PRELIMINARY VERSION: PLEASE DO NOT REDISTRIBUTE OR QUOTE

WITCH

A World Induced Technical Change Hybrid Model

by

Valentina Bosetti* , Carlo Carraro[#], Marzio Galeotti**, Emanuele Massetti*, Massimo Tavoni*

First Draft: November 2005, Reviewed: June 2006

Abstract

The need for a better understanding of future energy and technological scenarios, of their compatibility with the objective of stabilizing greenhouse gas concentrations, and of their links with climate policy, calls for the development of hybrid models. Hybrid because both the technological detail typical of Bottom Up (BU) models and the long run dynamics typical of Top Down (TD) models are crucially necessary. We present WITCH –World Induced Technical Change Hybrid model– a neo-classical optimal growth model (TD) with an energy input detail (BU) and endogenous technical change (ETC). In particular, the BU component includes both electric and non-electric energy use, with a total of seven technologies for electricity generation and six for non electricity generation. In contrast to BU model, the allocation of installed capacity among technologies is defined as an optimal inter-temporal strategy. The model endogenously accounts for technological progress, both through learning curves affecting prices of new vintages of capital and through R&D investments. In addition, the model captures the main economic interrelationships between world regions and is designed to analyse the optimal economic and environment policies in each world region as the outcome of a dynamic game. This paper provides a detailed description of the WITCH model, of its baseline, and of the model calibration procedure.

JEL: O33, O41, Q43

KEYWORDS: Climate Policy, Hybrid Modelling, Integrated Assessment, Technological Change.

* Fondazione Eni Enrico Mattei, C.so Magenta, 63, 20123 Milano. Phone +39-02-52036934. Fax +39-02-52036946.

[#] University of Venice and Fondazione Eni Enrico Mattei, Palazzo Querini Stampalia, Campo Santa Maria Formosa, 30122, Venezia. Phone +39 041 2711453. Fax +39 041 2711461.

** University of Milan and Fondazione Eni Enrico Mattei, C.so Magenta, 63, 20123 Milano. Phone +39-02-52036934. Fax +39-02-52036946.

This paper is part of the research work being carried out by the Climate Change Modelling and Policy Research Programme at Fondazione Eni Enrico Mattei. Comments and support from Andrea Bigano, Francesco Bosello and Marianna Russo are gratefully acknowledged.

1. Introduction

Climate change is a long run global phenomenon. Its impacts are felt over a long time horizon, with different adverse geographical and sectoral effects. Climate change negatively affects welfare of present and future generations. It is an uncertain phenomenon and its control is likely to be difficult and costly. Because no one really believes or is ready to accept that the solution to the climate change problem is to reduce the pace of economic growth, policy analyses have often focused on changes in technology that could bring about the long sought de-coupling of economic growth from generation of polluting emissions. It is indeed widely recognized that without a drastic technological change, in particular in energy technologies, it will be difficult to control the dynamics of climate change and its impacts on ecosystems and economic systems.

However, the above is not an easy task. A model of technology development, adoption and diffusion should also take into account the long run dimension of the climate change problem, the interdependence of the needs of present and future generations, the linkages and externalities between different geographical regions and economic sectors, the dynamics of investments and population, and the uncertainty pervading the climate change phenomenon and its effects. The ideal model would feature all the above aspects and should be computationally manageable. Unfortunately, at present this ideal model does not exist. Existing classes of models stress or describe in detail some but not all above aspects. Generally speaking, economists pay more attention to the economic dimension of climate change within their top-down (TD) models, whereas system analysts or engineers deepen the technological dimension of the problem in their bottom-up (BU) models

In this paper, we present a new model called WITCH -World Induced Technical Change Hybrid- designed to at least partly fill the gap we have briefly outlined above. WITCH is a top-down neo-classical optimal growth model with an energy input specification in the spirit of a bottom-up model. As such, it is a “hard-link” top-down-based hybrid model, meant to analyze optimal climate mitigation strategies within a game-theoretical framework, while portraying with adequate detail the evolution of energy technologies and allowing for endogenous technological progress. As such, it is in the best position -at least in principle- for appropriately describing the dynamics of the relevant variables of the problem and for determining the optimal inter-temporal policy decisions to control climate change across world regions and time.

The structure of the paper is as follows. In the next section we outline the structure of the model and its features. In section 3, we describe the calibration procedure. Section 4 outlines the main results of our baseline scenario. A few concluding remarks are contained in Section 5.

2. Model Description

2.1 General Features

WITCH is a Ramsey-type neoclassical optimal growth model. The model is defined for twelve macro regions as listed in Figure 1. For each of them a central planner chooses the optimal paths of the control variables -investments in different capital stocks and in fossil fuels inputs- so as to maximize welfare, defined as the regional present value of log per capita consumption.[1] WITCH is a truly dynamic model in the sense that at each time step, forward-looking agents maximize simultaneously and strategically with respect to the other decision makers. Therefore, the dynamic profile of optimal investments in different technologies is one of the outcomes of the model. In addition, these investment strategies are optimally determined by taking into account both economic and environmental externalities. The investment profile for each technology is the solution of an inter-temporal game between the twelve regions in which world is disaggregated within the model. More generally, these twelve regions behave strategically with respect to all decision variables by playing an open-loop Nash game. From a top-down perspective, this enables us to analyse both the geographical dimension (e.g. rich vs. poor regions) and the time dimension (e.g. present vs. future generations). All regions determine their optimal strategies by maximising social welfare, with climate damages taken into account through a feedback from a linked climate module.

Optimization growth models are usually very limited in terms of technological detail. This is a severe limitation for the analyses of climate change issues, that are closely related to the evolution of the energy sector. In WITCH the detail of the energy sector is considerably augmented with respect to other macro-growth models: the model separates electric and non-electric uses of energy, features 7 power generation technologies and includes the use of multiple fuels –oil, natural gas, coal, uranium, traditional biomass and biofuels. This kind of detail in the energy sector -although still much simpler than in large scale energy system models- is to our knowledge a novelty for this class of models and enables us to adequately portray future energy and technological scenarios and to assess their compatibility with the objective of stabilizing greenhouse gas concentrations. Also, by endogenously modeling fuel prices, as well as the cost of storing the CO_2 captured, we are able to evaluate the implication of mitigation policies on the energy system in all its components.

Following the recent research in climate modelling, WITCH incorporates a description of endogenous and induced technical change. Traditionally, Bottom Up models have modelled technological change through Learning by Doing, while Top Down ones have focused on investments in R&D, often reaching different conclusions (Clarke and Weyant (2002)). The hybrid nature of WITCH helps us to reconcile these distinct views. In the bottom up part of the model we encompass the learning by doing effects by bringing in experience curves for all energy technologies, while, in the

---

[1] Population is exogenous in the model. The model equations not listed in the text can be found in the Appendix.

top down part, we account for the accumulation of knowledge (via R&D) and for its effects on energy efficiency and the cost of advanced bio-fuels.

The model is solved numerically in GAMS/CONOPT for 30 5-year periods. Solution time is approximately 30 minutes on a standard Pentium PC. The code is available from the authors upon request.

2.2 The model structure

Output is produced by aggregating factors via nested Constant Elasticity of Substitution (CES) functions as shown in Fig. 2. Elasticities of substitution are also reported. Final production for region *n* at time *t* is obtained by aggregating a Cobb-Douglas bundle of capital K_C and labor *L* with energy services *ES* in the following way:

(1) $$Y(n,t) = TFP(n,t)\left[\alpha(n)\cdot\left(K_C^{\,1-\beta(n)}(n,t)L^{\beta(n)}(n,t)\right)^{\rho} + (1-\alpha(n))\cdot ES(n,t)^{\rho}\right]^{1/\rho} \Big/ \Omega(n,t),$$

where *TFP* represents total factor productivity which evolves exogenously over time and *Ω* is the damage that registers the feedback of temperature rise onto output production.

Consumption of the single final good is obtained via the economy budget constraint:

(2) $$\begin{aligned} C(n,t) = {} & Y(n,t) - I_C(n,t) - \sum\nolimits_j I_{R\&D,j}(n,t) - \sum\nolimits_j I_j(n,t) - \sum\nolimits_j O\&M_j(n,t) \\ & - \sum\nolimits_f P_f(n,t)X_f(n,t) - P_{CCS}(n,t)CCS(n,t) \end{aligned},$$

i.e. from output we subtract investments in final good, in energy R&Ds and in each energy technology labeled by j (including Operation and Maintenance). Expenditure for each fuel (labeled by *f*) is also subtracted, as well as the cost of transporting and storing the CO_2 captured. The latter is region specific and increases with the cumulative quantity of CO_2 injected.

