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Endogenous learning in European post-Kyoto scenarios: results from applying the market equilibrium model PRIMES

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Abstract: This paper describes the endogenous technical change mechanism that has been incorporated in the PRIMES model and the main quantitative results in post Kyoto CO_2 emission reduction scenarios for the EU energy system. The first section presents the learning mechanism as incorporated in the PRIMES model. Section 2 deals with the definition of alternative learning regimes in PRIMES and their impacts on model results. The achievement of the post Kyoto emission reduction target for the EU energy system under the different learning mechanism regimes is examined in Section 3. Finally the paper concludes with the evaluation of the benefits from technology change due to endogenous learning in achieving post Kyoto emission reduction targets.

Keywords: CO_2 emission reduction to 2030; marginal abatement costs; endogenous technical change; learning by doing; value of technology change.

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1 Induced technology progress effects in the PRIMES model

PRIMES is a dynamic energy system model. The dynamics involve a sequence of static equilibrium points linked to each other through capital accumulation. The behaviour of economic agents is assumed to involve myopic anticipations. Obviously, PRIMES dynamics are quite different from that of models performing inter-temporal optimisation, like MARKAL, involving perfect foresight.

The sequence of static market equilibrium as simulated by PRIMES may not be 'optimal' with reference to perfect foresight. This is particularly important for capacity expansion decisions and technology choice. For example, technology lock-ins may well be explained as a result of imperfect anticipation.

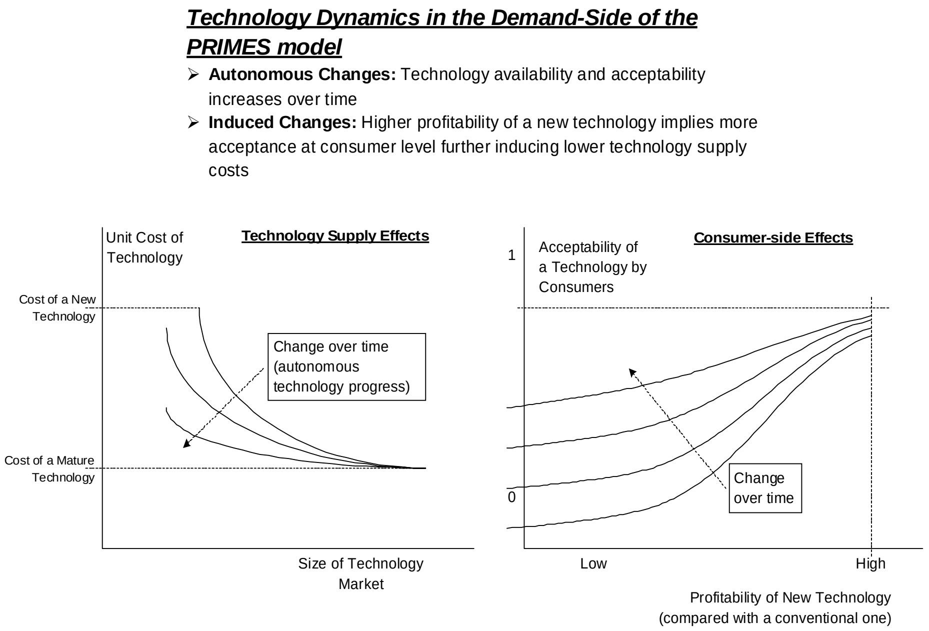
PRIMES do so because the model wants to mimic the real behaviour of economic agents and the eventual short-terms that often influences market equilibrium. Such behaviour obviously has consequences for both technology choice and dynamic evolution of technology.

