized photovoltaic (PV) production diffuse to their full technical potential also in the baseline scenario in the POLES model. This result is probably related to endogenous learning in combination with distribution functions. Even if a small amount of the technology is used in a time step (due to the distribution function), the cost will decrease in the next time step, which will allows for even larger diffusion. It is unclear whether wind power and solar PV will not diffuse to their full technical potential without climate policies, but it seems unlikely. These results could be an example on that their results may be due to the parameterization of the distribution functions and learning curves.

Furthermore, even though distribution functions partly is used to constrain too fast diffusion of new technologies, how well this is done of course depend on the parameterization. In Russ et al., 2009, results from the POLES models show that in 2020 around 5% of the CO2 emissions from the power sector are captured in the EU. The power sector in the EU-27 emits around 1300 Mton CO2/yr (IEA, 2010), which corresponds to approximately 10 full scale coal CCS plants in 2020, which must be considered unrealistic (Hazeldine, 2009).

These examples highlight that it is not necessarily the presence of the functions that determine whether the results become realistic or not, but the parameterization of the functions. However, given a frequent lack of data for parameterizing such functions, the parameter values must be based on educated guesses, which can lead modelers into two common errors. If a parameter is based on a guess and no reality check is performed on the results, they become irrelevant, or if the "right" results are seen as paramount, the model's outcome can become pre-determined through the tuning of parameters. These potential problems are often experienced when only a limited number of scenarios are generated, which is often the case, rather than performing a thorough sensitivity analysis of crucial parameters, see for instance Bakker et al. (2009); while Azar et al. (2006) and Hedenus, Karlsson, Azar and Sprei (2010) presents examples of more extensive sensitivity analyses.

3.2. Cost-effectiveness versus feasibility for reaching climate targets

The concepts of cost-effectiveness and feasibility are connected in the analysis of climate targets. By feasibility we mean the achievability of meeting the target at hand, while cost-effectiveness refers to the way in which this target can be met at the lowest possible cost. In the context of climate targets and emissions pathways an infinite number of emissions and technology pathways for meeting a target exist, given that the target can be met at all. Conversely, if the target is too stringent no pathway is feasible. Given a feasible climate target only one of the feasible pathways should be considered cost-effective, and this pathway will depend on the characteristics of the techno-economic model.

Determining the feasibility of emissions pathways is foremost dependent on the assumptions made regarding the geophysical system used in modeling. These assumptions include those of climate sensitivity, the parameterization of carbon cycle dynamics and parameterization of ocean heat uptake, among others. By considering only the geophysical system one would find the set of pathways that meets the constraints determined by the geophysical system, but leave out the constraints determined by the socio-techno-economic system. Adding characteristics on technologies, their costs and diffusion rates to the modeling would add information that could exclude some of the emissions pathways from the feasibility set that was based only on geophysical information. Hence, not necessarily all pathways that are feasible from a geophysical perspective are feasible from a techno-economic perspective.

One of these emissions pathways that is both geophysically and techno-economically feasible is the cost-effective pathway. This is practically how far one can get with the type of models discussed in this paper. However, not all of the pathways that are both geophysically and techno-economically feasible are feasible from a socio-political perspective. Hence, only a subset, if any, of the geophysically and techno-economically feasible pathways is socio-politically feasible, which cannot be assessed by techno-economic models. Potentially, none of the feasible pathways from a geophysical and techno-economical perspective are feasible from a socio-political perspective, and also, even if a few pathways are feasible from a socio-

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political perspective, these pathways may not necessarily include the pathway that is cost-effective.