Fossil fuels use generates CO_2 emissions, computed by applying stechiometric coefficients. The quantity of carbon captured is subtracted from the carbon balance. Emissions are fed into a stylized three-boxes climate module (the dynamics is described in Nordhaus and Boyer, 2000) which returns the level of temperature increases relative to pre-industrial levels. Through the region specific quadratic damage function *Ω* the increase in temperature creates a wedge between output gross and net of climate change effects

2.3 Non-cooperative Solution

The game theoretical structure of WITCH allows us to internalize the free riding behavior of different countries. Regions interact through five channels.

First, at each time period, the prices of oil, coal, gas and uranium depend on world cumulative extraction. Thus, investment decisions, consumption choices and R&D investment in any country at any time period indirectly affect all other countries' choices. Consider for example the impact of a massive reduction of oil consumption in the USA and in Europe alone, for instance stimulated by policies that promote the deployment of bio-fuels; the lower path of oil prices would modify the energy demand and technology adoption in the rest of the world. However, this effect works as a restraint for the countries that had lead the oil consumption reduction; as a consequence, the incentive to free-ride limits the innovative actions of first movers, indeed a very realistic feature. We thus describe rebound effects not only inside any region but also across regions. Second, at any time period, emissions of CO_2 from each region change the average world temperature and they affect the shadow value of carbon emissions in all other regions. Third, investment decisions in each electricity generation technology, in each country, at each time, affect other regions by changing cumulative world installed capacity which in turns affects investment costs via Learning-by-Doing. A fourth channel of interaction derives from the international (lagged) R&D spillovers that affect the costs of the advanced bio-fuel. Finally, the fifth channel is active when the model is used to analyze the effects of emission permits trading; when an emission permits market is open, regions interact via this channel which equalizes marginal abatement costs across regions, with all the necessary consequences of this result on R&D effort and investment choices. WITCH uses these five channels of interaction to characterize the interdependencies of all countries' climate, energy and technology policies.

In terms of the solution algorithm, we model the interactions among world regions as a non-cooperative Nash Game, which is solved recursively and yields an Open Loop Nash Equilibrium. The algorithm works as follows: at each iteration the social planner of every region takes as given the behavior of other players derived from the previous iteration and sets the optimal value of all choice variables; this newly computed level of variables is stored and then fed to the next round of optimizations. The process is iterated until each region's behavior converges in the sense that each region's choice is the best response to all other regions' best responses to its behavior, which is a way of characterizing Nash Equilibrium. Convergence is rather fast (around fifty iterations) and the uniqueness of the solution has been tested using alternative starting conditions. The way in which the algorithm is constructed makes the solution invariant to different regions orderings.

2.4 The Energy Sector

Let's further explain how we incorporated an energy sector in the models structure: again, we refer to Figure 2 for a diagrammatic description of the energy sector and its composing technologies.

The energy services factor of production *ES* is a combination of energy with a variable, *HE*, that represents technological advances stemming from energy R&D investments meant to improve energy efficiency. As in Popp (2004), an increase in energy R&D efforts improves the efficiency with which energy, *EN*, is translated into energy services, *ES*, e.g. more efficient car engines, trains, technical equipment or light bulbs (for more on this see next Section).

EN is an aggregate of electric, *EL*, and non-electric energy, *NEL*. Contrary to what specified in other top-down growth models -such as DEMETER (Gerlagh and van der Zwaan, 2004) and MIND (Edenhofer *et al*, 2005) -in WITCH the whole energy demand does not coincide with electricity. In our opinion this is a needed distinction as reducing emissions is traditionally more challenging in the non-electric sector, and its neglect would seriously over-estimate the potential GHG control achievements.

Non-electric energy is obtained by linearly adding coal and traditional biomass on the one hand and an oil-natural gas-biofuels *(OGB)* aggregate on the other. The use of coal in non-electric energy production *(COALnel)* is quite small and limited to a few world regions, and is thus assumed to decrease exogenously. The same applies for traditional biomass *(TradBiom)* The oil-biofuels-gas aggregate combines oil *(OILnel)*, biofuels *(Biofuels)* and natural gas *(GASnel)* sources. In WITCH ethanol is produced from sugar cane, wheat or corn *(Trad Biofuel)*, or from cellulosic rich biomass *(Advanced Biofuel)*;[2] the two different qualities of ethanol add up linearly so that only the cheaper is used. For more detail on parameter choice see Section 3.

As for the electric use of energy, nuclear power (*ELNUKE*) and renewables in the form of wind turbines and photovoltaic panels (*ELW&S*), are combined with a bundle of fossil fuel-based electricity (*ELFF*), obtained by aggregating thermoelectric plants using coal, oil and natural gas (*ELCOAL*, *ELOIL* and *ELGAS*). This way we are able to distinguish more interchangeable power generation technologies such as the fossil-fuelled ones. Coal based electricity itself is obtained by linear aggregation of traditional pulverized coal technologies *(ELPC)* and integrated gasification combined cycle with CCS *(ELIGCC)*. Hydroelectric power (*ELHYDRO*) is added to the total electric composite; given its constrained deployment due to limited site availability, we assume it evolves exogenously, in accordance with full resource exploitation.

By using CES functions, we aggregate different types of electricity non linearly, though we allow for considerable substitution possibilities (for details on the values of elasticity of substitution see Paragraph 3. Although we can no longer interpret the intermediate nests as quantities of electricity we believe this approach has some desirable properties. First, we model the energy system's low price responsiveness through the CES less-than-infinite elasticity of substitution: moving away from an established energy mix takes place at a higher cost than it would in a simple minimum cost minimization framework. This is in agreement with econometric studies on inter-fuel substitution in power generation, that find low sensitivities of power generation options with respect to own and cross fuel prices (on this see Section 3). Second, regional current energy mixes provide input data in calibrating the CES functions and can offer valuable information. Third, by using CES functions we allow for contemporaneous investments in different technologies, including the not yet cost-

[2] Cellulosic feedstock comprises agricultural wastes (wheat straw, corn stover, rice straw and bagasse), forest residue (underutilised wood and logging residues, dead wood, excess saplings and small trees), energy crops (fast growing trees, shrubs, grasses such hybrid poplars, willows and switchgrass). For a description of how the transformation process of cellulosic ethanol see IEA (2004b).

competitive ones such as new renewables, and thus document niche markets. This approach is not new as it is already used in many CGE models, and provides an alternative to the typical bottom-up least cost minimization: if in the latter a portfolio of different investments is achieved by imposing exogenous constraints on single (or combination of) technologies, the "production function" approach assumes electricity expenditures conform with base-year calibrated factor shares and chosen elasticity of substitution. The interpretation of expenditure rather than electricity itself helps reconcile this view with the usual production function framework.

For each technology *j* (wind and solar, hydroelectric, nuclear, traditional coal, IGCC with CCS, oil and gas), at time *t* and in each region *n*, electricity is obtained by combining three factors in fixed proportions: i) the installed power generation capacity (*K*), ii) operation and maintenance equipment (*O&M*) and iii) fuel resources consumption (*X*), when needed. The Leontief technology is then as follows:

(3) $$EL_j(n,t) = \min\{\mu_{n,j} K_j(n,t)\,; \tau_{n,j} O\&M_j(n,t); \varsigma_j X_{j,EL}(n,t)\}.$$

The parameters governing the production function take into account the technical features of each power production technology. μ translates power capacity (i.e. TW) into electricity generation (i.e. TWh) through the plant utilization rate (hours per year), which allows us to take into consideration the fact that some technologies, noticeably new renewables such as wind & power, are penalized by comparatively lower utilization factors. τ differentiates operation and maintenance costs among technologies, i.e. nuclear power is more expensive to run and maintain than a natural gas combined cycle (NGCC). Finally, the parameter ς measures (the reciprocal of) power plants fuel efficiencies and returns us the quantity of fuels needed to produce a KWh of electricity. *ELHYDRO* and *ELW&S* are assumed to have efficiency equal to one, as they do not consume any fuel, which reduces to assume a two-factor Leontief production function.

It is important to stress the fact that the power generation capacity is not equivalent to the cumulated investment in that specific technology: different plants have different investment costs in terms of final output, i.e.:

(4) $$K_j(n,t+1) = K_j(n,t)\left(1-\delta_j\right) + \frac{I_j(n,t)}{SC_j(n,t)},$$

where δ_j is the rate of depreciation and SC_j is the cost, in terms of final good, of installing power generation capacity of type *j*, which, as discussed more in depth in the next section, is time and region-specific. It is worth noting that the depreciation rates δ_j are set consistently with the power plants lifetime, so that again we are able to incorporate the technical specifications of each different electricity production technology.