The PRIMES model incorporates induced technology change (endogenous technology mechanism) in the demand side of the model. Technology choice at the consumer level is based on total technology cost, which further depends on technology supply costs and the acceptability of technology by the consumer. Both cost components can change endogenously. For example if a carbon constraint applies, the consumer might perceive more profitability from new technologies, the technology gets more acceptance and its penetration is further facilitated by decreasing technology supply costs; this leads to lower economic costs from complying with carbon constraints. Technology supply costs refer to the behaviour of equipment manufacturers and innovators, who, by anticipating higher market value for their products, may put in place a larger distribution network, more technical support and higher standardisation. All these factors are assumed to contribute to lower the perceived technology cost at the level of the consumer, who may then adopt this technology more frequently. Other authors have described the reticence of consumers to adopt best available technologies through the concept of barrier. In fact such barriers do exist and are related to the commercial immaturity of technologies, involving additional cost finally for the consumer who would adopt such a technology despite its immaturity. The overall context might change such a situation and accelerate the adoption of technologies in such a way that commercial maturity also progresses in acceleration.

PRIMES has set in place a formulation to mimic this mechanism for the case of demand side energy technologies. In some aspects, the mechanism acts similarly to learning by doing: the unit purchase costs reduce when a technology is used more to form capital stock. In another aspects, the mechanism in PRIMES is different from learning by doing: the perceived costs of technologies reduce when opportunity costs arising from using this technology increase, for example as a consequence of emission limitation targets.

Figure 1 illustrates these concepts regarding demand side technologies as formulated in PRIMES. The induced technology progress in the demand side results from combining the effects from the supply of a technology and the demand for the adoption of a technology. In supplying a technology, the anticipation of a bigger market induces economies of scale related to the minimum efficiency size of plants that manufacture the energy equipment. In demanding a technology, the anticipation of profitability in using that technology (opportunity cost), in other terms anticipating a bigger market size, induces higher acceptability by the consumers and lower costs associated to the use of the technology, like for example costs related to information, technical support, maintenance and reliability.

Figure 1 Technology dynamics in the demand side of PRIMES model



Technology Dynamics in the Demand-Side of the PRIMES model

- **Autonomous Changes:** Technology availability and acceptability increases over time
- **Induced Changes:** Higher profitability of a new technology implies more acceptance at consumer level further inducing lower technology supply costs

Under a driving force such as global emission constraints, the above mechanism triggers dynamics of technology change that differ from baseline conditions.

The imposition of emission reduction targets results in an increase in total energy system cost, partly due to the associated marginal abatement cost, which is defined as the cost incurred in avoiding the last ton of CO_2 that is necessary in order to meet the reduction target. The way that the imposition of the carbon-value affects different energy consumers depends on their ability to adapt to emission reduction targets through investment in new, more efficient technologies, structural shifts and changes in their choice of fuel mix.

As a response to the emission constraint, the consumer may accelerate the adoption of more efficient technologies along the schedule of normal replacement of his equipment, or even perform premature replacement of equipment. Advanced technologies are, almost by definition, significantly more costly to adopt initially, in terms of capital spending. However, once the carbon value exceeds a certain level and the adoption of these technologies becomes marginally cost effective their market penetration develops a strong momentum leading to the decline in the additional capital charges involved in the use of the new technology.

In other words, the anticipation of higher demand for advanced technologies leads energy equipment suppliers (manufacturers, maintenance and technical support operators) to make them more attractive and more acceptable by the market. This technology supply-side effect contributes to the acceleration of adoption of new technologies by consumers i.e., increased technology maturity makes consumers, in turn, find it more profitable to invest in new technologies as they have a better perception of their advantages. Of course, both the availability of technologies and the technology adoption mechanism take into account the time limitations for system adjustment given the emission target horizon.

The above mechanism allows for lower compliance costs for the system and higher penetration of demand side technologies, compared with cases that have a static view on technology change in demand side energy technologies.

2 Definition of alternative learning mechanisms in PRIMES

In order to evaluate the contribution of endogenous learning mechanisms under the setting of post-Kyoto emission reduction targets two alternative cases for technology acceptance by consumers were examined.