In 2010, two policy oriented reports (Fee et al., 2010 and UNEP, 2010) focusing on the relation between emissions of GHGs in 2020 (and 2050) and the possibility of reaching long term temperature stabilization targets were released. The primary climate target that was analyzed in these reports was the target of stabilizing the global annual mean surface temperature below 2ºC above the preindustrial level. Central for the analysis in these reports were emissions scenarios taken from such models as those included in this paper. For example, results from the ADAM and EMF-22 projects were central in both Fee et al (2010) and UNEP (2010) and contributed to a large share of the underlying emissions scenarios. The assessment of emissions level in 2020 (and 2050) and the probability of remaining below 2ºC above the preindustrial level were performed by using these emissions scenarios and running them in the simple climate model MAGICC (Meinshausen et al., 2011). Given certain assumptions on probability distributions for climate sensitivity, carbon cycle parameterization, parameterization of ocean heat uptake, etc., the probability of emissions scenarios leading to a global mean temperature change of less than 2ºC above the preindustrial level was assessed. The construction of such probability distributions is a very complex issue given very large uncertainties at hand. Although this issue is out of scope for this paper, it is worth repeating.

When interpreting the numbers suggested as benchmark levels for emissions in 2020 and 2050 in Fee et al. (2010) and UNEP (2010) it is important to recognize that the underlying assessed emissions scenarios are in general constructed to generate the least cost solution for meeting a certain concentration or radiative forcing target. Hence, the emissions scenarios are not least cost scenarios for meeting the 2ºC limit with certain probability level. Also, the models that generated the emissions scenarios were in general not run to generate direct insights to some of the questions in focus in Fee et al. (2010) and UNEP (2010), which sought answers to questions such as the year of peak GHG emissions, the compatibility of GHG emissions levels in different years with stabilizing the annual global mean surface temperature below 2ºC above the preindustrial level, and the highest realistically achievable rate of emissions decline beyond the emissions peak. Hence, even though energy-economy-climate models can be set to analyze such questions, they are seldom used in that way. See O'Neill et al. (2010) for an exception where feasibility rather than cost-effectiveness is in focus for scenarios leading to different temperature targets. Also, given the rather subjective approaches used to model, for example, technology diffusion in the underlying models, the benchmark numbers presented in Fee et al. (2010) and UNEP (2010) should be interpreted with care and seen as indicative numbers rather than strict levels.

3.3. Model comparisons

In this section we discuss two recent model comparisons in the climate mitigation field. In Edenhofer et al. (2010) five models are compared with respect to costs and mitigation strategies for meeting low CO2 stabilization targets: The models are MERGE, POLES, TIMER, REMIND, and E3MG. Calvin et al (2010) include the models called ETSAP-TIAM, FUND, GTEM, IMAGE, MERGE, MESSAGE, MiniCAM, POLES, SGM, WITCH to study similar questions.

In both these respective studies baseline assumptions among the models differ, and they include different energy technology portfolios, in Edenhofer et al (2010) oil and coal prices differ by more than a factor of 4 between the most dissimilar baseline scenarios. The only harmonized aspects were the climate stabilization targets.

With this wide range of assumptions in the models a large variety of scenarios can be produced, however it is difficult to gain more qualitative learning, as it is difficult to pinpoint the actual reason for different outcomes between models. Edenhofer et al (2010) showed that the cost of meeting a 400 ppm target differed between a cost of 2.5% of GDP for the MERGE model and below 1% REMIND. The authors discuss that the reason for this is partly due to that the MERGE model has a large amount of coal in its baseline while REMIND initiates a large fraction of renewable energy.

Also in Calvin et al (2010) the cost of meeting the climate stabilization target varies widely among the models. Still, one relatively robust feature with the models included in the study is that the technology rich models (in this case the bottom-up models ETSAP_TIAM, IMAGE, MESSAGE, MiniCAM) show a lower cost of meeting a 550 ppm CO2-eq target without overshoot as compared to models with less technological details.

O'Neill and Nakicenovic (2008) discussed model comparisons and concluded that more focus should be put on specific questions, rather than comparing more general stabilization scenarios and producing a variety of outcomes. We would also like to call for deepened analysis why models produce different results. This is a difficult task as it is inherently time consuming and difficult to understand the details of a new model. One could try to standardize features between models such as baseline, technologies available, parameters etc to provide better insight into what causes the different outcomes. An attempt in this spirit, even though the characteristics of the two models compared were quite similar can be found in Grahn, Azar, Lindgren, Berndes and Gielen (2007).

