Developing the PAGE2002 Model with Endogenous Technical Change

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ABSTRACT. Presented research demonstrates the inclusion of endogenous technical change into the PAGE2002 integrated assessment model of climate change. The 'experience curve' or learning-by-doing concept, made popular by the Boston Consulting Group during the 1960's provides a mechanism with which to describe cost reduction through experiential learning. The implementation of learning requires both a restructuring of the way costs are modelled as well as the inclusion of an explicit learning function with initial abatement costs and learning coefficients calibrated to historical renewable energy data. The discounted values for total abatement costs are calculated for both the standard PAGE2002 model without an explicit learning function and the modified PAGE2002 model. The results were found to be of a similar magnitude, partially due to the myopic effects of discounting, though the result was found to be highly sensitive to the learning rate used, which in our case was a conservative estimate.

Keywords: Endogenous Technical Change, Learning Curves, Climate Change

JEL Classification: O13 , Q55, Q56

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Chapter 1. Introduction

The research presented in this paper looks at the effects associated with Endogenous Technical Change (ETC) in the area of renewable energies and climate change. The aim was to devise a method for implementing ETC into a stochastic model of climate change. These models are often referred to as Integrated Assessment Models (IAM) or E3 models, representing the three fundamental elements, the environment, energy and economics.

During the last 5 years, there has been a lot of concern over the energy and economic aspects of E3 models and in particular the way that technical innovation has been modelled. Of all the techniques for reducing CO2 emission, such as improving efficiency or reducing consumption, it is government sponsored *Research and Development* (R&D) or strategic deployment of new technologies that appear to be the most acceptable solution. Yet, most E3 models have until recently used exogenous learning factors such as autonomous improvements in energy efficiency that ignore the role of policy and avoid the complicated issue of how learning actually takes place. It has been suggested that through explicitly modelling cost reductions through *ETC* these models would be better able to guide policy towards cheaper and more effective *abatement strategies*[3] than has previously been done. A general shift is taking place towards "a new generation of environmental-economic models" (Löschel, 2002) and the method of choice for incorporating ETC into E3 models has been to measure the acquired *learning-by-doing* or *learning-by-searching* of technology. This is a heuristic method of modelling costs, meaning that it is not based on any provable theory but, owing to its relatively consistent results, is a useful tool for our purposes. Groups such as the IMCP[4] have paid particular attention to this area of research, looking at both the benefits, drawbacks and caveats of applying such methods. The research presented in this paper relates to the introduction of an explicit learning-by-doing feature into the PAGE2002 Integrated Assessment model of climate change. In keeping with the structure of the PAGE2002 model, no energy sector has been incorporated. Instead of calculating the costs associated with energy technologies, abatement cost itself has been calculated directly, placing an artificially lower limit on the cost of greenhouse gas abating technologies. The overall results do

[3] An *abatement* strategy defines the amount of CO2 emissions that are reduced as compared to a normal scenario where no such measures have taken place.

[4] Innovation modelling comparison project (see Köhler et al. 2006)

coincide well with those of a number of other studies as published in the 2001 IPCC report and are able to shed some light on the importance of uncertainty in modelling ETC in a climate change model.

There has been some confusion regarding the terms “endogenous” learning and “induced” learning. We have used the term “endogenous” learning to describe the fact that changes in the abatement path through the learning function effects the costs of abatement. It is important to note however that the level of abatements made, and thus the costs, remain exogenous for any fixed stabilisation scenario, but becomes a decision variable for an optimisation of the PAGE2002 model. The term induced will be reserved to describe the actual changes in cost or performance as a result of policy change as modelled by PAGE2002.

The format of the paper begins with chapter 2 presenting a literature review of integrated assessment models and the theories on learning and innovation modelling. Chapter 3 goes on to look specifically at the PAGE 2002 model with an emphasis on the features that have been added or changed with the introduction of ETC into the model. The main results are then presented in chapter 4 and Chapter 5 concludes the paper by discussing how ETC has affected the PAGE2002 stabilisation results including suggestions for future research.

Chapter 2. Climate Modelling Background

2.1. Climate Change Models

Models that combine information on the numerous important areas of assessment are broadly referred to as Integrated Assessment Models, or IAMs, such as the PAGE2002 model. The model aim to better understand the correlation of the emission of ‘greenhouse’ gases to climate change, and how the impacts and abatement costs could shape the world over the coming decades or centuries. Table 1 presents a list of various popular models that have only recently been adapted to include ETC, one of which incorporates full stochastic features, the PAGE2002 model. Stochastic models are in many way ideally suited to the study of climate change due to the high level of uncertainty that exists in the field.

Table 1 E3 Models modified to include technical change[5]

Model	MODEL TYPE	INNOVATION MODELLING	Reference
MARKAL	Global energy system	Learning by doing	Barreto et al., 2004a
ERIS	Energy system optimisation	Two factor learning curve	Barreto et al., 2004b
R&DICE	Energy system optimisation	Innovation production function	Nordhaus, 2002
DEMETER	Computable general equilibrium	Learning by doing	Gerlagh et al. 2003
MERGE	IAM	Learning by doing	Kypreos, 2004
ENTICE	Macroeconomic model	Learning by searching	Popp, 2004
WIAGEM	IAM	Learning by searching and backstops	Kemfert, 2005
MESSAGE	Energy engineering optimisation	Learning by doing	Grubler & Al. 1998
MIND	Macroeconomic model	Two factor learning curve	Edenhofer, 2005
PAGE2002 (Modified)	IAM	Learning by doing	Current work

By using a distribution as opposed to a best guess estimate to calculate values, and by iterating through thousands of different possible outcomes, a stochastic model is able to avoid the ‘[f]law of averages’ as well as present substantial information on the uncertainty of outputs. The term ‘[f]law of averages’ describes a common error of assuming linearity between inputs and results when in fact the model is non-linear. In other words, it is to assume that by inputting average values, the model will also output the average result. By using a stochastic model that instead uses distributions as inputs instead of mean expected values, the model’s true output also in the form of a distribution can then be found.

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[5]Models referring to two factor learning curve (2FLC) refer to incorporating both learning by doing (cumulative production/capacity) and learning by searching (cumulative R&D). Cumulative capacity stands for a type of learning by doing function and cumulative R&D for a learning by searching function.

2.2. Modelling Technological Progress

In the overview of the 1998 Energy Economics special issue on 'The Optimal Timing of Climate Abatement', Carraro and Hourcade pointed out the notable influence that learning appeared to have on the calculation of abatement costs. According to their survey of E3 models, learning introduced around a 50% drop in abatements costs. The IEA publication 'Experience Curves for Energy Technology Policy' (IEA 2000) presents a broad overview of the work covered up to the end of the 1990's and also presents the findings from the 1999 IEA workshop on this subject. Their recommendation was that experience effects should be "*explicitly considered in exploring scenarios to reduce CO2 emissions and calculating the cost of reaching emissions targets*" (IEA 2000, p114).

The alternative to adopting ETC, the most common method used to date to explain changes in energy use, specifically the decoupling of economic growth from energy consumption has been the Autonomous Energy Efficiency Improvement (AEEI) parameter (Löshel 2002) which has been widely used in IAMs (Grubb & Köhler 2000). This exogenous factor, as presented in Equation 1, aims to define energy consumed as a function of Gross Domestic Product (GDP) and time and is calculated with the assumption that there are no changes in input energy costs (Manne & Richels 1992).

$$\mathrm{AEEI} = \%\,\Delta\ \frac{\text{Energy Use / GDP}}{\text{Time}}$$

Equation 1

There have been numerous criticisms made of this type of 'technical progress' and according to Grubb et al., it has been "widely recognised that the AEEI approach is inadequate" (2000), mainly this approach puts energy consumption/GDP as being independent of policy decisions, and thus supposes that public policy could not affect this ratio. Furthermore, due to the very long term nature of global warming, even small differences in the AEEI and carbonisation levels of energy sources used can have significant effects on the overall outcome (Grubb & Köhler 2000).

Modelling ETC is seen as an important factor in Climate modelling due to its ability to provide clues about the risks of technology 'lock-out' of potentially cheap and environmentally friendly technologies. Technology lock-out arises where traditional energy technologies have had their prices driven down through cumulative experience, while alternative technologies are unable to gain enough momentum to become cost competitive. This can be true even where the overall benefits of deploying new technologies far outweigh the costs in the long term. The following is a brief history of the development of experience curves, and a look at some of their benefits and drawbacks.