- In the first case, the ‘no-learning’ case, consumers were assumed to lack perception of emission reduction targets as regards their decision on new equipment. In that sense, acceptability of technology is unaffected by the introduction of carbon values. However, evolution of technology on the basis of increased maturity over time (expressing autonomous technical progress) still occurs as under baseline conditions;
- In the second case consumers were considered to fully understand the opportunities offered by advanced technologies and are willing to assume the corresponding opportunity cost without taking into consideration issues related to technology maturity and reliability. In this case, the acceptability of new technologies by consumers is the same as for conventional ones, which are mature and widely accepted. So this is the ‘fast-learning’ case.

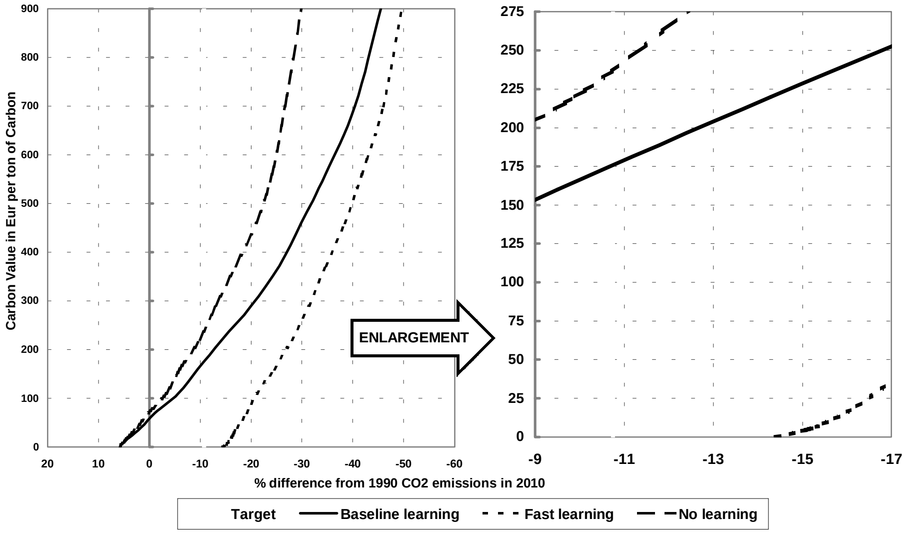
By using the PRIMES model under the three different settings concerning induced technology progress in the demand side (no-learning, ‘normal’ learning, fast learning) emission reduction paths are estimated. The marginal abatement cost curves for these emission paths under different assumptions of technology acceptance by consumers are shown in Figures 2(A to C).

In the Figures below it is clear that for small emission reduction targets there is little contribution from endogenous learning and therefore the marginal abatement cost curve under ‘baseline learning’ assumptions is close to that of ‘no-learning’. It must be mentioned here that the starting point of the above marginal abatement cost curves is the same. However, as stricter emission reduction targets are set, the model mechanism accelerates the evolution of technology change and the marginal abatement cost curve under ‘baseline learning’ approaches that of ‘fast-learning’.

In all cases, the marginal abatement cost curves corresponding to no-learning lie above the other curves, indicating that higher compliance costs are involved under a no-learning case. Conversely, the fast-learning case exhibits the mostly beneficial cost curve.