4. Discussion and conclusions

We have in this paper tried to characterize and discuss energy-environment-economy models and results from such models. When these models and their results are used in a policy planning process, the presentation of quantitative results to motivate policy proposals is often considered important. Results that are often highlighted in such a context are the cost of meeting a certain climate or emissions target, the expected carbon price needed to achieve the targets, emissions levels for specific target years and the diffusion of certain technologies. As a researcher it may appear tempting to prescribe which models that can provide the most accurate numbers for policy makers. However, that is wrong, instead one firm conclusion is that no single model can give the full picture What one may suggest is that some models include a more realistic representation of diffusion and learning-by-doing, foresight by economic agents or economic-wide effects. However, the estimates based on these models are not necessarily more accurate than the numbers presented by a simpler model. The uncertainties involved are vast, and some important mechanisms operating in the real world may still be missing, causing results to be skewed in one way or the other.

Uncertainties in this context, in general, highlight the importance of sensitive analysis. However, sensitivity analysis is often absent in both policy reports as well as in academic literature. Sensitivity analysis can be made in several different ways. Most often some scenarios that differ in technologies available or fuel prices are analyzed. Such an analysis gives some insight into the uncertainties, but in general, only a very limited set of possible future development s are examined. A more thorough analysis would be to test the main results with respect to changes in parameters such as technology costs, diffusion rates or resource availability. This kind of analysis may provide a much deeper understanding of the

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model and the results, but these kinds of analysis are rare also in the academic literature as it many times requires extensive programming.

Sensitivity analysis can also be made by using Monte Carlo methods, where some parameters are randomized given a specific probability distribution for each parameter in a large number of model runs. With this analysis one may get both an assessment of the uncertainty range of the variable studied (carbon price for instance) as well as an assessment of which parameters that are important to the results. The model cannot have too long solution time to make extensive Monte Carlo analysis possible. Here emerges a trade-off in model development. A more advanced and detailed model may capture more interlinkages but creates on the other hand difficulties for performing a Monte Carlo analysis due to computing time requirements.

A yet different form of sensitivity analysis is the variation of some structural characteristics of the model. This could include running the model with or without endogenous learning, with longer or shorter foresight, with or without a hard link to a simple climate model and with or without a hard link to the land use model for instance.

One alternative to structural sensitivity analysis is a multi-model assembly in which several different models are used to analyze a mutual question. However, such model results are generally compared, and little effort is made to explain and analyze the difference in the model outcome, which makes the results to have limited values as policy inputs, see also O'Neill and Nakicenovic (2008), who share this view. However, a few papers exist in which differences in results from different models are analyzed in greater detail, see for example Grahn et al. (2007).

It may be less difficult under specific circumstances to assess which models can produce qualitative insights into different issues. For instance the study of long-term effects on technology specific policy instruments (like green certificates) in a prefect foresight model is not very useful, as the model anyhow can foresee cost reductions in the future. A model such as GAINS is relevant to estimate the techno-economic potential in different sectors, but may be not as good for studying the expected effects of a certain policy, as the behavioral representation is rather simple.

Finally we would also like to raise the importance of the modeling team. As there are so many uncertainties at hand, and so many unknown parameters in the models, the modeling team must know the real underlying system they are studying as well as the model they are using. Knowledgeable researchers can with a very simple model offer important insights both for research and policy planning. Without a proper understanding of the real system one may easily make unrealistic assumptions or use the model for questions for which it was not intended to be used. However, our experience tells us that building and running a model is a good way of gaining insight in how the real world system works. Thus, just running a few scenarios on a readymade model, imposes a risk that odd results may be presented, and without actually gaining understanding of what may occur in the real world.

From this we can conclude that in general perhaps less focus should be put on which model that is used, given that the model includes the basic characteristics that are needed to analyze the questions posed. More important for reliable and robust results that are usable for informing a policy process is that extensive sensitive analyses are performed and that the modeling is led by a skilled modeling team(s). Finally, and maybe most importantly the results from the model must be possible to explain in terms of the mechanisms that drives the model. Otherwise the modeling exercise does not provide much learning.

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