An important feature of WITCH is that the cost of electricity generation is endogenously determined. WITCH calculates the cost of electricity generation as the sum of the cost of capital invested in plants, and the expenditures for O&M and fuels. Since the cost of capital is equal to its marginal product, as capital accumulation proceeds, capital-intensive electricity generation technologies, such as nuclear or wind & solar, become more and more preferable to variable cost-intensive ones such as gas. Indeed, whereas at the beginning of the optimization period regions with high interest rates such as the developing ones disfavor capital intensive power generation technologies, in the long run the model tends to prefer capital-intensive rather than fuel-intensive electricity production. Note that this feature is not shared by energy system models, as they are not able to ensure capital market equilibrium, as noted in Bauer (2005). Since investment costs, O&M costs, fuel efficiency for each technology and fuel prices are region-specific, we obtain a high degree of realism in constructing relative prices of different ways of producing electricity in the twelve regions considered. To our knowledge internal derivation of electricity prices is a novelty in macroeconomic growth I.A. models.

Four natural resources are employed in electricity generation: coal, crude oil, natural gas and uranium. These are non renewable resources whose price obeys to a long-term trend that reflects their exhaustibility. We abstract from short-term fluctuations and we model resource *f* price time path, where *f* stands for coal, crude oil, natural gas and uranium, starting from a reduced-form cost function that allows for non-linearity in the ratio of world cumulative extraction to resource base:[3]

(5) $$c_f(n,t) = \sum_n X_f(n,t) \cdot \left(\chi_f(n) + \pi_f \left[Q_f(t-1) / \left(\vartheta_f \overline{Q}_f(t) \right) \right]^{\psi_f} \right),$$

where c is the regional cost of resource f, depending on Q_f -the cumulative world extraction- and a region-specific markup, χ_f (n). $\overline{Q}_f$ is the amount of total resources discovered at time t and ϑ_f measures the fraction of total resources at which scarcity becomes a relevant problem.[4] π_f measures the relative importance of the depletion effect. Thus, with the assumption of competitive markets, price Pf is equal to marginal cost,

(6) $$\begin{aligned} P_f(n,t) &= \chi_{f,n} + \pi_f \left[Q_f(t-1) / \left(\vartheta_f \overline{Q}_f(t) \right) \right]^{\psi_f} \\ Q_f(t) &= Q_{0f} + \sum_{s=0}^{t} \sum_n X_f(n,s) \end{aligned},$$

where the second expression represents cumulative extraction.

Finally, since WITCH offers the possibility of tracing consumption of fossil fuels, GHGs emissions that origin from their combustion are derived by applying the corresponding stechiometric

---

[3] Hansen, Epple and Roberds, (1985) use a similar cost function that allows for non linearity also in the rate of extraction $c_f(n,t) = q_f \left(\chi_{f,n} + \gamma_f \, q_f(t) + \pi_f \left[Q_f(t-1) / \overline{Q}_f \right]^{\psi_f} \right)$

[4] We explain with more detail how we modeled resources growth in paragraph 3.3.1 .

coefficients to total consumption. Even though we presently use a climate module that is reactive only to CO_2 emissions, a multi-gas climate module can easily be incorporated in WITCH thus allowing the introduction of gas-specific emissions ceilings.[5] For each region *n*, CO_2 emissions from combustion of fossil fuels are derived as follows:[6]

(7) $$CO_2(n,t)=\sum_f \omega_{f,CO_2} X_f(n,t)-CCS(n,t),$$

where ω_{f,CO_2} is the stechiometric coefficient for CO_2 emissions of fuel *f* and *CCS* stands for the amount of CO_2 captured and sequestered while producing electricity in the IGCC power plant.

2.5 Endogenous Technical Change

As noted above, in WITCH technical change is endogenous and is represented both through Learning by Doing (LbD), and energy R&D investment.

By incorporating LbD effects in electricity generation, we are able to reproduce the observed empirical relation for which the investment cost of a given technology decreases with accumulation of knowledge represented by cumulative installed capacity. This representation has shown explanatory power in areas such as the renewable energy sector, where, for example, the installation costs of wind turbines have steadily declined at a constant rate. Learning rates depend on a variety of factors – not least of public nature – and vary considerably across countries. In our framework we resorted to use world-learning curves, where investment costs decline with the world-installed capacity. That is, we assume perfect technology spillovers and constant learning rates across countries, which is fairly reasonable considering that any time step in the model corresponds to five years. Also we initially allow learning effects in the Wind and Solar technology only.

In the learning curves, the cumulative (installed) world capacity is used as a proxy for the accrual of knowledge that affects the investment cost of a given technology, *j*:

(8) $$SC_j(t+1)=B_j\cdot\sum_t\sum_n K_j(n,t)^{-\log_2 PR_j},$$

where *PR* is the progress ratio that defines the speed of learning. With every doubling of cumulative capacity the ratio of the new investment cost to its original value is constant and equal to *PR*, until a fixed floor level is reached. By having several electricity production technologies, the model is given the flexibility to change the power production mix and invest in the more appropriate technology for

[5] As in Nordhaus and Boyer (2000) we take into account GHGs emissions other than CO_2 by including an exogenous radiative forcing when computing temperature deviations from pre-industrial level. Thus, when we simulate stabilization policies of GHGs concentrations we consider this additional component and constrain CO_2 emissions accordingly to the global target.

[6] The climate model of WITCH delivers emissions from land use and change that are added to emissions from combustion of fossil fuels to determine atmosphere concentration and then temperature.

each given climate policy, thus creating the conditions to foster the learning-by-doing effects for the clean but yet too pricey electricity production techniques.[7]

We also, model endogenous technical change through investments in energy R&D which serve different purposes. First, they increase energy efficiency. Following Popp (2004) technological advances are captured by a stock of knowledge that aggregates with energy in a constant elasticity of substitution (CES) function, and thus stimulates energy efficiency improvements:

(9) $$E(n,t) = \left[\alpha_H HE(n,t)^{\rho} + \alpha_{EN} EN(n,t)^{\rho}\right]^{1/\rho}.$$

The stock of knowledge $HE(n,t)$ derives from energy R&D investments in each region through an innovation possibility frontier that models diminishing returns to research, and depreciates similarly to a physical stock:

(10) $$HE(n,t+1) = aI_{R\&D}(n,t)^{b} HE(n,t)^{c} + HE(n,t)(1-\delta_{R\&D}),$$

$\delta_{R\&D}$ being the depreciation rate of knowledge. As social returns are found to be higher than private ones in the case of R&D, the positive externality of knowledge creation is accounted for by assuming that the return on energy R&D investment is four times higher than the one in physical capital. At the same time, the opportunity cost of crowding out other forms of R&D is obtained by double counting the R&D investments in the budget constraint.

A second set of energy R&D investments are dedicated to lowering advanced biofuels costs. Conditioned on research efforts, its cost may become lower than that of currently used fuels. R&D efforts needed to win lock-out inertia are calibrated in order to be induced by scenarios where emissions are strongly constrained, as for example in the case of a scenario aiming at stabilizing atmospheric GHGs below 450 ppmv, whereas in the baseline the advanced bio-fuels do not step in, at least not in the time horizon considered.

The cost of the cellulosic biofuels, $P_{ADVBIO}(n,t)$, is modeled as decreasing with investments in dedicated R&D through a power formulation:

(12) $$P_{ADVBIO}(n,t) = P_{ADVBIO}(n,0)\cdot(TOT_{R\&D,ADVBIO}(n,t))^{-\eta},$$

where η stands for the relationship between new knowledge and cost and $TOT_{R\&D,ADVBIO}(n,t) = \sum_{n} K_{R\&D,ADVBIO}(n,t-2) + \sum_{\tau=t-1}^{t} I_{R\&D,ADVBIO}(n,\tau)$ represents the world R&D expenditure for advanced biofuels cumulated up to period *t-2*, to which the two preceding periods R&D investments of country *n* only are added. We thus assume that the effects of any region-cumulated R&D influence other regions with a 10-year (2 model periods) delay. Modeling a lag time

[7] In a future extension of the model, we will introduce two-factor learning curves, in which both learning-by-researching and learning-by-doing are taken into account.

accounts for the advantage of first movers in innovation, and we thus allow for an incentive effect counteracting typical underinvestment in R&D.