Empirical evidence for learning curves was first discovered in 1925 at the Wright-Patterson Air Force Base where it was discovered that plotting an aeroplane's manufacturing input against cumulative number of planes built on a log/log scale was found to result in a straight line. The benefits in efficiency found were proclaimed by Wright as being the result of "Learning by Doing" in his 1936 publication. This "learning curve" was calculated for a manufacturing input such as time as shown in Equation 2, where N_t is the labour requirements per unit output for period (t), X_t is the cumulative output in units by the end of the period. In the equation 'a' is the constant and 'b' the learning coefficient as determined by regression analysis.

$$\log N_t = a - b \log X_t$$ **Equation 2**

The next major advancement in learning curves was made by Arrow in his 1962 publication (Arrow 1962, IEA 2000). He was able to generalise the learning concept and also put forward the idea that technical learning was a result of experience gained through engaging in the activity itself. Undertaking an activity, Arrow suggested, leads to a situation where "favourable responses are selected over time" (Arrow 1962, p156).

During the 1960's the Boston Consulting Group (BCG) popularised the learning curve theory. They further developed the theory and published a number of articles on the subject (BCG 1968 in IEA 2000, Henderson 1973a, Henderson 1973b). They also coined the term "experience curve", as distinct from "learning curve" which related to 'unit total costs' as a function of 'cumulative output', rather than 'unit inputs' as a function of 'cumulative output' as shown in Equation 3. In this Equation the cost per unit 'C_t' depends on the cumulative number of units produced 'X_t' and the constant 'a' and coefficient 'b' that are found using a regression style analysis. This can be rewritten into a more simple form, as shown by Equation 4 to Equation7. A similar but much more useful representation of this formula for modelling purposes is to compare costs at a future time 't' to present known costs. This type of formulation is shown in Equation 8 and Equation 9. The Progress Ratio (PR) is a widely used ratio of final to initial costs associated with a doubling of cumulative inputs. The simple algebraic manipulation is presented in Equation 10 through to Equation 12. The learning rate represents the cost savings made as presented in the last of these Equations.

$$\log C_t = a - b \log X_t \qquad \textbf{Equation 3}$$

$$C_t = e^{a - b \log X} \qquad \textbf{Equation 4}$$

$$C_t = e^a e^{-b \log X} \qquad \textbf{Equation 5}$$

$$C_t = const \cdot e^{\log X^{-b}} \qquad \textbf{Equation 6}$$

$$C_t = const \cdot X^{-b} \qquad \textbf{Equation 7}$$

$$\frac{C_t}{C_0} = \frac{const \cdot X_t^{-b}}{const \cdot X_0^{-b}} \qquad \textbf{Equation 8}$$

$$C_t = C_0 \left(\frac{X_t}{X_0} \right)^{-b} \qquad \textbf{Equation 9}$$

$$\frac{C_t}{C_0} = \left(\frac{2 * X}{X} \right)^{-b} = 2^{-b} \qquad \textbf{Equation 10}$$

$$PR = 2^{-b} \qquad \textbf{Equation 11}$$

$$LR = 1 - PR \qquad \textbf{Equation 12}$$

Despite a strong preference for the use of cost data in the calculation, lack of such information often leads to replacing costs with price data which are more readily available (IEA 2000). This leads to an equivalent formulation as presented in Equation 13 and Equation 14, where b is the learning coefficient and P_0 and X_o are the price and cumulative output during the initial period.

$$\log P_t = a - b \log X_t \qquad \textbf{Equation 13}$$

$$P_t = P_0 \left(\frac{X_t}{X_0} \right)^{-b} \qquad \textbf{Equation 14}$$

The use of price data reduces the quality of the empirical analysis as prices can vary due to market influences. As proposed by BCG, reductions in cost that are made early in the product's development are often not passed on to the buyer, as shown in Figure 1. This situation can remain until there is a 'shake-up' of the industry due to increased competition (BCG 1968 in IEA 2000). Furthermore, due to the discovery that knowledge diffusion could have a serious impact on long-term cost advantages (Lieberman, 1987), learning curves began to lose favour.

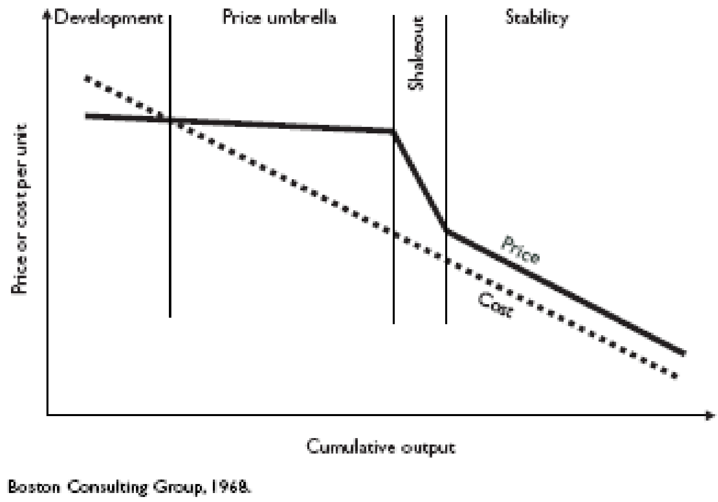


Figure 1 Price development of a new product as formulated by BCG (Source IEA 2000)

However, much of what is described by the jagged line in Figure 1 relates only to a transfer of funds, and as such, would have little effect on the net costs of abatement. This allows integrated assessment modellers and policy-makers, facing long term strategic decisions, to use experience curves in order to predict how costs of low-carbon technologies might evolve thereby helping them to calculate the overall costs of abatement. So with a new emphasis on global cost reductions rather than sustained competitive advantages, these ideas have once again enjoyed great popularity.

Learning rates for a number of electricity producing curves have been calculated, as shown in Figure 2. Electricity costs in 1990 US dollars per kWh have been graphed against cumulative production in TWh on a log/log graph with the associated progress ratios included. The line of best fit for each technology has a linear slope equal to the '-b' as described in Equation 3. This can also be transferred into a Progress Ratio (PR) as shown by Equation 11. For example in this study, photovoltaics has a PR of 65% (the very upper limit of published findings) which means that if there was a doubling of the amount of cumulative photovoltaic electricity production, the price would generally be reduced to 65% of the present value. Alternatively one could say that for every doubling of cumulative production, there is a cost reduction equal to the Learning Rate (LR) which is 1-PR, or 35%.

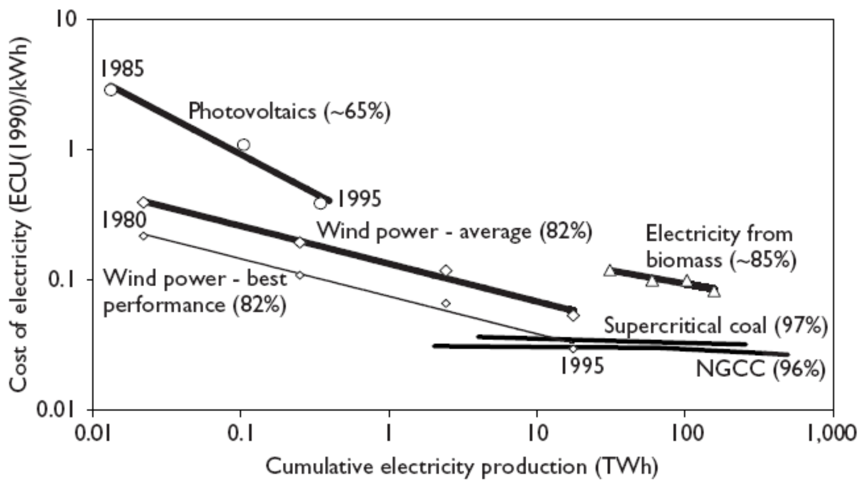


Figure 2 Progress Ratios of Electric Technologies in EU, 1980-1995 (Source IEA 2000)

Another related area of research has focused on the prediction of the "Break-even" point of low-carbon alternatives. That is, the amount of cumulative production required and associated costs such that the unit cost of a relatively new and expensive technology such as solar can become comparable to the unit cost of traditional technologies. In Figure 3, the area shaded in grey represents the cumulative costs needed to reach the break-even point. A similar problem exists here than what has been found for the AEEI, where a small amount of uncertainty in the average rate can lead to large errors in the determination of future costs. As presented by Figure 3, a small error of less than 2% in the learning rate can lead to an error in the final Break-even point of close to an order of magnitude.