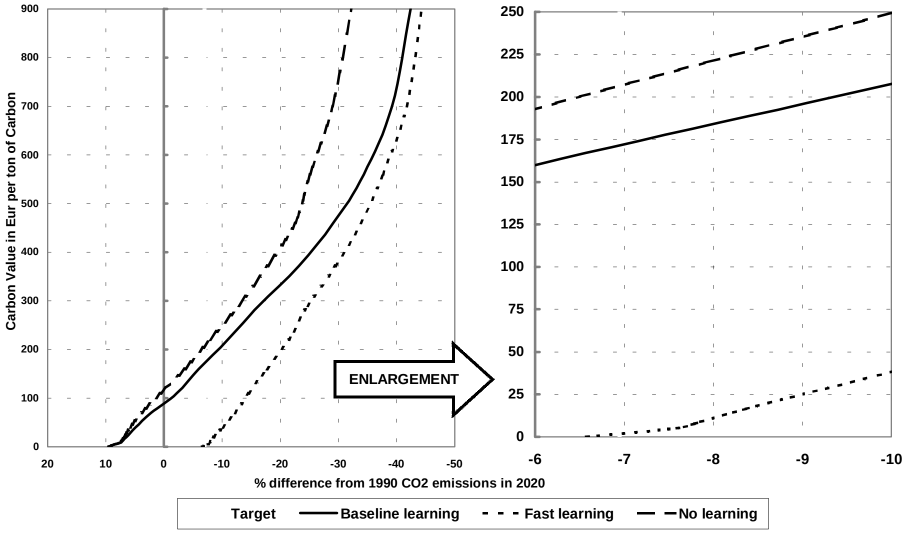
At very high emission reduction targets, the ‘normal’ learning curves tend to converge to the fast learning ones, since the opportunity costs from adopting advanced technologies become extremely high pushing learning to an extreme.

Figure 2 (A) Marginal abatement cost curves for different regimes of technology acceptance, 2010



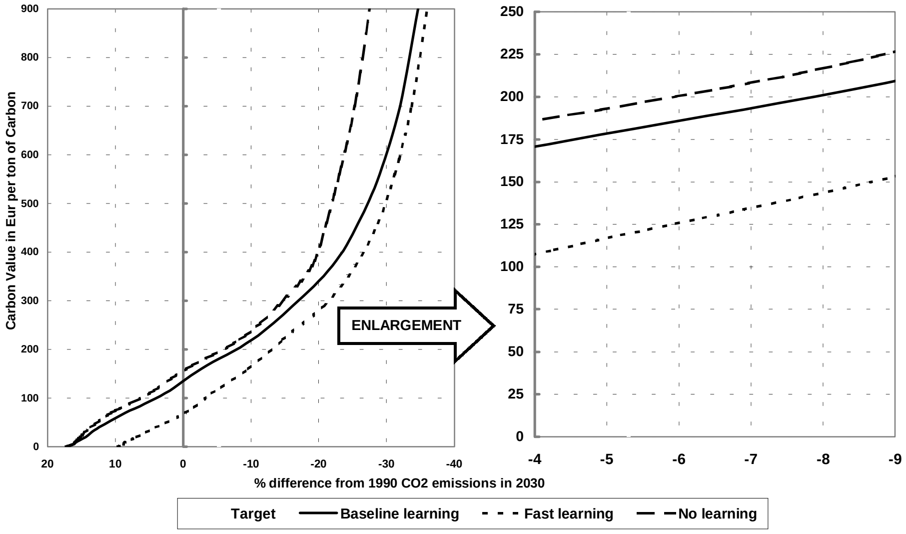
Source: PRIMES

Figure 2 (B) Marginal abatement cost curves for different regimes of technology acceptance, 2020



Source: PRIMES

Figure 2 (C) Marginal abatement cost curves for different regimes of technology acceptance, 2030



Source: PRIMES

The above graphs clearly illustrate the role of autonomous technical progress over time. PRIMES, as all models, assume that independently of the inducement factors, technology characteristics evolve over time autonomously. As time evolves, consumers move towards the use of advanced technologies, which even under ‘no-learning’ conditions gain in terms of maturity and acceptance. The potential for further technological improvement, in the absence of a ‘backstop’ technology that would improve over time, becomes limited in the long run and this results in the narrowing of the gap between ‘no-learning’ and ‘fast-learning’ marginal abatement cost curves in the long run.