3. Calibration

A complete exposition of the calibration procedure is not possible here for editing limitations. We will sketch the main features and assumptions in the following, and refer the interested reader to Bosetti *et al* (2006) for a exhaustive description.

To begin with, we have chosen the values for elasticities of substitution for the CES production functions shown in Figure 2. We have followed the existing modeling literature for the aggregation of the capital/labour bundle with energy (Manne *et al* (1995), Whalley and Wigle (1990)), and the survey of econometric estimates conducted by Burniaux *et al* (1991) for the Cobb-Douglas aggregation of capital and labour. As for the lower nests, we have chosen figures that are in line with the empirical literature on substitutability in energy (see Babiker *et al* (1997), Dahl (1993), Ko and Dahl (2001), Lee *et al* (1994) and Soderholm (1998)).

To calibrate the remaining parameters (factor shares and productivities) of the CES functions, we have computed the first order conditions with respect to all the choice variables, and equated all the marginal products to their prices. This is crucially important to avoid "jumps" in the first optimization steps. Euler equations allowed us to calculate the prices of intermediate nests. This has yield a system of 40 non-linear simultaneous equations that has been solved with GAMS. Prices and quantities for each factor of production have been taken from various data sources (ENERDATA (2004, 2005), IEA (2004a), NEA/IEA (1998, 2005), World Bank (2004)). The base year of calibration is 2002.

For the technology specification currently represented in the model, we have assumed that learning occurs in the Wind and Solar electricity production only, at the progress ratio of 0.87- i.e. an investment cost decrease of 13% for each doubling of world capacity installed. As for the learning parameter for advanced biofuels, we have set it to 0.1, yielding a learning factor of 7%.

Population is exogenous and follows the Common POLES IMAGE (CPI) baseline (van Vuuren *et al.,* 2004). The climate module is adopted from Nordhaus and Boyer (2000). Figures have been adjusted for the different time step length and initial base year. Intertemporal discount rate is also as in Nordhaus and Boyer (2000), set equal to 3% in the base year, and then declining at a constant 0.25% rate per year. Total factor productivity is assumed to exogenously grow over time to reflect technological progress and all the other structural changes that are difficult to represent in a simplified Ramsey-type growth framework, especially in the case of developing countries. The exponential trend is calibrated to fit the output projection underlying the Common POLES IMAGE (CPI) baseline (van Vuuren *et al.*, 2004).

Finally, the extraction cost functions for each fuel -coal, oil, natural gas and uranium- are calibrated based on resource availability surveys (IEA (2004a), MIT (2003), USGS (2000)) and expert judgment.

4. WITCH Baseline Scenario

In this Section we present the results of the Baseline scenario, that is the non-cooperative solution that we have run without imposing any external GHGs mitigation policy. The results thus return the optimal choices of the control variables with respect to the whole optimization time (now-2100), accounting for the free-riding behaviour of each region. Let us recall that the control variables are investments in all energy technologies, in physical capital and in R&D, together with the direct use of fossil fuels. The solution algorithm was described in Section 2.3.

Let us start by describing the macroeconomic features of our Baseline scenario. Figure 3 shows the dynamics of GDP in two macro-region aggregates. World output is 34 1995USD Trillions in 2002 and grows steadily to 240 trillions in 2100, a seven fold increase. This is similar to the IPCC-SRES B2 scenario. NON-OECD countries will overcome OECD in terms of output after mid century, and take the lead afterwards, pushed by the continued rise in population. Annual growth rates per region are shown in Figure 4: developing countries experience higher growth figures, but all regions mildly converge by the end of the century.

Figure 5 shows the reductions in energy and carbon intensity of energy throughout the century. Again for sake of simplicity we show the results for two macro-region aggregates only. The (primary) energy intensity of output decreases considerably throughout the century -see the horizontal axis: investors take into account the increasing costs of energy sources and therefore reduce the amount of energy per unit of output over time. This is also coherent with the historical evolution of the energy intensity that, for example, in the U.S. halved in the past 50 years. The graph also tells us that the reductions in energy intensity are expected to be stronger in the NON-OECD countries: these regions are more energy intensive now, but have large margins of improvement in energy efficiency, and indeed converge to the world average as their economies evolve in time. This reflects some positive environmental features of the energy policy in all countries.

However, if we look at the evolution of the carbon intensity of primary energy -on the vertical axis, we note small improvements only in the OECD countries and actually a worsening -though very limited- in NON-OECD ones. This designs a continued carbon based evolution of the energy mix, especially in the developing countries. As a term of comparison, the carbon intensity of primary energy in the U.S. has remained somewhat stable in the second half of the century, see Nakicenovic (1997).

Indeed, by looking at the evolution of the world primary energy demand portrayed in Figure 6, we predict a continued use of fossil fuels throughout the century. Oil, coal and natural gas are expected to satisfy the growing need for energy -especially in the form of electricity, by maintaining their shares almost constant. Such a projection clearly depends on the underlying assumption on fuel resources availability and prices We project a four-fold real terms increase over the century in oil prices, threefold for natural gas and coal. However, given the low base year price, oil reaches 85 1995USD/barrel by the end of the century. This figure might seem too optimistic given current prices in the market, but it is in line with the estimates that account for the large non conventional oil resources (tar sands, shale oil, coal liquefaction etc), see IEA (2005b). Therefore, our baseline assumes -in line with other projections such as Lackner and Sachs (2005)- that the energy resource base will be sufficient to provide energy demand of a fast-growing world economy in the next century.

The world power generation mix is shown in Figure 7: fossil based power generation is expected to continue through the century. Coal reinforces its leading role, especially in the developing countries, in line with what we have found in the carbon intensity graph. The rise in oil and gas prices keeps the nuclear option alive and constant around the 20% share. New low carbon technologies do not become competitive to gain substantial market shares: Wind & Solar electricity increases very marginally, and Carbon Capture and Sequestration do not enter the electricity mix.

As for technical change, energy efficiency improving R&D investments increase 4 times during the century, passing from 9 1995USD Billions to almost 40. This not negligible amount is though not enough to increase the share of energy R&D over GDP. As regards Learning by Doing, the presence of international learning spillovers reduces the incentives of early investments in Wind & Solar technologies. This is shown in Figure 8, where investments in Wind & Solar with and without international spillovers are confronted. The free-riding incentives that characterise the game delay the adoption of the climate friendly technology in the very early period. Thereafter, the world experience effect allow significant investment cost decreases and a faster penetration of the technology.

There are several factors that support this carbon intensive baseline. First, the absence in the Baseline of any climate policy keeps the carbon prices down to very low values, and prevent the deployment of carbon free technologies. The negative feedbacks from the climate module is not strong enough to induce significant emissions cuts, mainly because costs and benefits of emissions reductions have different timings: regions have to bear costs for adopting more virtuous technologies first, and they will benefit from lower temperatures only later. This way discounting puts more weight on the costs than on the benefits. Second, and more importantly, the regions free riding behaviour we account for in our non-cooperative solution -on CO_2, fuel prices, technology spillover etc- doesn't provide enough incentive to moderate pollution considerably, since any effort is dampened by a non cooperative behavior of the other players.

This is made very clear in the Figure 9, in which the world industrial CO_2 emissions are reported. The non-cooperative solution foresees a growth in emissions to 20 GtC in 2100, a result that falls in the IPCC-SRES B2 range of scenarios. However, in the same Figure we also show the emission profile assuming a cooperative behavior among world regions, i.e. assuming a social planner maximizes world welfare. In this case emission would be reduced to almost half the level of the non-cooperative case. This result quantifies the magnitude of the various externalities we account in our model, and stresses the relevance of the promotion of cooperation among countries to avoid free-riding.

5. Conclusions

This paper has presented the main characteristics and properties of a new model designed to be used for climate policy analysis. This model, called WITCH (World Induced Technical Change Hybrid), is a top-down macro model that is game theoretically founded and features a specification of the energy sector. The optimal investments are the outcome of a dynamic open loop Nash game with perfect foresight. Investments depend on the dynamics of technical change, which is its self endogenous and depends on investment paths as well as on prices and other economic and climatic variables (including climate policy). Investment decisions in one country depend on those in the other countries, given the several interdependency channels specified in the model.

The model has been carefully calibrated using the information available in the empirical literature and we managed to ensure that the optimality conditions are satisfied in the first period.