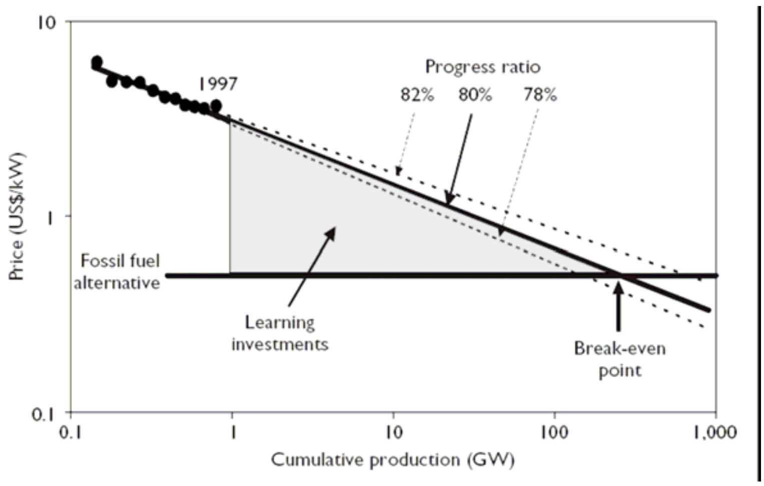


Figure 3 Making Photovoltaics Break-Even (IEA 2000, p15).

The IEA has paid special attention to the whole learning curve concept and has suggested that all models relating climate change to the economy should explicitly define technical innovation. Not only have the standard “experience curves” been used, but a number of more complex versions have also been developed. One common example is the 2 Factor Learning Curve (2FLC) which combines both ‘leaning-by-searching’ and ‘learning-by-doing’ that relates cost reductions to both cumulative experience and cumulative R&D as described in Equation 15.

$$P_t = P_0 * \left(\frac{X_t}{X_0} \right)^{-b} * \left(\frac{K_t}{K_0} \right)^{-c}$$ **Equation 15**

This presupposes that spending on R&D can also help achieve cost reductions, through all stages of a product’s life cycle, and thus can become an important factor when any sort of optimisation is made. There are, however, serious limitations on publicly available data about private R&D expenditure and so an accurate representation of this factor can sometimes be difficult to make (Junginger 2005). Lack of such data explains perhaps while Single Factor Learning Curves (SFLC) are sometimes preferred. It has also been found by some authors that R&D has only a minor and often statistically insignificant effect on costs when used with historical data (Papineau 2004). Other authors, who prefer the use of the SFLC, suggest that “*cumulative production or capacity is a surrogate for total accumulated knowledge gained form many different activities whose individual contributions cannot be readily discerned or modelled*” (Rubin et al. 2004). An explanation for some of the difficulty in arriving at accurate data for the 2FLC is a “‘virtual cycle’ or positive feedback loop between R&D, market growth and price reduction which stimulated its development” (Wanatabe 1999 in Barreto & Kypreos 2004a, p616). Here the authors concluded that “sound models for the role of R&D in the energy innovation system are not yet available (Barreto & Kypreos 2004a, p616).

The aim of the two factor learning curve is to increase the accuracy of the predictions made using experience style curves yet the overall results have been far from conclusive. Papineau found the results of R&D “disappointing” for wind and solar production. She suggested that this may be due in part to the relative benefits of other forms of government intervention “such as direct subsidisation” (Papineau 2004), which would lead to increased cumulative production, rather than increased R&D. For the sake of completeness, the formulation of the 2FLC is shown in Equation 15.

The question of floor-costs has also been raised and efforts to calculate their value with respect to minimum material costs for specific technologies has been carried out (Zweibel 1999, Neuhoff 2005). Zweibel looked at long term goals for the solar market and concluded that costs of 1/3 USD/Wp could be reached, thus making it a financially viable option to fossil fuel electricity (1999). Another important issue raised by various authors is the need for more accuracy of data and the inherent uncertainty associated with the learning model itself (Papineau 2004, IEA 2000). Grübler et al. (1998) also listed uncertainty in learning as one of their “final caveats” and acknowledged the potential drawbacks of “‘best guess’ parameterisation” (p510). Furthermore inaccurate predictions and dynamic variability of the learning rate may lead to situations where prices do not fall as planned (IEA 2000) and where apparently optimal uptake strategies may in fact become very costly. One approach to this problem is to “incorporate stochastic learning curve uncertainty” directly into the model (Papineau 2004, p10), potentially reducing the danger of using the learning curve phenomenon. A stochastic style of modelling allows an appreciation of true mean expected values as well as describing the level of uncertainty in the prediction.

A greater understanding of the learning curve phenomenon offers solutions to policy makers through the “creation of new energy technology options by exploiting the learning effect, e.g., through niche markets” (IEA 2000, p19). For much the same reasons, it may also be true that the private sector, armed with more accurate knowledge about long term learning rates and diffusion rates would be encouraged to invest in low-carbon technologies foreseeing their widespread uptake.

Chapter 3. The PAGE2002 Integrated Assessment Model

As the focus of this present work is directly on the issue of abatement costs, and not on the calculation of impacts, it is requested that interested readers refer directly to Hope (2004) for a full explanation of all other aspects of the model such as the calculation of impacts and the carbon-cycle, both remaining unchanged in the modified PAGE2002 model presented here.

3.1. Model Design and Stochastic Features

The PAGE2002 model is a stochastic IAM of climate change that uses a number of simplified formulas to replicate the complex environmental and economic interactions as presented in the literature. Furthermore, the coefficients and data ranges used often come directly from the Third Intergovernmental Panel on Climate Change (IPCC 2001a, 2001b, 2001c) assessment report (Hope 2004). The stochastic features are designed to embrace the remaining uncertainty of the best available knowledge found in the literature, or the randomness of nature itself, and is generated through the '@Risk' and 'Risk Optimiser' applications installed over an existing Excel platform (Palisade). These programs, designed specifically for stochastic modelling, allow the user to define the type of distribution used for all model inputs. The model simulates the outcome by running a set number of iterations and presents statistical summaries of the correlation coefficients between the model's inputs and various outputs.

The PAGE2002 model uses triangular distributions and a total of 5000 simulations are used for calculating the costs and impacts of stabilisation scenarios. The model is defined by ten different time intervals spanning 200 years, divides the world into eight regions, and considers three different gases as described in Table 2.

As shown, the model uses shorter time steps at the beginning and uses longer time steps towards the end of the model's time span, with time steps ranging from one year to 50 years. This has been done so that the "*computational effort is concentrated in the earlier years because emission forecasts become less accurate with time, and because later emissions have a smaller influence on costs and realised global temperature increase to 2200*" (Hope 2002).

Table 2 Definition of gases, regions and years

g	Gas	i	Year
1	carbon dioxide (CO2)	0	2000 (base year)
2	methane (CH4)	1	2001
3	third gas (SF6)	2	2002
r	**Region**	3	2010
0	The European Union (focus region)	4	2020
1	The United States of America	5	2040
2	Other OECD nations	6	2060
3	Africa and the Middle East	7	2080
4	China and Centrally Planned Asia	8	2100
5	India and South East Asia	9	2150
6	Latin America	10	2200
7	Former Soviet Union & E. Europe		

The standard version of PAGE2002 used in this research considers three greenhouse gasses that cause global warming, Carbon Dioxide (CO2), Methane (CH4) and Sulfur Hexafluoride (SF6). Only CO2 costs have been modelled using ETC in the modified version of PAGE2002, although a similar representation could be made for the other important greenhouse gas, CH4.