3 The post-Kyoto target under different learning assumptions

In the absence of any emission reduction target the consideration that advanced technologies are equally accepted as the conventional ones – the ‘fast-learning’ case – would lead in a decrease of CO_2 emissions in 2010 by 14.4% compared to 1990, a decrease which is well below the Kyoto target. The decrease in comparison to baseline scenario for 2010 exceeds 20%. The corresponding figures for 2020 and 2030 are 16% and 7.5%. The adoption of advanced technologies is still under economic terms but they are more attractive than under baseline conditions. The results indicate that adopting best available technologies as if they were supplied in fully mature terms would induce increased improvement of average technology used in the demand side and would greatly contribute to emission limitation even under baseline conditions. This result is comparable to the so-called ‘bottom-up’ studies that show how important for emissions would be the massive adoption of best available technologies.

Table 1 provides the key results for the ‘no-learning’ and ‘fast learning’ in comparison to the ‘baseline learning’ post-Kyoto scenario. It is assumed that all three cases face the same level of marginal carbon abatement costs as it is necessary under ‘baseline learning’ for meeting the post-Kyoto targets. All definitions for the ‘baseline learning’ post-Kyoto scenario are the same as the post-Kyoto scenario defined and discussed in [1].

Table 1 Post-Kyoto under ‘no-learning and ‘fast-learning’ assumptions, 2010, 2030

	2010				
	Post Kyoto	**No-learning**	**%Difference from Post Kyoto**	**Fast learning**	**%Difference from Post Kyoto**
Gross Inland Consumption (Mtoe)	1397	1438	2.9%	1215	-13.0%
Fossil fuel inputs in electricity and steam generation (Mtoe)	360	378	4.8%	282	-21.6%
Electricity and steam output (TWh)	4133	4263	3.1%	3571	-13.6%
Final energy demand (Mtoe)	942	975	3.5%	804	-14.6%
Total CO_2 (Mtn CO_2)	2738	2854	4.2%	2255	-17.6%
demand side	1740	1803	3.6%	1466	-15.7%
supply side	998	1051	5.3%	790	-20.9%
Energy intensity (toe/MEUR90)	170.5	175.5	2.9%	148.3	-13.0%
Carbon intensity (tn CO_2/toe)	2.0	2.0	1.3%	1.9	-5.3%
Import dependency (%)	49.0	50.4	1.4%	43.3	-5.7%
	2030				
	Post Kyoto	**No-learning**	**%Difference from Post Kyoto**	**Fast learning**	**%Difference from Post Kyoto**
Gross Inland Consumption (Mtoe)	1425	1446	1.5%	1349	-5.3%
Fossil fuel inputs in electricity and steam generation (Mtoe)	469	478	2.0%	426	-9.1%
Electricity and steam output (TWh)	5059	5178	2.4%	4631	-8.5%
Final energy demand (Mtoe)	1002	1018	1.6%	951	-5.1%
Total CO_2 (Mtn CO_2)	2905	2936	1.0%	2743	-5.6%
demand side	1676	1695	1.2%	1621	-3.3%
supply side	1229	1240	0.9%	1123	-8.7%
Energy intensity (toe/MEUR90)	122.9	124.8	1.5%	116.4	-5.3%
Carbon intensity (tn CO_2/toe)	2.0	2.0	-0.4%	2.0	-0.3%
Import dependency (%)	64.7	64.9	0.2%	63.6	-1.1%

Source: PRIMES

The strong potential for technology improvement that remains unexplored in the short run is clearly revealed when examining the results obtained from the ‘fast learning’ scenario for 2010 and compared to the post-Kyoto (baseline-learning) scenario. Energy intensity improves by 13% resulting in a decrease of CO_2 emissions by 17.6% when compared to the ‘baseline learning’ post-Kyoto scenario. Final energy demand decreases by more than 14.5%. As an auxiliary effect electricity and steam production also decreases by 13.6% in comparison to the ‘baseline learning’ scenario. This significant decrease allows the power and steam generation system to better utilise existing capacities given the rather limited potential for new investment in the short run. CO_2 emissions reduction in the supply side is more pronounced reaching 21% while in the demand side emissions reduction is close to 16%.

