WITCH hybrid modeling of induced technical change in an optimal growth model (FEEM)

Introduction

The World Induced Technical Change Hybrid WITCH model (Bosetti, et al. 2006) is an energy-economy-climate model developed by the climate change group at FEEM. The model has been used extensively for the analysis of the economics of climate change policies[1].

WITCH is an economic model with a specific representation of the energy sector, thus belonging to the new class of fully integrated (hard link) hybrid models. It is a global model, divided into 12 macro-regions. For the present analysis the distinguishing features of the model are two.

The first one is the representation of endogenous technical change in the energy sector. Advancements in carbon mitigation technologies are described by both diffusion and innovation processes. Learning by Doing and by Researching allow to devise the optimal investment strategies in technologies and R&D in response to given climate policies. Moreover, knowledge in a country does not depend solely on R&D investments in that country but it is partially affected by other countries' R&D investments, via an international spillovers mechanism. The second relevant modeling feature is the game-theoretic set up. The model is able to produce two different solutions, one assuming countries fully cooperate on global externalities, the so called globally optimal solution. The second is a decentralized solution that is strategically optimal for each given region in response to all other regions choice, the definition of a Nash equilibrium. This modelling features allows to account for externalities due to all global public goods (CO2, international knowledge spillovers, exhaustible resources etc.), making possible to model free riding incentives.

Endogenous Technical Change (ETC) in the WITCH model[2]

In the basic version of WITCH, technical change is endogenous and is driven both by learning by doing (LbD) and by public energy R&D investments. These two drivers of technological improvements display their effects through two different channels: LbD is specific to the power generation industry, while energy R&D affects overall energy efficiency in the economy.

The effect of technology diffusion is incorporated based on experience curves that reproduce the observed negative empirical relationship between the investment cost of a given technology and cumulative installed capacity. Specifically, the cumulative installed world capacity is used as a proxy for the accrual of knowledge that affects the investment cost of a given technology:

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[1] See www.feem-web.it/witch for a list of applications and papers.

[2] This is an extract from: Bosetti, V., C. Carraro, R. Duval, A. Sgobbi, M. Tavoni (2009) "The Role of R&D and Technology Diffusion in Climate Change Mitigation: New Perspectives using the WITCH Model" OECD Economics Department Working Paper, No. 664, OECD publishing, © OECD. doi:10.1787/227114657270.

$$SC\left(t+1\right)=A\cdot\sum_{n}K\left(n,t\right)^{-\log_2 PR} \quad (1)$$

Where SC is the investment cost of technology j, PR is the so-called progress ratio that defines the speed of learning, A is a scale factor and K is the cumulative installed capacity for region n at time t. With every doubling of cumulative capacity the ratio of the new investment cost to its original value is constant and equal to $1/PR$. With several electricity production technologies, the model is flexible enough to change the power production mix and modify investment strategies towards the most appropriate technology for each given policy measure, thus creating the conditions to foster the LbD effects associated with emission-reducing but initially expensive electricity production techniques. Experience is assumed to fully spill over across countries, thus implying an innovation market failure associated with the non-appropriability of learning processes.

R&D investments in energy increase energy efficiency and thereby foster endogenous technical change. Following Popp (Popp, 2004), technological advances are captured by a stock of knowledge combined with energy in a constant elasticity of substitution (CES) function, thus stimulating energy efficiency improvements:

$$ES(n,t)=\left[\alpha_H(n)HE(n,t)^{\rho}+\alpha_{EN}(n)EN(n,t)^{\rho}\right]^{1/\rho} \quad (2)$$

Where $EN(n,t)$ denotes the energy input, $HE(n,t)$ is the stock of knowledge and $ES(n,t)$ is the amount of energy services produced by combining energy and knowledge. The stock of knowledge $HE(n,t)$ derives from energy R&D investments in each region through an innovation possibility frontier characterized by diminishing returns to research, a formulation proposed by Jones (Jones, 1995) and empirically supported by Popp (Popp, 2002) for energy efficient innovations in the United States:

$$HE(n,t+1) = aI_{R\&D}(n,t)^{b}HE(n,t)^{c}+HE(n,t)(1-\delta_{R\&D}) \quad (3)$$

Where $\delta_{R\&D}$ is the depreciation rate of knowledge, and b and c are both between 0 and 1 so that there are diminishing returns to R&D both at any given time and across time periods. Reflecting the high social returns from energy R&D, it is assumed that the return on energy R&D investment is four times higher than that on physical capital. At the same time, the opportunity cost of crowding out other forms of R&D is obtained by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, $\psi_{R\&D}$, so that the net capital stock for final good production becomes:

$$K_C(n,t+1) = K_C(n,t)(1-\delta_C)+(I_C(n,t)-4\psi_{R\&D}I_{R\&D}(n,t)) \quad (4)$$

where δ_C is the depreciation rate of the physical capital stock. New energy R&D is assumed to crowd out 50% of other R&D, as in Popp (2004). This way of capturing innovation market failures was also suggested by Nordhaus (2003).