3.2. The Standard PAGE2002 Model

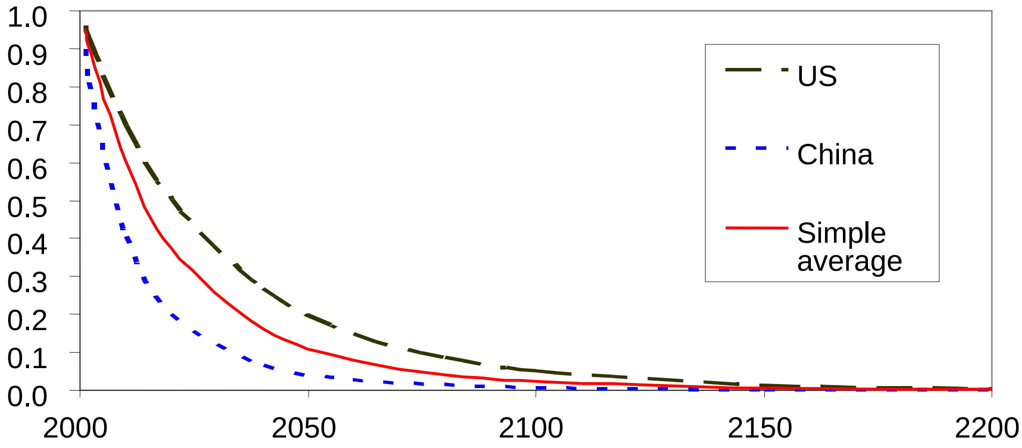
The standard PAGE2002 model does not incorporate energy or industry activity variables. Instead the model takes the simplifying assumption that costs can be directly associated to the emission reductions themselves. The calculation begins with each region's allocation of an emissions path as described by the scenario being modelled, and compares this to the BAU scenario. The abatements made for each region is the difference between these two emission paths. Using a set of fixed unit costs associated with abatement, the model uses this information to calculate the total costs of abatements as well as the adaptive costs and impacts caused by the climate change as induced by the scenario's emissions levels[6].

The abatement costs are divided into cheap and added-cost cutbacks. Cheap cutbacks refer to a cost that relates to all cutbacks made. The distribution of cheap cutback 'costs' can incorporate negative values in the standard version, describing situations where abatements actually lead to reduced overall costs. Added-cost cutbacks refer to cutbacks made above a certain fixed level relative to base year emissions, and incur costs that are added to the cheap

[6] The model does not, on the other hand, include a feedback loop where high abatement levels could slow down the economy.

cutback costs. As the abatement levels increase, a larger proportion of cutbacks are made at the added-cost cutback level, increasing the average cost of abatement. The total costs of an abatement scenario as compared to the BAU scenario can then be compared to the total reduction in impacts gained through reduced global warming impacts. The difference of these two values represents the Net Present Value (NPV) of the abatement strategy being tested with a positive NPV meaning that discounted benefits outweigh the discounted costs. The details of the standard methods for calculating abatement costs and associated formulas for the three greenhouse gases, as developed in the standard PAGE2002 model, can be found in Hope (2004).

Figure 4 Present value of future benefits or damages as a proportion of future value



The PAGE2002 model has shown to be highly sensitive to the method of discounting used. The model allows for variable discount rates for each time period and region following what is known as the "prescriptive approach[7]".

$$dr_{r,i} = ptp + e_u \bullet \left(g_{r,i} - p_{r,i}\right) \qquad \textbf{Equation 16}$$

This approach calculates the discount rate ($dr_{r,i}$), using a Ramsey type optimal growth function (Cline 2004) with a pure rate of time preference (ptp). This is shown in Equation 16 where 'e_u' represents the elasticity of utility and 'g' and 'p' show the growth rates of GDP

[7] The preferred terminology for the IPCC (IPCC, 2001a)

and population respectively, with variables indexed by region ‘r’ and period ‘i’. The average, highest and lowest results of the discounting method can be seen in Figure 4.

3.3. Modified Energy Aspects and Abatement Costs for CO2

The energy/emission/abatement assumptions made in the standard PAGE2002 model have created an interesting challenge for the development of a learning mechanism in the modified PAGE2002 model. This is mainly due to the highly aggregate nature of CO2 abatement. For instance abatements can be the result of changing energy production methods on one hand or by reducing demand for energy on the other, each with different associated financial and social costs. Furthermore, abatements can be made in the electricity sector or transport sector, by either individual or industry consumers.

Since PAGE2002 does not explicitly model the energy sector, costs are not defined as the difference between two forms of energy production, but instead as a function of CO2 abatements directly. This means that, apart from an initial calibration procedure, all aspects relating to energy production are directly calculated in the PAGE2002 model in terms of abatements. This includes backstops that represent a cheaper way to abate CO2 rather than referring to a particular energy producing technology. Cheap cutbacks can represent any mix of technologies able to reduce CO2 emissions easily and cost effectively. Added-cost cutbacks again represent any number of technologies able to extensively cut back CO2 emissions past a certain threshold, and these come at an extra cost.

In the versions used in this study of both the standard and the modified PAGE2002 models, the cutbacks are calculated as the difference between the IMCP prescribed stabilisation scenarios and the BAU scenario. As one might expect, the BAU scenario has essentially zero abatement costs associated with it as it is assumed the most cost effective measure would generally be chosen. In the modified model, the threshold between cheap and expensive cutbacks has been designated in a slightly different manner to the standard model. Whereas the standard PAGE2002 model has defined the threshold level as a percentage of base year emissions, in the modified version they are calculated as a percentage of the region’s zero cost emissions, as indicated by the business-as-usual emissions for the year in question. Hence as the general tendency goes towards higher emission levels, the amount of cutbacks that are cheap or come with added-costs varies proportionally.

These changes can be described by Equations 17 through 20 for $CBH_{i,CO2,r}$, which represents the added-cost cutbacks as a percentage of base year emission. All of the following formulas can be found in Annexe 1 where the formula number in square brackets [] refers to the formula numbers used in Hope (2004) which have been changed in the modified PAGE2002 model with learning (for CO2 abatement only). Equation 18 for total cutbacks $CB_{i,CO2,r}$ remains unchanged however it has also been included for the sake of completeness. Equations 19 and 21 for $CCB_{i,CO2,r}$ and $CCBH_{i,CO2,r}$ are the cumulative cheap and added-cost cutbacks for a given region and time period where $E_{0,CO2,r}$ represents the base year emissions converting cutbacks measured in percentage points to physical cutbacks in million tonnes.

Equation 22 for CBT and Equation 23 for CBHT represent the total amount of cheap cutbacks and added-cost cutbacks made for all regions for a particular time period 'i'.

3.4. Endogenous Technical Learning

As well as the inclusion of a single factor learning function to the PAGE2002 model, other alterations in the cost structure have also had to be made. The standard model allowed the distribution of cheap cutback costs to include negative values, whereas in the modified model all cutback costs are positive. This implies that at any point in time, all technologies leading to abatements are more expensive than the cost of traditional fossil fuel energies. Due to positive cutback costs, the modified model implicitly includes a floor cost (albeit variable) for energy production equal to that of fossil fuels, beneath which it is assumed low-carbon alternatives cannot fall and towards which their costs gradually tend as a result of learning. Cost-reductions are described by an experience curve style function with a small autonomous learning element, however, unlike traditional experience curve functions that look at costs as a function of cumulative investments or output, we have applied the function to CO2 abatements made.

Cheap cutbacks, Equation 24, and added-cost cutbacks, Equation 25, for region 'r' and period 'i' are also shown. Initial costs are calculated as a fraction of the model's focus region, the EU. CPF_r represents the ratio of the initial costs in region 'r' to those of the model's focus region. Naturally, the value for the CPF of the focus region is unitary, i.e. $\mathrm{CPF}_0 = 1$. Hence, the total CO2 abatement cost in US$(2000) for analysis year i and region r is as shown in Equation 26.

3.5. Choice of sector

A particularly difficult choice with regards to the design of the modified model was to decide how or on which sector to base the learning assumptions and calibration. There are three main industrial sectors that emit CO_2, the electricity sector, the transport sector and a variety of other industries such as the steel industry. Despite the fact that electricity accounts for less than half of CO_2 emissions, it has been chosen as the representative sector for two main reasons.

1) There exists a substantial body of literature in the area of electricity costs and ETC. This would allow a more rigorous representation of the model as a whole with the possibility for amendments as knowledge about the transport and other sectors becomes available.

2) As the transport industry moves towards larger CO_2 abatements, a similar set of technologies to the electricity sector abatements may be used. This includes the use of electric vehicles, hydrogen or flywheel power storage systems, distributed energy technologies and greater use of electrified public transport. This could lead not only to an increased importance of the electricity sector, but may also allow for a direct transfer of technologies from one sector to the other.