This paper briefly describes the properties of the non-cooperative baseline scenario produced by WITCH. In our Baseline scenario, free-riding incentives characterise the development and adoption of new climate-friendly technologies. For example, even though the model explicitly allows for the possible use of carbon sequestration, in the absence of any climate policy, all investors in all world regions do not find it convenient to adopt them. For the same reasons, climate friendly R&D investments are also limited. As a consequence, the fuel-mix remains fairly stable over the time.

Therefore, the Baseline produced by WITCH is fairly conservative. By comparing the results of the non-cooperative and cooperative solutions, we managed to quantify the relevance of the free-riding incentives to prevent the stabilization of the GHGs and avoid potential damages from global warming. This indeed stresses the need for the analysis of climate policies: it is thus crucial to analyse what would be the impacts of different climate policies (e.g. stabilisation targets or emission trading) in WITCH. Given the many channels of transmission of climate policy into the economic system (from forward looking investments to learning by doing, from energy R&D expenditure to technological spillovers, etc.), climate policy is likely to have an important impact of the dynamics of the main economic variables in WITCH. Under what conditions can climate policy achieve the goal of stabilising GHG concentrations? What are the features of an optimal climate policy? How much would it be technology-based? All these above are issues and questions that WITCH can easily address and that will be the subject of future applications of the model.

References

Babiker, M. H., Maskus, K. E., and T. F. Rutherford. 1997. “Carbon Taxes and the Global Trading System,” Working Paper 97-7, University of Colorado, Boulder

Bauer, N., O. Edenhofer and S. Kypreos (2005), “Linking energy system and macroeconomic growth models. Is the supply curve enough?”, submitted for publication.

Bosetti, V., E. Massetti and M. Tavoni (2006), “WITCH: Energy Patterns,Technology Options and CO2 Emissions”, mimeo

Burniaux, J. M., Nicoletti, G., and J. Oliveira-Martins. (1992). “GREEN: A Global Model for Quantifying the Costs of Policies to Curb CO2 Emissions,” OECD Economic Studies No. 19, Winter, 49-92.

Clarke, L.E. and Weyant, J.P., (2002). "Modelling Induced Technical Change: an Overview", in A. Grubler, N. Nakicenovic, and W.D. Nordhaus, eds., Technological change and the environment. Resources for the future, Washington D.C.

Edenhofer, O., N. Bauer, and E. Kriegler (2005), “The Impact of Technological Change on Climate Protection and Welfare: Insights from the Model MIND”, Ecological Economics, 54, 277–292.

ENERDATA (2005), Energy Statistics, April 2005. T. Collett (2001), “Natural Gas Hydrates – Vast Resources, Uncertain Future”, USGS Fact Sheet 021 01.

Ko, J. and C. Dahl, (2001) “Interfuel substitution in US electricity generation“, Applied Economics, 33, 1833-1843

C. Dahl (1993)”A Survey of Energy Demand Elasticities in Support of the Development of the NEMS”

Gerlagh R., and B.C.C. van der Zwaan (2004), “A sensitivity analysis on timing and costs of greenhouse gas abatement, calculations with DEMETER”, Climatic Change, 65, 39-71.

Hansen, L., D. Epple and W. Roberds (1985), “Linear Quadratic Duopoly Models of Resource Depletion”, in: T. J. Sargent (ed.), Energy, Foresight, and Strategy, Resources for the Future, Washington, DC.

IEA (2000), “Experience Curves for Energy Technology Policy”, OECD/IEA, Paris.

IEA (2004a), “World Energy Outlook 2004”, OECD/IEA, Paris.

IEA (2005a), “Energy Prices and Taxes - Quarterly Statistics - Fourth Quarter 2005”, OECD/IEA, Paris.

IEA (2005b), “Resources to Reserves – Oil & Gas Technologies for the Energy Markets of the Future”, OECD/IEA, Paris.

Lackner K. and J. Sachs, (2005)”A robust strategy for sustainable energy” Brookings Papers on Economic Activity, 2:2005

Lee, H. J. Oliveira-Martins and D. van der Mensbrugghe (1994), “The OECD GREEN Model: an Updated Overview”, OCED Development Centre, Working Paper No. 97, OECD, Paris.

Manne, A. R., Mendelsohn and R. Richels (1995), “MERGE: a Model for Evaluating Regional and Global Effects of GHG Reduction Policies”, Energy Policy, Vol. 23, No. 1, pp. 17-34, 1995.

MIT (2003), “The Future of Nuclear Power – An Interdisciplinary MIT Study”, MIT, 2003.

NEA/IEA (1998), “Projected costs of generating electricity: 1998 update”, OECD, Paris.

NEA/IEA (2005), “Projected costs of generating electricity: 2005 update”, OECD, Paris.

N. Nakicenovic (1997), “Technological change and diffusion as a learning process”, *Perspectives in Energy*, Volume 4, Number 2:173–189

Nordhaus, W.D. and J. Boyer (2000), Warming the World, Cambridge: MIT Press.

Popp, D. (2004), "ENTICE-BR: The Effects of Backstop Technology R&D on Climate Policy Models", NBER Working Paper N.10285.

P. Soderholm (1998) "The modeling of fuel use in the power sector: a survey of econometric analyses", The Journal of Energy Literature, IV 2

Thompson, P., Taylor, T.G., (1995), "The capital–energy substitutability debate: a new look", Review of Economics and Statistics, 77, 565– 569.

U.S. Geological Survey (2000), World Petroleum Assessment, USGS World Energy Assessment Team.

van Vuuren, D.P., Eickhout, B., Lucas, P.L. and den Elzen, M.G.J. (2004). 'Long-term multi-gas-scenarios to stabilise radiative forcing - exploring costs and benefits within an integrated assessment framework", Energy Policy (accepted).

Whalley, J. and R. Wigle (1990), "The International Incidence of Carbon Taxes", paper prepared for a conference on "Economic Policy Responses to Global Warming", Rome, 4-6 October.

World Bank, (2004), "World development indicators 2004", The World Bank

Appendix

Model Equations:

In this appendix we reproduce the main equations of the model. The list of variables is reported at the end of the Appendix. In each region, indexed by *n*, a social planner maximizes the following utility function

(A1) $$W(n) = \sum_t U\left[C(n,t), L(n,t)\right]R(t) = \sum_t L(n,t)\left\{\log\left[c(n,t)\right]\right\}R(t) ,$$

where *t* are 5-years time spans and the pure time preference discount factor is given by:

(A2) $$R(t) = \prod_{v=0}^{t} \left[1+\rho(v)\right]^{-5} ,$$

whereas the pure rate of time preference *ρ(v)* is assumed to decline over time. Moreover, $c(n,t) = \dfrac{C(n,t)}{L(n,t)}$ is per capita consumption.

Economic module

The budget constraint defines consumption as net output minus investments:

(A3) $$\begin{aligned} C(n,t) = {} & Y(n,t) - I_C(n,t) - I_{R\&D}(n,t) - \sum_j I_j(n,t) - \sum_j O\&M_j(n,t) \\ & - \sum_f P_f(n,t) X_f(n,t) - P_{CCS}(n,t) CCS(n,t) \end{aligned} .$$

Output is produced through a nested CES function between a capital-labor aggregate and energy; capital and labor are combined via a Cobb-Douglas function. The climate damage Ω reduces gross output, and to obtain the net output we subtract the costs of the natural resources and CCS (*j* indexes technologies):

(A4) $$Y(n,t) = TFP(n,t)\left[\alpha(n)\cdot\left(K_C^{1-\beta(n)}(n,t)L^{\beta(n)}(n,t)\right)^{\rho} + (1-\alpha(n))\cdot ES(n,t)^{\rho}\right]^{1/\rho} \Big/ \Omega(n,t)$$

Total factor productivity *TFP(n,t)* evolves exogenously with time. Final good capital accumulates following the usual perpetual role:

(A5) $$K_C(n,t+1) = K_C(n,t)(1-\delta_C) + I_C(n,t)\ .$$

Labor is assumed to be equal to population and evolves exogenously. Energy services is an aggregate of energy and a stock of knowledge through a CES function:

(A6) $$ES(n,t) = \left[\alpha_H HE(n,t)^{\rho_{ES}} + \alpha_{EN} EN(n,t)^{\rho_{ES}}\right]^{1/\rho_{ES}}\ .$$

The stock of knowledge *HE(n,t)* derives from energy R&D investments:

(A7) $$HE(n,t+1) = aI_{R\&D}(n,t)^b HE(n,t)^c + HE(n,t)(1-\delta_{R\&D})\ .$$

Energy is a combination of electric and non-electric energy:

(A8) $$EN(n,t) = \left[\alpha_{EL} EL(n,t)^{\rho_{EN}} + \alpha_{NEL} NEL(n,t)^{\rho_{EN}}\right]^{1/\rho_{EN}}\ .$$

Each factor is further decomposed into several sub-components. Figure 2 shows a graphical illustration of the energy sector. Factors are aggregated using CES, linear and Leontief production functions.