The contribution of the ‘baseline learning’ mechanism is, however, quite important in the time horizon to 2010. In its absence (the ‘no-learning’ scenario), CO_2 emissions would be 4.2% higher. Energy and carbon intensity as well as import dependency would also be worse. The increased demand for electricity and steam by 3.1% when compared to the ‘baseline learning’ post-Kyoto scenario combined with the lack of alternatives in the power and steam generation system, result in an increase of emissions from the supply side by 5.3%. The corresponding increase from the demand side reaches 3.6%.

In the long run, the effect of the – driven by the introduction of a CO_2 emission reduction target – endogenous learning becomes less important than in the short run. The increased technology acceptance resulting from the autonomously evolving maturity of new technologies over time seems to explain why varying the learning mechanism has few impacts in the long run. As a consequence the ‘no learning’ mechanism provides by 2030 an additional 1.0-% increase of CO_2 emissions compared to the ‘baseline-learning’ case. Final energy demand in the ‘no-learning’ case would be 1.6% higher than that of the post-Kyoto scenario whereas electricity and steam demand would increase by 2.4% in 2030. Changes in the fuel mix result in an increase of emissions from the demand side by only 1.2%. Increase of CO_2 emissions in the supply side reaches 0.9% when compared to the post-Kyoto scenario. This increase is well below the level of increase of electricity and steam production because of changes in the fuel mix and a shift towards the use of non-fossil energy forms. Overall carbon intensity exhibits an improvement of 0.4% in the ‘no-learning’ case when compared to the post-Kyoto scenario for 2030.

The potential for further technological improvement, as already discussed, becomes rather limited in 2030. The results obtained from the ‘fast learning’ post-Kyoto scenario in 2030 confirm this statement. In the fast-learning case CO_2 emissions decrease by about 5.6% when compared to the ‘baseline learning’ post-Kyoto scenario. Final energy demand decreases by 5.1%, however emission reduction in the demand side is only 3.3%. This is due to the significant decrease of demand for electricity and steam (-8.5%) which in turn results in a decrease of emissions from the supply side by 8.7%. Energy intensity of the European energy system improves by 5.3%, carbon intensity by 0.3% and import dependency decreases by 1.1%. Tables 2 and 3 summarise the improvement of energy intensity indicators for the different demand sectors in 2010 and 2030.

The role of endogenous learning for the short run (2010) varies across the different sectors. This depends on three factors:

- The potential of technology improvement that is reflected in the gap between ordinary and advanced technology generations as modelled for each sector. The wider this gap, the bigger are the effects on energy intensity of the sector;
- The relative adoption of advanced technologies under baseline conditions. The high degree of such adoption in a sector implies lower potential for further improving the technology when learning possibilities are greater; and
- The subjective discount rate used for the sector. PRIMES mimicking relative behaviour of investment choices has introduced different discount rates in the sectors. For example, households are assumed to use higher discount rates than heavy industry where large companies are involved. When using a relatively high discount factor, a sector is more reluctant in adopting advanced technologies, so any improvement of learning would imply a higher degree of adoption.

Table 2 Energy intensity improvement in the demand side, 2010

indicator (1995=100)	1995	post Kyoto - 2010		
		No-learning	**Baseline learning**	**Fast learning**
Industry (production related)				
iron and steel	100.0	81.5	80.6	72.1
non ferrous metals	100.0	83.0	82.1	86.1
chemicals	100.0	78.3	77.5	72.7
building materials	100.0	98.0	96.1	84.6
paper and pulp	100.0	93.8	91.1	84.4
food drink tobacco	100.0	97.4	94.0	87.9
engineering	100.0	96.6	92.2	82.7
textiles	100.0	97.3	93.6	86.0
other	100.0	96.8	93.3	85.0
Tertiary (value added related)	100.0	73.7	67.8	58.5
Households (income related)	100.0	73.9	72.4	62.0
Transports				
passenger (income related)	100.0	84.1	81.9	60.1
goods (GDP related)	100.0	78.8	75.3	70.9

Source: PRIMES

Assuming that the higher beneficial results for the environment are obtained through the energy intensity improvement involved in the 'fast learning' scenario, relative performances under other learning assumptions, range in the industrial sectors from 10-35%. Energy intensive industries that exhibit a significant improvement in terms of energy intensity on the basis of autonomous technical progress are less affected than other sectors by varying the degree of the learning mechanism. On the contrary, the contribution of endogenous learning is more significant in the case of less energy intensive industrial sectors for which autonomous technical progress is rather limited.