Another important decision considers which of the many possible current and future technologies or strategies should be taken as representative of overall abatements. Despite the effectiveness that a sharp reduction in energy consumption would have on CO_2 emissions, it would be difficult for a government to, for instance, reduce peoples mobility without causing political problems (IPCC 2001c, p65). Innovation would seem to be the preferred method to reach substantial CO_2 abatements.

Present abatement technologies fall into three general categories, renewables, nuclear (both fission and fusion), and Carbon Capture and Sequestration (CCS). The first of these, renewables, are chosen as they represent the only known final solution to the problem of CO_2 abatement without necessarily creating other future environmental problems such as nuclear waste. For the electricity industry, the most economic form of renewable energy that can still be expanded to fulfil a large proportion of our energy needs is onshore and offshore wind power. The use of wind power will be constrained by the availability of sites and the overall stability of the electricity infrastructure due to the intermittent nature of the wind. Beyond a certain level, the energy system then enters into the expensive cutbacks, with the addition of ‘added costs’ to take into account the use of more expensive electricity generation technologies or changes in the overall infrastructure. For these added costs, solar energy is considered as the backstop technology.

3.6. Cheap versus expensive cutbacks

The threshold separating cheap and expensive cutbacks is based on an assumption that around 30% of reductions could be met through the production of relatively inexpensive renewable energy, such as wind power. As suggested by Smith et al. (2004) the variation in electricity production of wind power could start to become problematic at the 10% level, and may be moderately problematic with 20% or more of electricity production coming from this source. A distribution with a higher range of minimum 10%, average 30% and maximum limit of 50% has been used for three reasons. Firstly, as suggested by Smith, improvements in forecasting can improve the above ratio. Short of applying another learning curve to this value, a higher judgement-based upper limit has been used. Secondly, technological advancements may improve this ratio as experience builds in such areas. Furthermore, other renewable energies may form part of the mix and, so long as they are not highly correlated with wind production, would increase the ratio of cheap renewable electricity that could be produced without impacts on stability of supply.

Added-cost cutbacks are those that relate to energy production requiring the use of expensive technologies such as solar photovoltaic electricity and, because of the increased level of production from renewable technologies, may also require an overhaul of electricity transmission and storage systems.

3.7. Cost of cutbacks

Both wind energy and particularly solar energy have been attacked for their high energy requirements in the production phase. According to the World Energy Council comparison of lifecycle emissions, an average amount of CO2/kWh over the entire product life cycle was found to be 60g of CO2/kWh for solar PV and 10g of CO2/kWh for wind power[8](WEC,

[8] The values used are also much the same as the values shown (IEA 2002)

2004). The CO2 abatement realised as compared to coal or gas powered electricity is described by Equations 27 and 28. It is important to note that the analysis has been used to get mean approximate values, however the model then uses very wide distributions.

The value of 22c/kWh for solar PV plus distribution or storage costs as used in Equation 28 is close to the values presented by Zwaan and Rabi (2004) for stand alone solar systems that included the significant storage costs required for large scale abatements by solar photovoltaics.

Since the cost per tonne of CO2 remains positive in this version of the PAGE2002 model, the mean zero cost scenario is set at 5% below the CPI Baseline, suggesting that, on average, the first 5% of reductions as compared to the BAU scenario have a zero average cost.

3.8. Initial Cumulative Experience

In order for the model to take into account learning, an estimation of the total amount of CO2 already saved through the two backstop technologies is required. As the values used represent the cutbacks made in the electricity industry, and do not consider similar types of abatements in other sectors that make up two thirds of all emissions, the historical abatements made for the electricity backstop are multiplied by three. This assumes that similar abatements and learning has taken place in these other sectors. Furthermore, as these values serve as a proxy, a wide distribution is used in order to encompass the true value.

According to IEA data, the sum of wind capacity installations per year over the period from 1990 to 1999 is around 50 000 with the units of MW*years. As there were small amounts of wind power before that date, the total value is increased to 60 000 MW years. A similar appraisal of available data has been made by Junginger et al. (2005) who have carried out an in depth study of global wind power learning rates. For the added-cost cutbacks, according to the BP website, the cumulative solar capacity*years is around 2 400 MW years up to but not including the year 2000. From these values we can calculate the cumulative historical CO2 abatements made by each of these two technologies.

3.9. Regional cross-over effects

Our revised learning curve formula calculates the marginal cost of CO2 abatement, as a function of total abatement to date and, for the modified PAGE2002 model, incomplete sharing of experience across the eight regions is allowed. For the initial experience gained before the year 2000, 100% sharing is assumed across all regions. The range for the Regional Crossover rate (RC) in the future starts from 100% sharing as used in the ERIS model (Barreto & Kypreos 2004b) , as well as partial sharing, while maintaining a relatively high average of 87% as shown in Table 3. The distribution used is judgement based, however with time a more accurate appraisal should be available. Furthermore, as suggested by Junginger et al. (2005), as large international companies service more clients around the world, learning becomes a global, rather than local phenomenon, perhaps leading to regional cross-over rates that should increase with time.

3.10. Learning rates for endogenous technical change

Due to the aggregate nature of CO2 abatement and the lack of previous work done to measure CO2 abatement learning rates explicitly, quite a wide distribution of learning rates is incorporated. In this way, it is the aim of the modified PAGE2002 model to encompass the general results presented in the literature, as put forward by Zwaan & Rabi (2004), Junginger et al. (2005), Rubin (2004), WEA (2000), IEA (2000) and Papineau (2004).

For solar energy alone, the learning rates found in the literature have been quite varied. They have ranged from 35% to 18% in the IEA (2000) publication, depending on how and from which region the values have been calculated. Papineau (2004), on the other hand, has found values of 5% to 19%, once again, depending on the chosen region and type of calculation made. The rates of mature technologies, on the other hand, such as coal and CCGT were found to be around 4% to 10% according to IEA (2000) and FGD and SCR scrubbers[9] have also been found to have learning rates of 11% and 12% respectively (Rubin, 2004).

The learning rates used for both types of technologies have a mean triangular distribution of 0.13 with a maximum value of 0.22 and minimum value of 0.03. This range encompasses all values except the one highest value published by the IEA (2000) for solar, and also encompasses the learning rates of the more mature technologies. These lower rates were included because abatements need to be modelled over the next two centuries, and it is

[9] A process that reduces pollutants such as SO2 and NOx emissions, particularly important for fossil fuel powered electricity generation.

possible that learning rates for these new and growing technologies will eventually slow down to levels commonly found by mature technologies.

3.11. Autonomous learning rates

Table 3 Summary Table of coefficient ranges used.

Code	Key learning coefficient distributions	Mean	Units	Min	Mode	Max
	Uncertainty in baseline emission levels	-5	%	-30	-5	20
CL	CO2 abatement cost (cheap=L)	17	US$(2000)/*t CO2*	0	10	40
CH	CO2 abatement cost (added-cost=H)	250	US$(2000)/*t* CO2	100	250	400
AL	Autonomous technical change L	0.10	%/Year	0	0.1	0.2
AH	Autonomous technical change H	0.25	%/Year	0	0.25	0.5
	Approx. Learning rate (LR) L	0.13		0.03	0.13	0.22
BL	Learning coefficient L	0.2		0.04	0.2	0.36
	Approx. Learning rate (LR) H	0.13		0.03	0.13	0.22
BH	Learning coefficient H	0.2		0.04	0.2	0.36
EL	Initial experience stock L	1000	MT of CO2	100	1000	1900
EH	Initial experience stock H	10	MT of CO2	1	10	19
RC	Regional crossover of experience L & H	87	%	70	90	100
MAX	maximum cheap emissions as percentage of zero cost emissions	30	%	10	30	50

As well as endogenous technical learning, the modified PAGE2002 model also includes a small amount of autonomous technical learning. These values have been made on judgement and their coefficients are as shown in Table 3[10]. A sensitivity analysis is carried out as part of this research to identify the most pertinent coefficients.