For illustrative purposes, let us show how electricity is produced via capital, operation and maintenance and resource use through a zero-elasticity Leontief aggregate:

(A10) $$EL_j(n,t) = \min\left\{\mu_{n,j} K_j(n,t);\tau_{n,j} O\&M_j(n,t);\varsigma_j X_{j,EL}(n,t)\right\}.$$

Capital for electricity production technology accumulates in the usual way:

(A11) $$K_j(n,t+1) = K_j(n,t)\left(1-\delta_j\right) + \frac{I_j(n,t)}{SC_j(n,t)}\ ,$$

where the new capital investment cost *SC(n,t)* decreases with the world cumulated installed capacity by means of learning-by-doing:

(A12) $$SC_j(n,t) = B_j(n)[\sum_t \sum_n K_j(n,t)]^{-\log_2 PR_j}\ .$$

Operation and maintenance is treated like an investment that fully depreciates every year. The resources employed in electricity production are subtracted from output in equation (A4). Their prices are calculated endogenously using a reduced-form cost function that allows for non-linearity in both the depletion effect and in the rate of extraction:

(A13) $$P_f(n,t) = \chi_f(n) + 2\gamma_f\, q_f(t) + \pi_f \left[Q_f(t-1)/\overline{Q}_f\right]^{\psi_f},$$

where q is the extraction rate and Q the cumulative extraction:

(A14) $$Q_f(t-1) = Q_{0f} + \sum_{s=0}^{t-1} \sum_n X_f(n,s).$$

Climate Module:

GHGs emissions from combustion of fossil fuels are derived by applying the stechiometric coefficients to the total amount of fossil fuels utilized minus the amount of CO2 sequestered:

(A15) $$CO_2(n,t) = \sum_f \omega_{f,CO_2} X_f(n,t) - CCS(n,t).$$

The damage function impacting output varies with global temperature:

(A16) $$\Omega(n,t) = \frac{1}{1 + \left(\theta_{1,n} T(t) + \theta_{2,n} T(t)^2\right)}.$$

Temperature increases through augmented radiating forcing *F(t)*:

(A17) $$T(t+1) = T(t) + \sigma_1 \left\{F(t+1) - \lambda T(t) - \sigma_2 \left[T(t) - T_{LO}(t)\right]\right\}.$$

It depends on CO2 concentrations:

(A18) $$F(t) = \eta \left\{\log\left[M_{AT}(t) / M_{AT}^{PI}\right] - \log(2)\right\} + O(t),$$

caused by emissions from fuel combustion and land use and change:

(A19) $M_{AT}(t+1)=\sum_n \left[CO_2(n,t)+LU_j(t)\right]+\phi_{11}M_{AT}(t)+\phi_{21}M_{UP}(t)$,

(A20) $M_{UP}(t+1)=\phi_{22}M_{UP}(t)+\phi_{12}M_{AT}(t)+\phi_{32}M_{LO}(t)$,

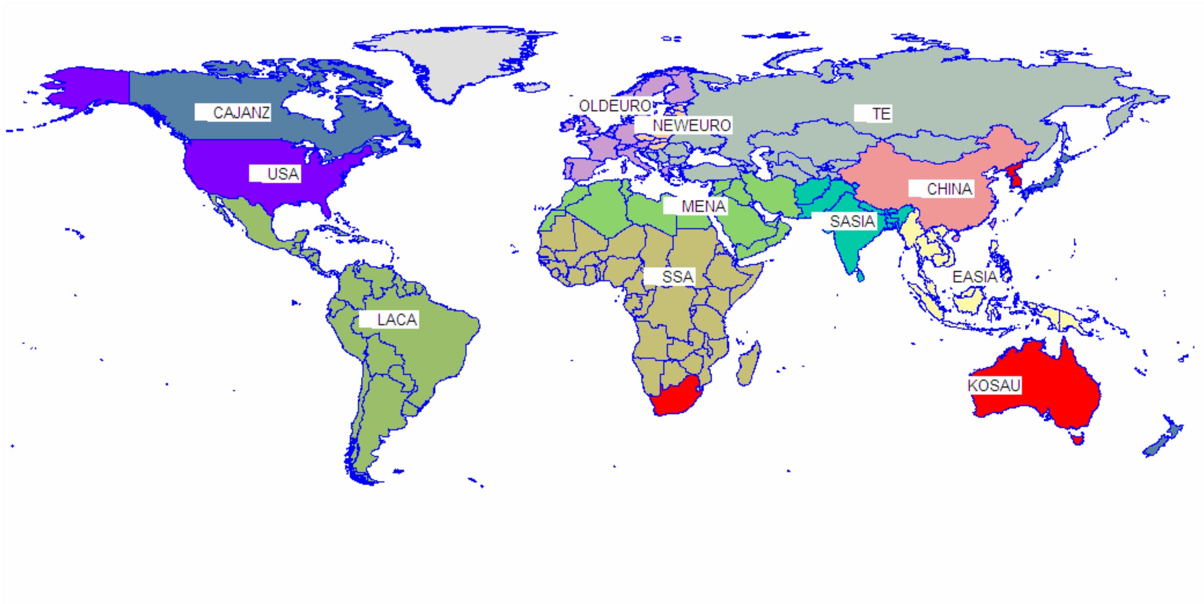
(A21) $M_{LO}(t+1)=\phi_{33}M_{LO}(t)+\phi_{23}M_{UP}(t)$.

List of variables:

W = welfare
U = instantaneous utility
C = consumption
c = per-capita consumption
L = population
R = discount factor
Y = production
I_c=investment in final good
$I_{R\&D}$=investment in energy R&D
I_j=investment in technology j
O&M=investment in operation and maintenance
TFP=total factor productivity
K_c=final good stock of capital
ES=energy services
Ω = damage
P_j= fossil fuel prices
X_j= fuel resources
P_{CCS}= price of CCS
CCS=CO2 sequestered
HE=energy knowledge
EN=energy
EL=electric energy
NEL=non-electric energy
K_j= stock of capital of technology j
SC_j=investment cost
CO2= emissions from combustion of fossil fuels
M_{AT} = atmospheric CO_2 concentrations
LU = land-use carbon emissions
M_{UP} = upper oceans/biosphere CO_2 concentrations
M_{LO} = lower oceans CO_2 concentrations
F = radiative forcing
T= temperature level

Figures and Tables:

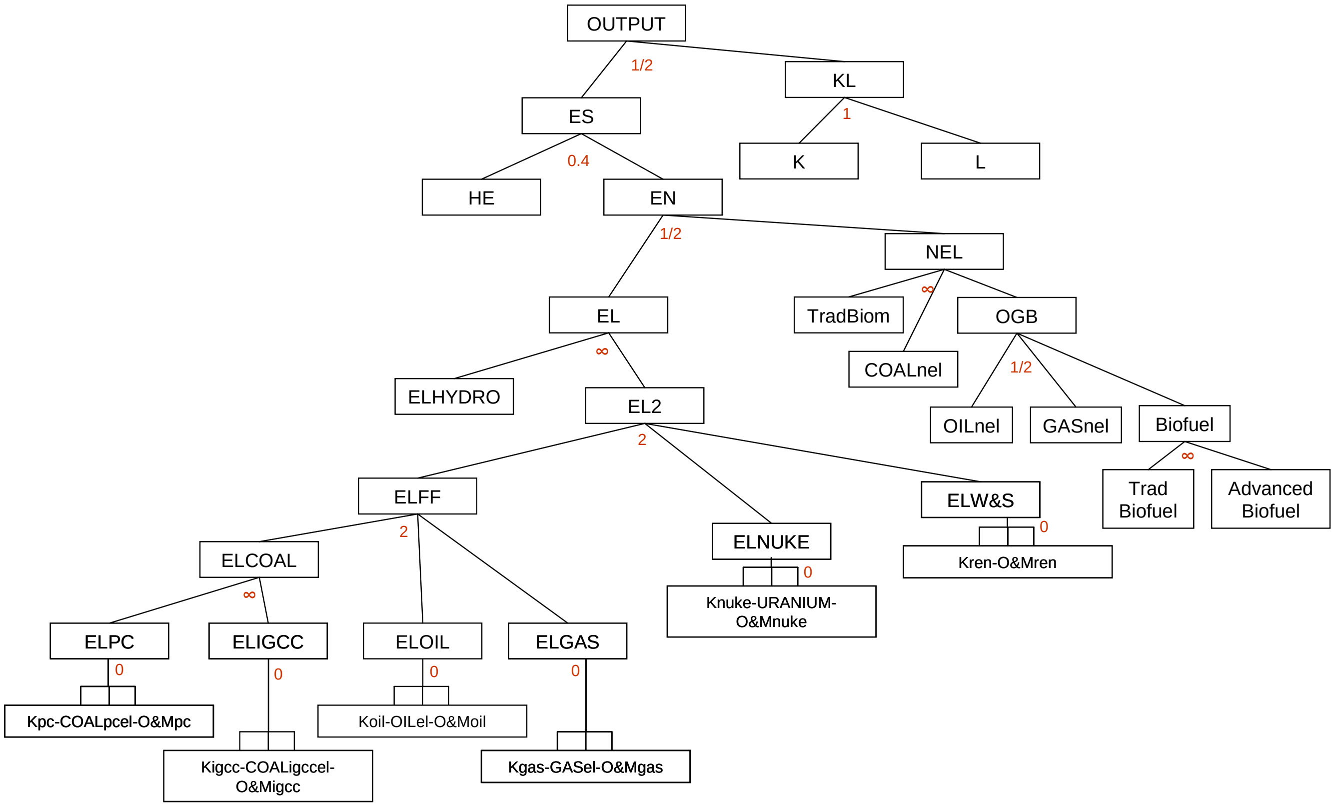
Figure 1: Regions of the WITCH Model



Regions:

1) CAJANZ (Canada, Japan, New Zealand)
2) USA
3) LACA (Latin America, Mexico and Caribbean)
4) OLDEURO (Old Europe)
5) NEWEURO (New Europe)
6) MENA (Middle East and North Africa)
7) SSA (Sub-Saharan Africa excl. South Africa)
8) TE (Transition Economies)
9) SASIA (South Asia)
10) CHINA (including Taiwan)
11) EASIA (South East Asia)
12) KOSAU (Korea, South Africa, and Australia)

Figure 2: The production nest and the elasticities of substitution



KL= capital-labour aggregate
K = capital invested in the production of final good
L= Labor
ES = Energy services
HE = Energy R&D capital
EN = Energy
EL = Electric energy use
NEL = Non-electric energy use
OGB = Oil, Gas and Biofuel nest
ELFF = Fossil fuel electricity nest
W&S= Wind and Solar
ELj = Electricity generated with the technology j
TradBiom= Traditional Biomass
Kj = Capital for generation of electricity with technology j
O&Mj = Operation and Maintenance costs for generation of electricity with technology j
‘FUELj’el = Fuel use for generation of electricity with technology j
‘FUELj’nel = Direct fuel use in the non-electric energy use