The tertiary sector seems to be the most sensitive to the degree of the learning mechanism. Although significant improvement in terms of energy intensity (26%) is achieved in the tertiary sector through autonomous technical progress, as seen in the case of 'no-learning' post-Kyoto scenario for 2010 compared to 1995, the 'baseline learning' mechanism leads to an additional improvement of 6 percentage units. Further gains of about 40% in terms of intensity improvement could be achieved under 'fast learning' assumptions. The role of endogenous learning is also important for households and transport.

Similar results referring to 2030 are shown in Table 3. Varying the degree of learning has significantly smaller impacts in the long run than in the short run. This confirms the importance of assumptions about autonomous technical progress for the long run perspective. In 2010, the difference of energy intensity improvement could reach up to 25% between the 'no-learning' and the 'fast-learning' scenario (see passenger cars in Table 2). When comparing the same scenarios in 2030 one can see that the potential improvement becomes rather limited and does not exceed 7%, ranging in most sectors between 2.5 to 5%. Consequently, the role of endogenous learning is less significant in the long run in terms of potential from additional energy intensity gains.

However, the economic benefits from fast learning in the long run are considerable when considering the cost of complying with emission reduction targets. Figure 2C shows that to obtain the same emission reduction target in 2030, the fast learning case implies a marginal abatement cost that is half of that for the no-learning case.

Table 3 Energy intensity improvement in the demand side, 2030

indicator (1995=100)	**1995**	**post Kyoto - 2030**		
		No-learning	**Baseline learning**	**Fast learning**
Industry (production related)				
iron and steel	100.0	52.1	51.7	49.8
non ferrous metals	100.0	61.8	61.1	60.2
chemicals	100.0	64.6	63.4	61.2
building materials	100.0	82.4	81.2	77.8
paper and pulp	100.0	75.8	74.8	73.2
food drink tobacco	100.0	86.1	84.8	83.3
engineering	100.0	80.8	79.3	77.1
textiles	100.0	85.7	84.0	81.6
other	100.0	83.5	82.0	79.6
Tertiary (value added related)	100.0	62.7	60.5	55.5
Households (income related)	100.0	57.6	57.2	52.9
Transport				
passenger (income related)	100.0	55.8	55.3	52.5
goods (GDP related)	100.0	57.3	56.0	56.5

Source: PRIMES

4 Sensitivity analysis

A sensitivity analysis scenario was also examined, so as to further exploit the features and the mechanisms of the PRIMES model. In this scenario, named hereafter as the ‘fuel cells – fast learning’ scenario, it was assumed that consumers fully understand early enough the opportunities offered by fuel cell cars beyond 2010 while market acceptance of all other technologies evolves on the basis of the ‘baseline learning’ mechanism. It is assumed that all sectors face a uniform marginal abatement cost per unit of carbon avoided equal to that obtained under ‘baseline learning’ for the post-Kyoto scenario.

Table 4 shows the main results of this scenario and compares it to the other cases. The results obtained from the ‘fuel cells – fast learning’ scenario, are impressive and show that technology changes in the transport sector may exert high influence on all other sectors in the presence of emission reduction targets.

Fuel cell cars become the dominant car type as they gain more than 55% of private cars stock in 2030. The high market acceptance of fuel cells operates to their favour in terms of technology supply costs and at the same time to the detriment of advanced technologies of other car types. The latter do not gain in terms of market share and, consequently, their market acceptance does not increase through the ‘baseline learning’ mechanism further facilitating the penetration of fuel cell cars.