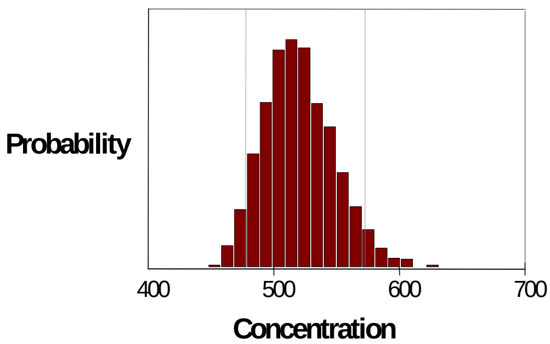
[10] The autonomous technical change level is smaller for the cheap cutbacks due to the fact that the CPI baseline from which emission reductions are calculated shows a reduction in total emissions. This has been assumed to reflect increased competitivity of renewable energies that are near to being competitive already, and as such would already be part of the cheap cutbacks category.

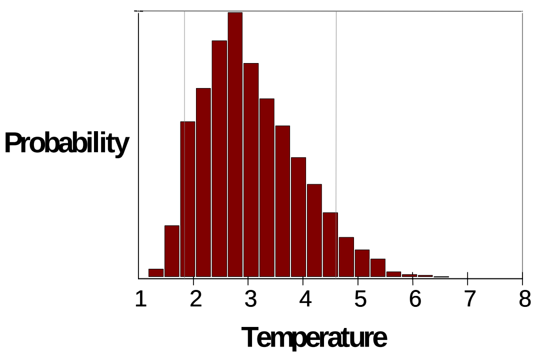
Chapter 4. Modelling results

4.1. CO2 concentration and global mean temperature for the '450 ppm' scenario

Figure 5a CO2 Concentration in 2100 under the 450ppm scenario with a mean of 521ppm and 5% and 95% confidence levels at 477ppm and 572ppm Respectively.

Figure 5b Global Mean temperature change in 2100 from 2000 levels with a mean rise of 3.1 degrees centigrade and 5% and 95% confidence levels at 1.8 and 4.6 Respectively.





The standard CO2 emission scenario that is supposed to lead to a 450 ppm stabilisation target for the year 2100 is found to give a higher CO2 concentration when applied to the PAGE2002 model, as shown in **Figure 5**a. This is due to a feedback loop in the PAGE2002 model's carbon cycle which limits the ocean's carbon sequestration ability as the temperature rises (Hope, 2004). This result also applies to the 500 and 550 ppm stabilisation scenarios. Furthermore, due to the stochastic nature of the model and the distributions for the input coefficients, it can be seen that the final concentration levels are far from certain. The resulting temperature rise by 2100, shown in Figure 5b, and abatement costs in Figure 7 show similarly large variations.

For the purpose of compatibility to other models, and since the focus of the comparison project is on preventative costs and innovation, and not on the carbon cycle, the projects standardised emission scenarios are used throughout. Hence any reference to, for example, a '450 ppm' stabilisation scenario refers in fact to a higher stabilisation level within the PAGE2002 model. Once again interested readers should refer to Hope (2004).

4.2. CO2 abatement costs for the '450ppm' scenario

Figure 6 shows the inputs that have the biggest positive and negative influence on the total preventative costs. The importance of the learning coefficient (for added cost cutbacks) and the elasticity of utility, which contributes to the discount rate, are evident. They are even more important than present day unit costs of CO_2 abatement for low and added-cost cutbacks or initial knowledge stock and autonomous technical change coefficients.

Due to their evident importance, future versions of the PAGE2002 model would greatly benefit from more accurate distributions. With the existing model, the total preventative costs discounted to today in year 2000 dollars is between 2 and 13 Trillion dollars, with a mean value of 6 trillion dollars.

Figure 6 Correlation sensitivity analysis of Total Preventative Costs for the '450 ppm' stabilisation scenario.

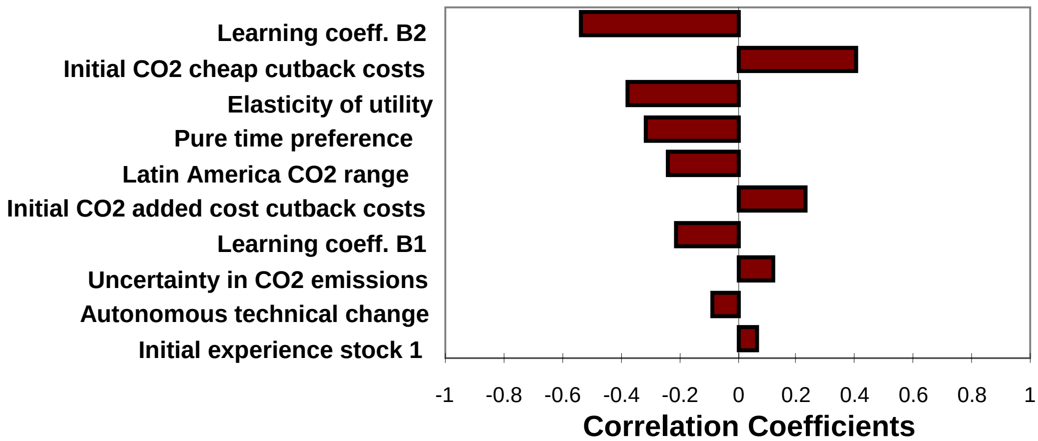
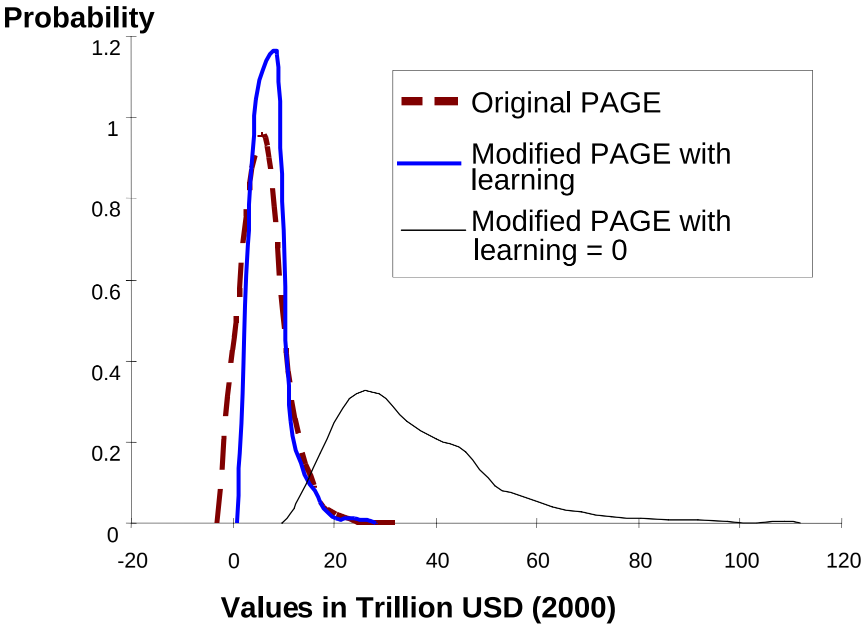


Figure 6 Distribution of Total Preventative Costs for the '450 ppm' stabilisation scenario.



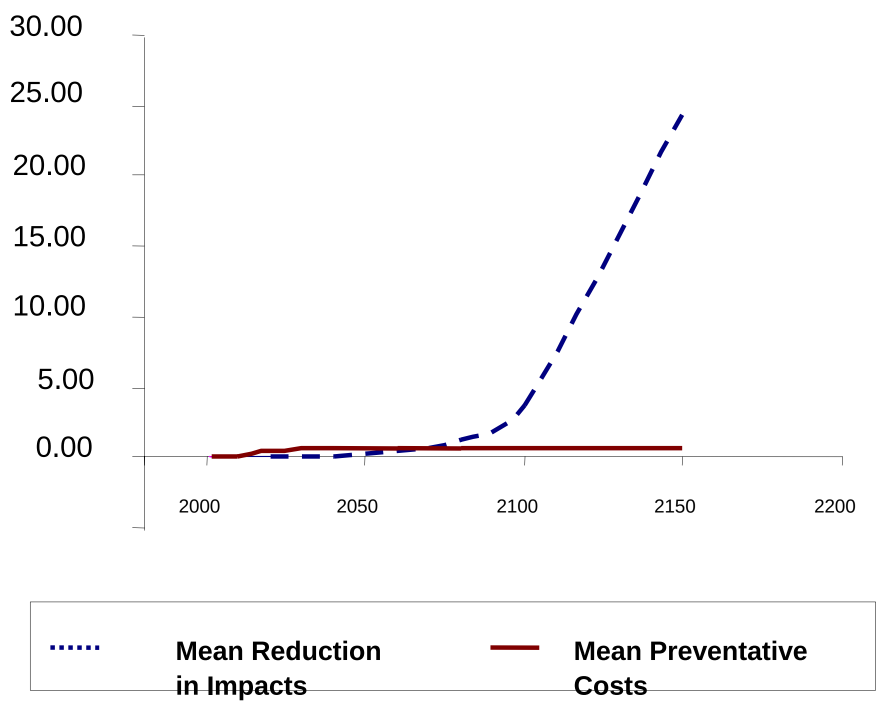
Despite the many differences in the way in which the original PAGE2002 model and the revised PAGE model with learning deal with abatement costs, the distribution of total preventative costs is remarkably similar. Not only is this true with the '450 stabilisation' scenario, but similar results are found for the 500 and 550 scenarios. The third line representing the revised model with no learning (neither autonomous nor learning by doing) uses the costs of abatement if renewable technologies were to remain fixed at 2000 prices. Unsurprisingly, these costs are well above the model with endogenous technical change.

