Induced Technological Change in a Limited Foresight Optimization Model

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

1. INTRODUCTION

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

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

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

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

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

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

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

The aim of the paper is to:

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

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

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

2. MODEL DESCRIPTION

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

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

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

2.1 Learning-by-doing

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

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

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

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

2.2 Limited Foresight

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

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

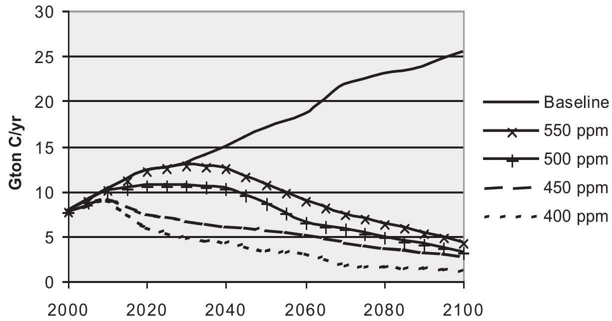
The model aims to simulate a market with complete spillover of know-how between companies and with an emission target set by policy makers. In this setting, companies would not invest in immature more expensive technologies, since in a perfect market (according to standard theory), investments are made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

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

2.3 Scenarios and Cases With and Without ITC

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

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



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

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

3. RESULT

3.1 The Baseline Scenario vs. ITC Stabilization Scenarios

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

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

3.2 Comparing ITC and no-ITC Cases

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

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

Figure 2. The Primary Energy Supply

Figure 2a. Baseline Scenario

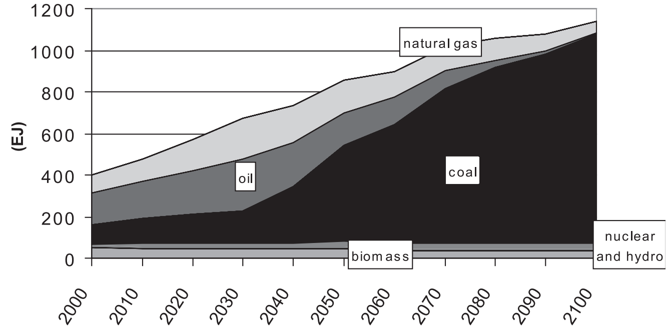


Figure 2b. 450ppm Stabilization Scenario With ITC

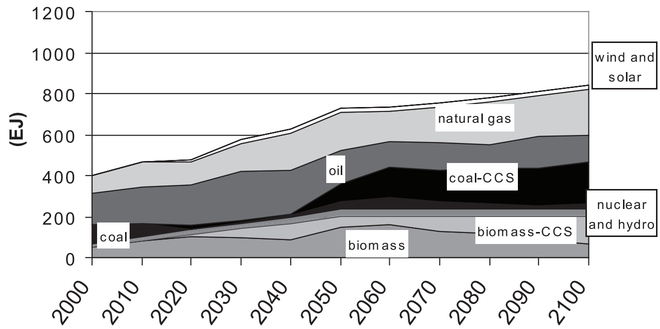
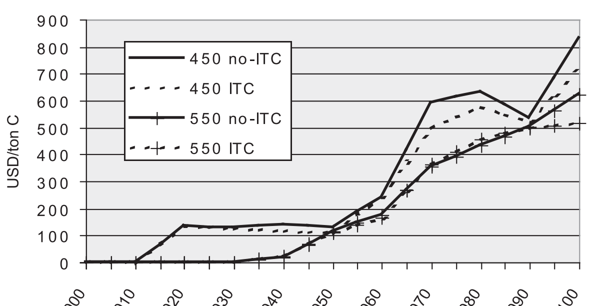


Figure 3. Carbon Price in the 450 and 550 ppm Scenario, With ITC and Without ITC



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

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

3.3 Explanation for the Low Impact of ITC

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

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

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

3.4 ITC and Technology Specific Policies

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

Figure 4. Transportation Fuels

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

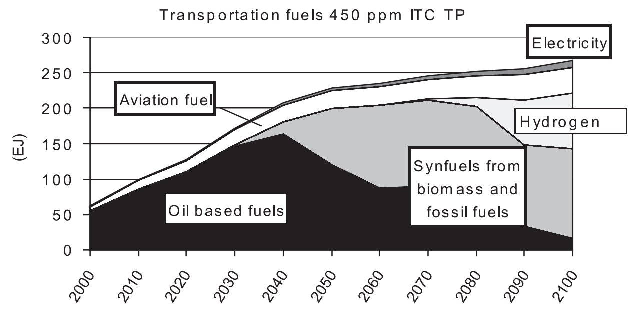
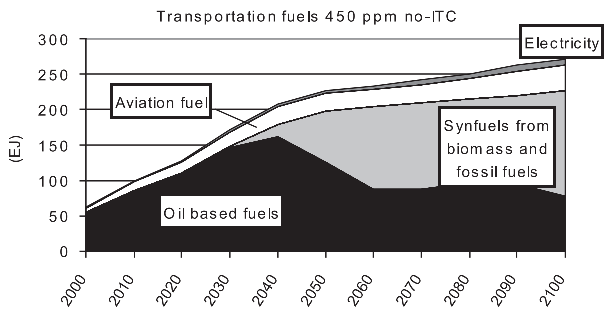