CO_2 emissions reduction reaches 5.7% when compared to the post-Kyoto scenario for 2030, 0.1% more than the emission reduction achieved in the ‘fast-learning’ scenario. The emissions reduction in the transport sector reaches 32% as a result of higher car efficiency (13.9% improvement compared to post-Kyoto) and the use of hydrogen and methanol in fuel cells. However, part of this emission reduction is counterbalanced by increased emissions in the supply side in the process of producing hydrogen and methanol. The main fuels used are mainly natural gas and biomass secondarily, because biomass supply is considered to be limited in Europe.

The decrease in demand for liquid fuels leads to a significant improvement of the import dependency indicator by 3.5 percentage units. Carbon intensity also improves by 6.5% when compared to the post-Kyoto scenario. Availability of biomass, about 60 additional Mtoe required in 2030, and natural gas, 53 additional Mtoe required in 2030, is the crucial factor for the consistency of the 'fuel cells – fast learning' scenario.

Table 4 The 'fuel cells – fast learning' scenario, 2030

	2030	**% Difference in 2030**		
	Post Kyoto	**No-learning**	**Fast learning**	**Fuel cells - Fast learning**
Gross Inland Consumption (Mtoe)	1425	1.5%	-5.3%	0.8%
Final energy demand (Mtoe)	1002	1.6%	-5.1%	-2.3%
Transports sector	305	1.3%	-3.1%	-7.6%
Vehicles efficiency (toe / Mpkm)				
passenger transport	28	0.9%	-4.9%	-11.1%
private cars	26	0.8%	-3.0%	-13.9%
Total CO_2 (Mtn CO_2)	2905	1.0%	-5.6%	-5.7%
demand side	1676	4.0%	-13.1%	-32.1%
transport sector	881	1.3%	-3.1%	-31.8%
supply side	1229	-3.0%	7.5%	26.3%
Energy intensity (toe/MEUR90)	122.9	1.5%	-5.3%	0.8%
Carbon intensity (tn CO_2/toe)	2.0	-0.4%	-0.3%	-6.5%
Import dependency (%)	64.7	0.2%	-1.0%	-3.8%

Source: PRIMES

5 The benefits from technology change in relation to endogenous learning under climate change pressure

As mentioned before the three 'learning' cases consider that all sectors face a uniform marginal carbon abatement cost (in other terms an environmental charge for each carbon emitted) as estimated under 'baseline-learning' conditions within the post-Kyoto scenario.

Compared to the post-Kyoto scenario (with baseline-learning) the 'no-learning' and the 'fast learning' scenarios lead to an increase by 30 $MtCO_2$ and a decrease by 166 $MtCO_2$, respectively, of CO_2 emissions in 2030.

In order to achieve the same emission reduction as in the post-Kyoto scenario, i.e. -5.3% from 1990 levels of CO_2 emissions, the marginal abatement cost of 190 Eur'90 per ton of carbon avoided would be necessary under the 'no-learning' case and 117 Eur'90 per ton of carbon avoided under the 'fast learning' case.

Under baseline-learning the total cost for meeting the post-Kyoto target reaches 17230 MEur'90, or 0.15% of EU gross domestic product in 2030. The corresponding costs – defined as the area bounded by the target, the marginal abatement cost curve and the horizontal axis (see Figure 2, A-C) – in the 'no-learning' and the 'fast learning' cases are 19400 MEur'90 and 7315 MEur'90, respectively. The gain resulting from endogenous baseline-learning as in the post-Kyoto scenario is 2180 MEur'90, or 0.02% of EU gross domestic product. The potential gain under the 'fast learning' assumption, when compared to the ‘baseline learning’ post-Kyoto scenario, reaches 9915 MEur’90, or 0.09% of EU gross domestic product.

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