4.3. The cost of prevention and global warming impacts.

In terms of comparative costs, the average cost impacts including large scale discontinuities far outweigh the relatively minor costs of abatement, as shown in **Figure 8**. However, due to the effect of discounting, these two costs become comparable in present terms, with the NPV of abatement highly dependant on the abatement levels chosen.

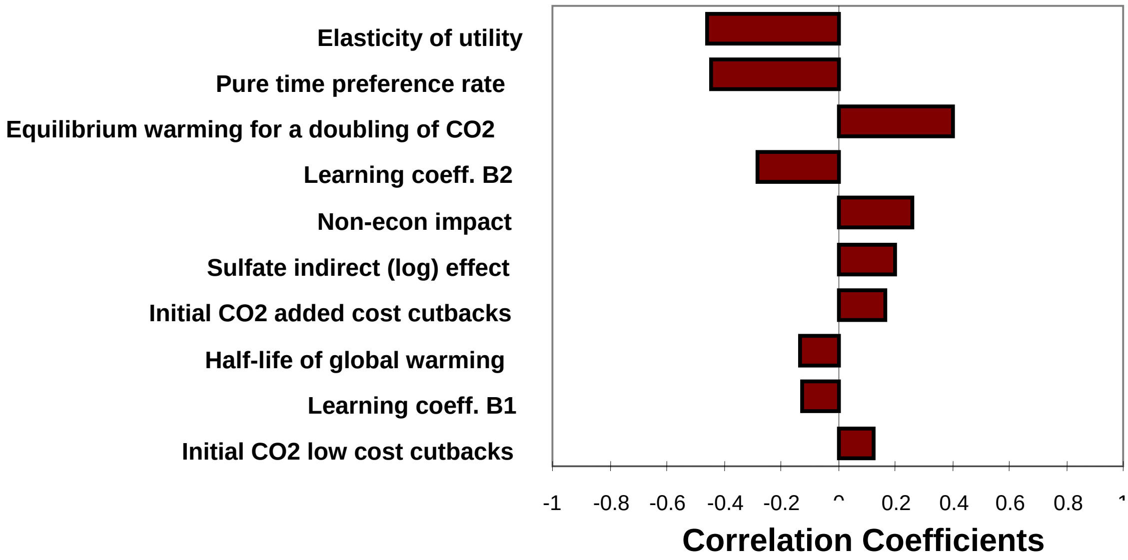
The 450 ppm stabilisation scenario for example returns an NPV of $0.45 Trillion, whereas the 500 stabilisation rises to an NPV of $1.8 Trillion and the 550 stabilisation level falls again to $1.4 Trillion. Similar values were found for the PAGE2002 model with implicit technical learning, showing once again the similarity of the two models.

Figure 8 Cost of impacts versus preventative measures for 450ppm scenario



The sensitivity analysis in **Figure 9** reveals the importance of learning for the sum of total abatement and impact costs, with the added cost (BH) learning coefficient in 4th place.

Figure 7. Correlation sensitivity analysis of total impacts and costs



4.4. Cost of abatement over time for the '450 ppm' scenario

Figure 10a Unit CO2 abatement costs for cheap cutbacks – 450ppm

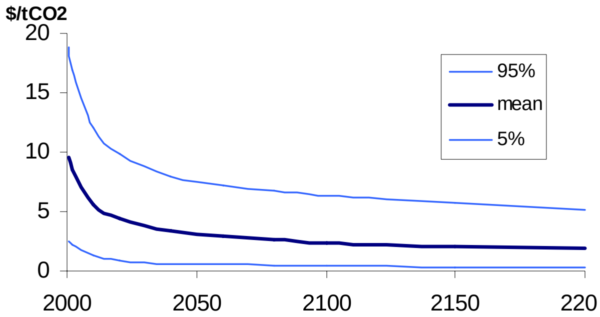
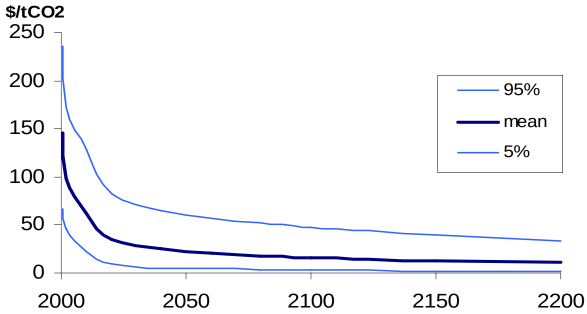


Figure 10b Unit CO2 abatement costs for added cost cutbacks – 450ppm



With the 450 emission levels, both the cheap and added cost cutbacks, as shown in **Figure 10a** and **Figure 10b**, benefit from major cost reductions. Costs for the expensive cutbacks are quick to come down due to their relative newness as technologies and thus their existing position low down on the learning curve. This allows large cost reductions for relatively minor levels of technology deployment. As expected, this initial drop in costs slows down substantially as the technology moves further up the experience curve, and is less dramatic for the higher stabilisation levels. The variation in future costs is also substantial. As shown **in Figure 10b**, expensive cutbacks in the year 2050 may cost as much as \$50/tCO_2 at the 95% level or as little as \$3/tCO_2 at the 5% level depending on the parameters chosen at random from the given ranges. The mean value was \$15.7/tCO_2.

Figure 7. Preventative Cost Comparison of implicit and explicit learning models – 450 ppm scenario

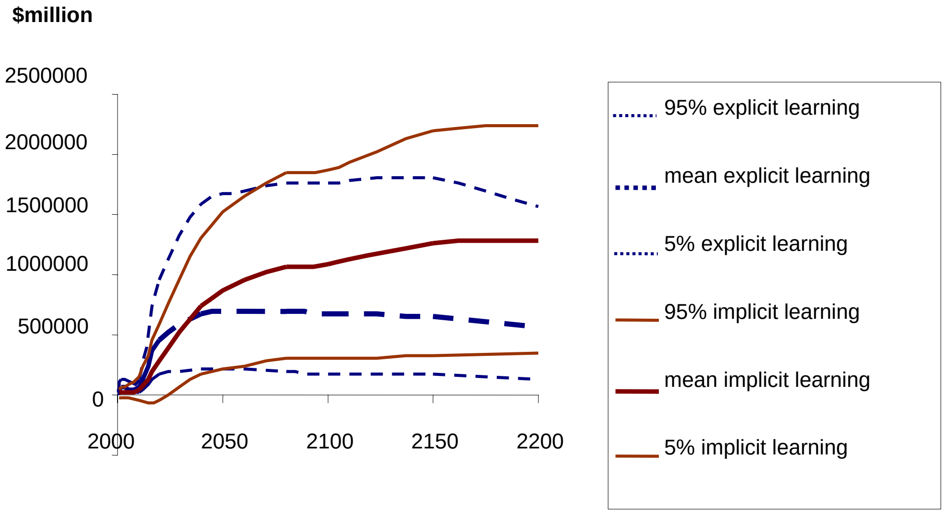


Figure 11 gives perhaps the clearest representation of how the implementation of explicit learning has affected the PAGE2002 model. Due to higher initial costs, cutbacks over the first part of the century actually cost more than in the standard model. These cost increases are gradually reduced to the point where the two models predict similar outcomes around the year 2040. After this point, costs in the revised model remain well below the levels in the standard model as technology continues to advance.