Figure 4b. 450 ppm Scenario in the Case Without ITC (no-ITC)

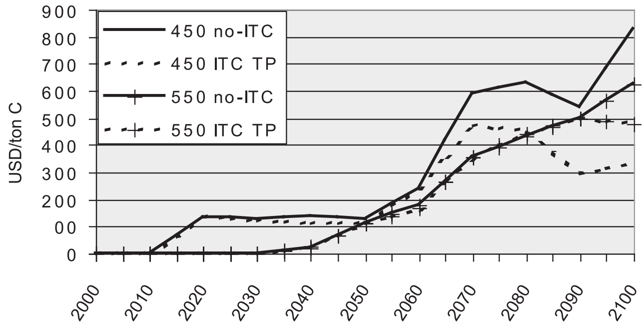


induced by the emission cap as well as technology specific policies. We define technology specific policies as those that are primarily aimed at supporting the commercialization of immature but promising technologies. Such policies include feed-in tariffs, green certification and directed subsidies.

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

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

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



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

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

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

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

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

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

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

3.5 Sensitivity Analysis

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

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

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

4. CONCLUSION AND DISCUSSION

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

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

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

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

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

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

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REFERENCES

Arrow, K.J. (1962). "The economic implications of learning by doing." *The review of economic studies* 3(29): 155-173.

Atkinson, J. and Manning, N. (1995) "A survey of international energy elasticities. Published in Barker, T. Ekins, P. and Johnstone, N. (eds) *Global warming and energy demand*. Biddles Ltd, Guildford and King's Lynn. Great Britain.

Azar, C. and Dowlatabadi, H. (1999). "A Review of Technical Change in Assessments of Climate Change Policy." *Annual review of energy and the environment* 24:513-544.

Azar, C., Lindgren, K., Larson, E. and Mollersten, K. (2005). "Carbon capture and storage from fossil fuels and biomass – Costs and potential role in stabilizing the atmosphere." *Climatic Change*, in press

Azar, C, Lindgren, K., and Andersson, B. (2003). Global energy scenarios meeting stringent CO_2 constraints - cost effective fuel choices in the transportation sector. *Energy Policy* 31 (10): 961-976.

Bahn, O. and Kypreos, S. (2002). *MERGE-ETL: An optimization* equilibrium model with two different endogenous technological *learning formulation*. Paul Scherrer institute.

Barreto, L. (2001). *Technological Learning in Energy Optimisation Models and Deployment of Emerging Technologies*. PhD Dissertation No 14151. Swiss Federal Institute of Technology Zurich.

Grubler, A. (1999). *Technology and Global Change*. Cambridge University Press. UK.

Houghton, J. T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P. J. and Xiaosu, D. (2001). *The Scientific Basis Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climatic Change*. Cambrige University Press.

Kram, T., Seebregts, A., Schaeffer, G.J., Barreto, L., Kypreos, S., Messer, S. and Schrattenholzer, L. (2000). "Technology dynamics in energy systems models with perfect foresight". *International journal of global energy issues*. 14:48.64.

McDonald, A. and Schrattenholzer, L. (2001) "Learning rates for energy technologies". *Energy Policy* 29:255-261.

Manne, A. and Richels, R. (1997). "On stabilization CO_2 concentration: Cost-effective emission reduction strategies". *Environmental Modeling and Assessment* 2:254-265.

Martinsen, D., Krey, V., Markewitz, P. and Vögele, S. (2004). "A New Dynamical bottom-up energy models for Germany model structure and model results". Systems Analysis and technology Evaluation (STE). Preprint 20/2004

Mattsson, N. and Wene, C-O. (1997). "Assessing new energy technologies using an energy system model with endogenised experience curves". *Journal of Energy Research* 21:385-93.

Nakicenovic, N. (eds) (2000). *Special report on emissions scenarios. Intergovernmental Panel on Climate Change*. Cambridge University Press

Nyqvist, B. (2005) *Limited Foresight in a Linear Cost Minimisation Model of the Global Energy System*. Master of Science Thesis, Chalmers, Göteborg.

Riahi, K., Rubin, E.S., Taylor, M.R., Schrattenholzer, L. and Hounsell, D. (2004). "Technological learning for carbon capture and sequestration technologies." *Energy Economics* 26:539-564.

Rogner H.-H. (1997). "An Assessment of World Hydrocarbon Resources." *Annual Review of Energy and the Environment*, 22:271-262.

Sandén, B. and Azar, C. (2005). "Near-term technology policies for long-term climate targets – economy wide versus technology specific approaches." *Energy Policy* 33(12):1557-1576.

Seebregts, A., Kram, T., Schaeffer, G.J. and Bos, A. (2000). "Endogenous learning and technology clustering: analysis with MARKAL model of the Western European energy system." *International journal of global energy issues* 14

Vuuren, van D.P., Elzen, M.G.J., den Berk. M.M., Lucas, P., Eickhout, B., Eerens, H. and Oostenrijk, R. (2003). *Regional costs and benefits of alternative post-Kyoto climate regimes Comparison of variants of the Multi-stage and Per Capita Convergence regimes*. RIVM report 728001025/2003. National Institute of Public Health and the Environment. Bilthoven. The Netherlands