Figure 3. GDP level per macro-region

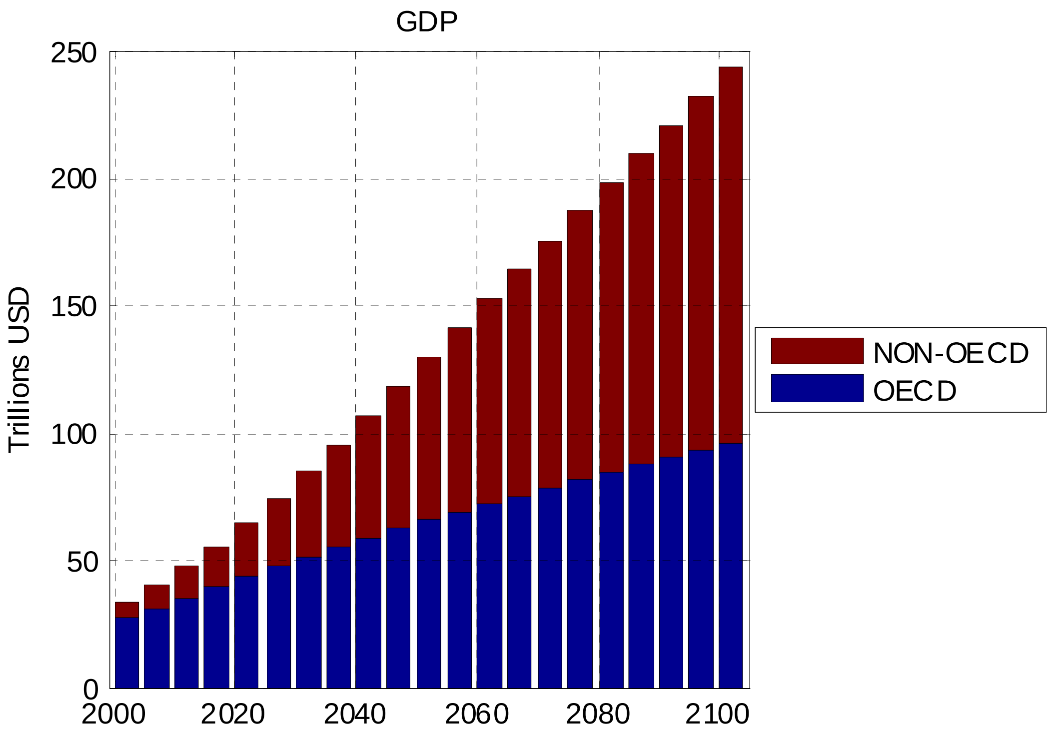


Figure 4. Output growth by region

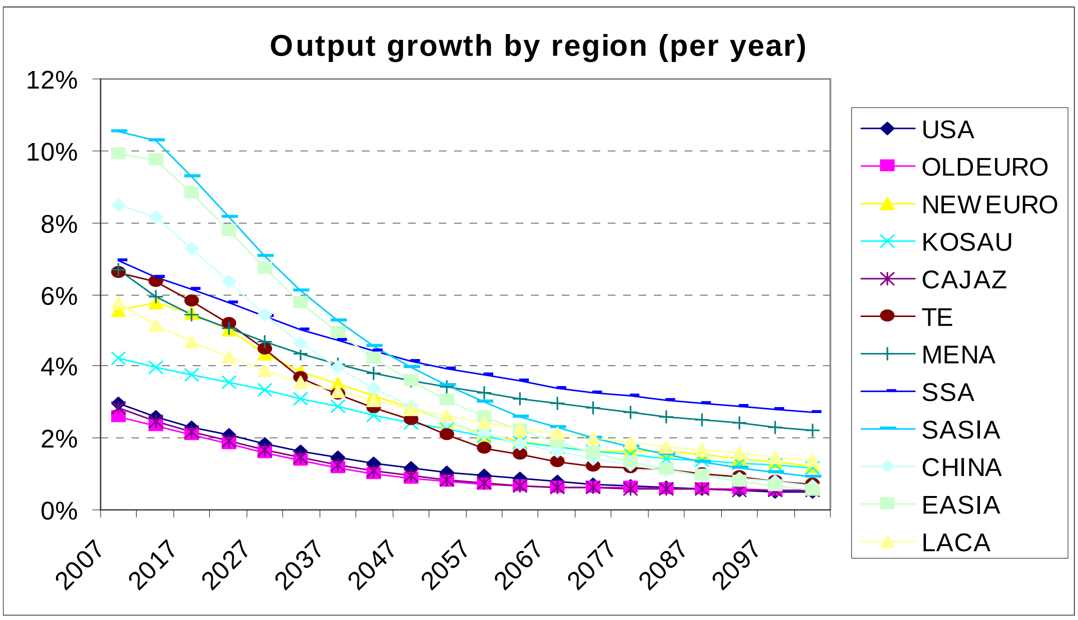


Figure 5. Energy Intensity and Carbon Intensity of Energy variations w.r.t. 2002

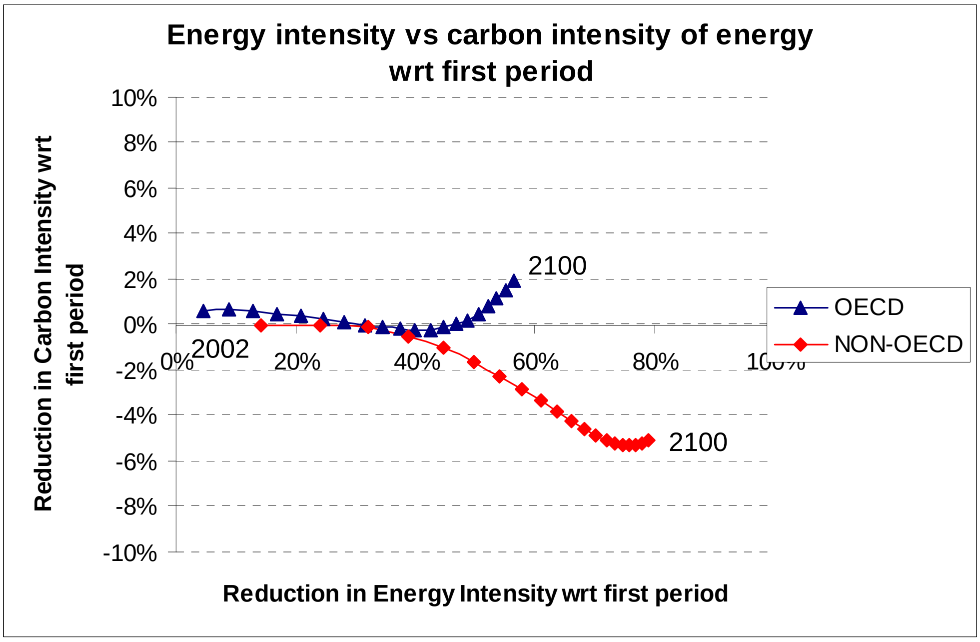


Figure 6. World Primary Energy Demand by fuel

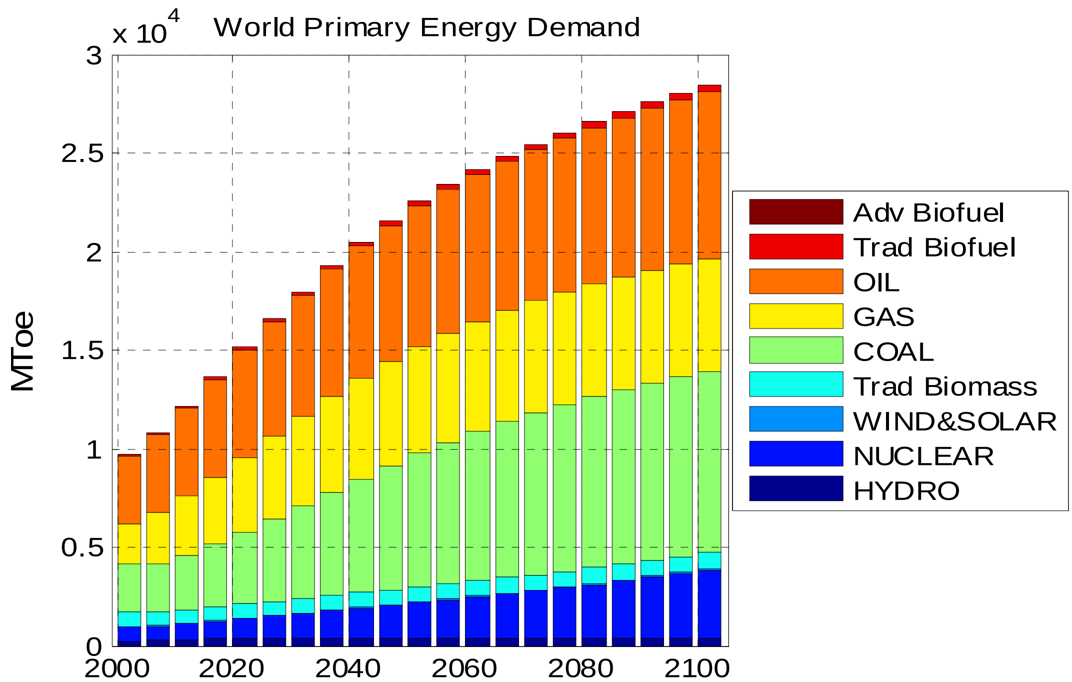


Figure 7. World Electricity Mix

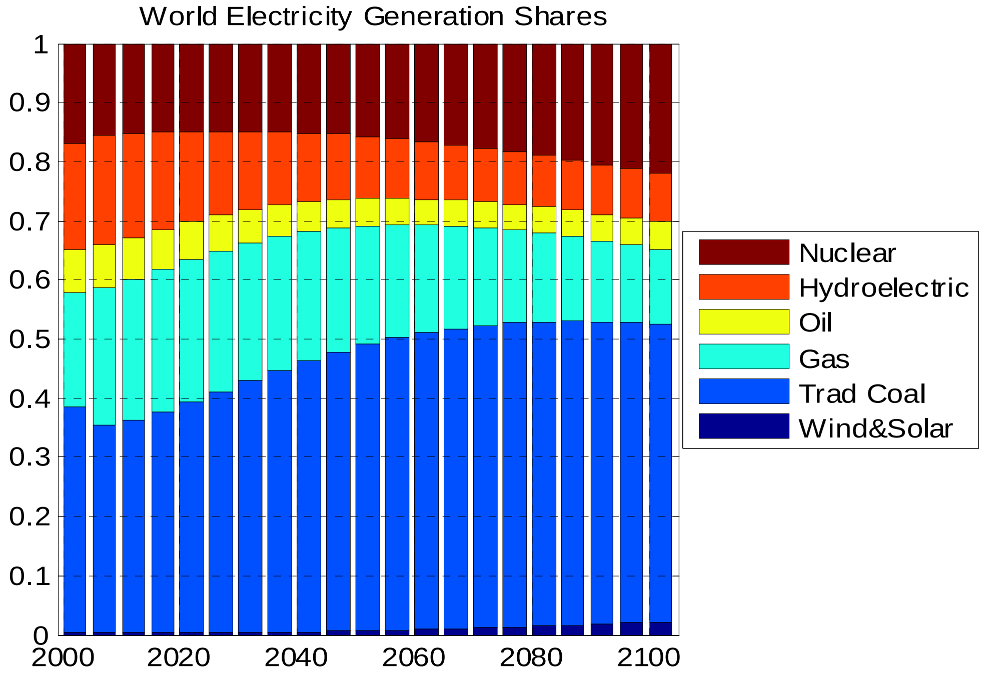


Figure 8. Spillover effects in Learning by Doing

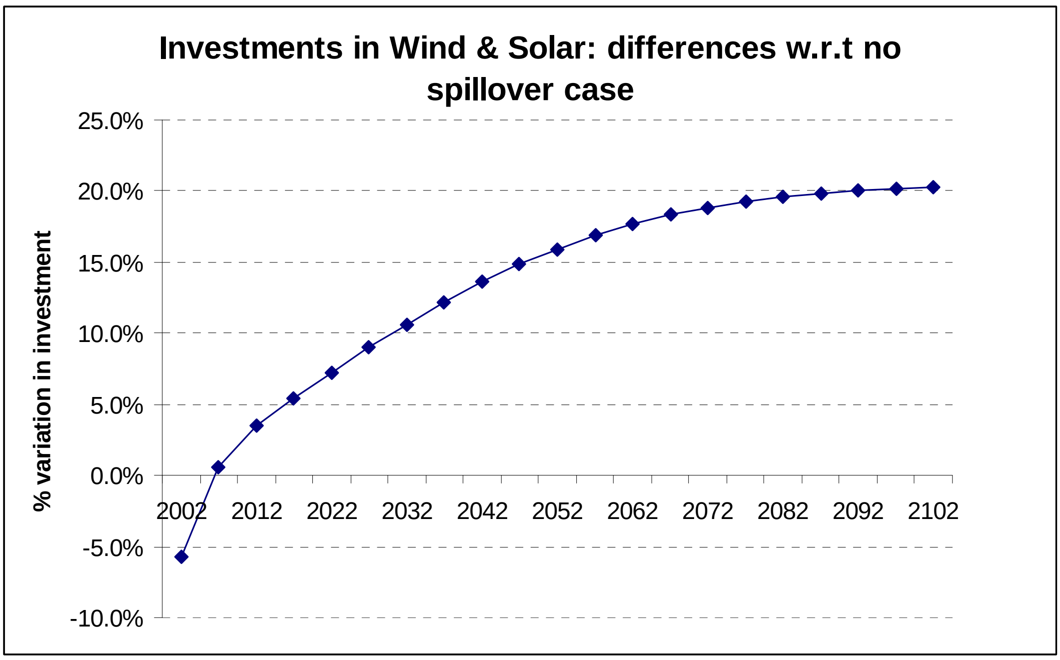


Figure 9. Carbon emissions