4.5. Comparison of the 450, 500 and 550 ppm scenarios

Due to the large emission reductions required for all of the stabilisation scenarios it is found that the mean unit costs of CO2 cutbacks remained similar across the scenarios. For example, the mean added cost cutbacks in the year 2100 varied from \$15.7/tCO_2 for the 450ppm scenario to \$18.3/tCO_2 for the 550 scenario, down from over \$200/tCO_2 before learning occurred. For all three of the scenarios, the total abatement costs closely match those found in the standard PAGE2002 model where only implicit learning is used.

Chapter 5. Discussion and Conclusion

5.1. Main findings

Despite a number of important changes in the way abatement costs were modelled and the addition of technical learning, the discounted cost results for the three abatement scenarios in question remained very similar to those in the standard PAGE2002 model. This was found to be the result of a relatively small increase in immediate abatement costs traded off against a much larger reduction in heavily discounted future abatement costs. It is important to note however that these results are highly sensitive to both the learning rate as well as the discount rate used.

A clear advantage of using explicit learning within the model was the supplementary information that it provided, such as the distribution of unit abatement costs as a function of time. Another exercise that may prove interesting for the revised PAGE2002 model would be an optimisation scenario. Here the subtle differences in abatement cost structures may lead to results that diverge more from the standard model. Furthermore, the revised model should allow for more accurate optimisation predictions.

5.2. Limitations and areas of future research

Clearly there are limitations in the accuracy of the data as well as limitations of the learning model itself, due to a relative neglect in the literature of the ability for aggregate variables to perform in learning curve analysis. In our case, CO2 cutbacks represent extremely complex systems, and even the measurement of abatement costs poses interesting and new problems. However, part of the solution has been to use relatively broad distributions for all input values, and then to test the importance of the variables as part of the sensitivity analysis incorporated in the results. This highlights one of the practical advantages of stochastic modelling in areas of great uncertainty.

The key areas for improvement, as described by the sensitivity analysis, would be to gather further data on the aggregate values of abatement learning rates, or to define and implement a more precise energy model system within the PAGE2002 model. Another important area of further research would be the comparison of abatement costs to the shadow price of CO2, particularly to move towards optimisation scenarios.

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Annexe 1

Table 4 –Descriptions of learning variables used

List of new variables used	
AH	Autonomous learning (expensive cutbacks)
AL	Autonomous learning (cheap cutbacks)
BH	Learning parameter for added cost cutbacks
BL	Learning parameter for cheap cutbacks
CB	Cutbacks made
CBHT	Cumulative expensive cutbacks made for all region
CBT	Cumulative Cutbacks made for all region
CCB	Cumulative Cutbacks made for region given
CCBH	Cumulative expensive cutbacks made for region given
CH	Cost of added-cost control measures
CL	Cost of cheapest control measures
CPF	Regional cost factor as compared to region 0 (EU)
E	Base year emissions made
EH	Existing added-costs abatements made prior to period 1
EL	Existing low cost abatements made prior to period 1
g	Gas type indices
i	Time period indices
MAX	Abatements made before added costs begin to occur
PC	Preventative Cost
ptp	Pure rate of time preference
r	Region indices
RC	Regional Cross-over rate
Y	Representative Year
Yhi	Last year of period given
Ylo	First year of period given
ZC	Zero Cost emissions

Page 2002 modified formulas

[41a]
$$CB_{1,g,r} = \max\{0, ZC_{1,g,r} - \mathrm{ER}_{1,g,r}\}$$
% Equation 17

$$g = 1-3, r = 0-7$$

[41b]
$$CB_{i,g,r} = \max\{CB_{i-1,g,r}, ZC_{i,g,r} - \mathrm{ER}_{i,g,r}\}$$
% Equation 18

$$g = 1-3, r = 0-7, i = 2-10.$$

[41c]
$$CCB_{i,CO2,r} = \frac{(CB_{i,CO2,r} \cdot \mathrm{E}_{0,CO2,r} \cdot (Y_i - Ylo_i))}{100} + \sum_{i=0}^{i-1} \frac{(CB_{i,CO2,r} \cdot \mathrm{E}_{0,CO2,r} \cdot (Yhi_i - Ylo_i))}{100}$$
% Equation 19

[41d] $$CBH_{i,CO2,r} = \max\left\{CB_{i,CO2,r} - MAX_{CO2,r} \cdot ZC_{i,CO2,r}, 0\right\}$$ **% Equation 20**

[41e] $$CCBH_{i,CO2,r} = \frac{\left(CBH_{i,CO2,r} \cdot \mathrm{E}_{0,CO2,r} \cdot (Y_i - Ylo_i)\right)}{100} + \sum_{i=0}^{i-1} \frac{\left(CBH_{i,CO2,r} \cdot \mathrm{E}_{0,CO2,r} \cdot (Yhi_i - Ylo_i)\right)}{100}$$

r = 0 – 7, i = 1 – 10 ***MTonnes*** **Equation 21**

[41f] $$CBT_{i,CO2} = \sum_{r=0}^{7} CCB_{i,CO2,r}$$ ***MTonnes*** **Equation 22**

[41g] $$CBHT_{i,CO2} = \sum_{r=0}^{7} CCBH_{i,CO2,r}$$ ***MTonnes*** **Equation 23**

[42] $$\mathrm{CL}_{i,CO2,r} = \mathrm{CL}_{0,CO2} \cdot \mathrm{CPF}_r \cdot \left(\frac{EL + RC \cdot CBT_{i,CO2} + (1-RC) \cdot CCB_{i,CO2,r}}{EL}\right)^{-BL} \cdot (1-AL)^{Y_i - Y_0}$$

$$g = 1(CO2), r = 0-7, i = 1-10$$ **US$(2000)/*tonne*** **Equation 24**

[43] $$\mathrm{CH}_{i,CO2,r} = \mathrm{CH}_{0,CO2} \cdot \mathrm{CPF}_r \cdot \left(\frac{EH + RC \cdot CBHT_{i,CO2} + (1-RC) \cdot CCBH_{i,CO2,r}}{EH}\right)^{-BH} \cdot (1-AH)^{Y_i - Y_0}$$

US$(2000)/*tonne* **Equation 25**

[44] $$PC_{i,CO2,r} = \left\{\mathrm{CL}_{i,CO2,r} \cdot CB_{i,CO2,r} + \mathrm{CH}_{i,CO2,r} \cdot CBH_{i,CO2,r}\right\} \cdot \mathrm{E}_{0,CO2,r}$$

US$(2000) **Equation 26**

Wind - Cheap cutbacks $$\frac{\Delta Cost}{\Delta CO2} = \frac{\Delta \cos t / kWh}{\Delta CO2 / kWh}$$

= *6 (Wind power[11]) – 5 (Fossil fuel[12]) cents/kWh*

((450g (gas) + 950g (coal) /2)-10 (wind))/kWh

= *14.5 US$(2000)/tonne CO2 saved* **Equation 27**

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[11] Cost estimates used for wind are within the range but on the lower end of those found by Neuhoff (2005)

[12] Year 2000 European average electricity wholesale price, down by 40% from 1995 levels according to IEA "Prices and taxes" data.

Solar - Added-cost $\dfrac{\Delta Cost}{\Delta CO2} = \dfrac{\Delta \cos t / kWh}{\Delta CO2 / kWh}$

$= \dfrac{22(solarPV^{13} / distribution) - 5(Fossil) - 1(wind)\ cents/kWh}{((450g\ (gas) + 950g\ (coal)\ /2) - 60\ (solar))/kWh}$

= 250 US$(2000)/tonne CO2 abated **Equation 28**

Cheap cutbacks - Wind[14]

*Cumulative CO2 Reduction = kW*Years*360*24 * CO2 saved/kWh * %load * 3 sectors*

*= 60 000 000*24*360*.0007*0.3*3*

=327 m Tonnes of CO2 saved **Equation 29**

Added-cost cutbacks – Solar

Cumulative *CO2 Reduction = kW*Years*360*24 * CO2/kWh * %load * 3(other sectors)*

*= 2 500 000*360*24*0.0006*0.2*3*

=8 m Tonnes of CO2 saved **Equation 30**

[13] For solar PV, similar values have been used by other authors including Neuhoff (2005) and Zwaan & Rabi (2004) that include grid connecting technologies.

[14] Load factor of 0.3 of peak power for wind and 0.2 for solar has also been used by Neuhoff (2005)