The WITCH model has been extended to carry out the analysis presented in this paper to include additional channels for technological improvements, namely learning through research or "learning-by-searching" (LbS) in existing low carbon technologies (wind and solar electricity, electricity from integrated gasifier combined cycle (IGCC) plants with carbon capture and storage (CCS)), and the possibility of developing breakthrough, zero-carbon technologies for both the electricity and non-electricity sectors.

Breakthrough technologies

In the enhanced version of the model used for this research, backstop technologies in both the electricity and non electricity sectors are developed and diffused in a two-stage process, through investments in R&D first and installed capacity in a second stage. A backstop technology can be better thought of as a compact representation of a portfolio of advanced technologies. These would ease the mitigation burden away from currently commercial options, but they would become commercially available only provided sufficient R&D investments are undertaken, and not before a few decades. This simplified representation maintains simplicity in the model by limiting the array of future energy technologies and thus the dimensionality of techno-economic parameters for which reliable estimates and meaningful modelling characterisation exist.

Concretely, the backstop technologies are modelled using historical and current expenditures and installed capacity for technologies which are already researched but are not yet viable (e.g. fuel cells, advanced biofuels, advanced nuclear technologies etc.), without specifying the type of technology that will enter into the market. In line with the most recent literature, the emergence of these backstop technologies is modelled through so-called "two-factor learning curves", in which the cost of a given backstop technology declines both with investment in dedicated R&D and with technology diffusion (see e.g. Kouvaritakis, Soria et al. 2000). This formulation is meant to overcome the limitations of single factor experience curves, in which the cost of a technology declines only through "pure" LbD effects from technology diffusion, without the need for R&D investment (Nemet, 2006). Nonetheless, modelling long term and uncertain phenomena such as technological evolution is inherently difficult, which calls for caution in interpreting the exact quantitative results and for sensitivity analysis (see below).

Bearing this caveat in mind, the investment cost in a technology *tec* is assumed to be driven both by LbS (main driving force before adoption) and LbD (main driving force after adoption), with $P_{tec,t}$, the unit cost of technology *tec* at time t, being a function of the dedicated R&D stock $R\&D_{tec,t}$ and deployment $CC_{tec,t}$:

$$\frac{P_{tec,T}}{P_{tec,0}} = \left(\frac{R\&D_{tec,T-2}}{R\&D_{tec,0}}\right)^{-e} * \left(\frac{CC_{tec,T}}{CC_{tec,0}}\right)^{-d} \qquad (5)$$

where the R&D stock accumulates with the perpetual inventory method and CC is the cumulative installed capacity (or consumption) of the technology. A two-period (10 years) lag is assumed between R&D capital accumulation and its effect on the price of the backstop technologies, capturing in a crude way existing time lags between research and commercialisation. The two exponents are the LbD index ($-d$) and the learning by researching index ($-e$). They define the speed of learning and are derived from the learning ratios. The learning ratio lr is the rate at which the generating cost declines each time the cumulative capacity doubles, while lrs is the rate at which the cost declines each time the knowledge stock doubles. The relation between d, e, lr and lrs can be expressed as follows:

$$1 - lr = 2^{-d} \quad \text{and} \quad 1 - lrs = 2^{-e} \tag{6}$$

The initial prices of the backstop technologies are set at roughly 10 times the 2002 price of commercial equivalents. The cumulative deployment of the technology is initiated at 1000 TWh, an arbitrarily low value (Kypreos, 2007). The backstop technologies are assumed to be renewable in the sense that the fuel cost component is negligible. For power generation, it is assumed to operate at load factors (defined as the ratio of actual to maximum potential output of a power plant) comparable with those of baseload power generation.

This formulation has received significant attention from the empirical and modelling literature in the recent past (see, for instance, Criqui, Klassen et al. 2000; Bahn and Kypreos, 2003; Söderholm and Sundqvist, 2003; Barreto and Klaassen, 2004; Barreto and Kypreos, 2004; Klassen, Miketa et al. 2005; Kypreos, 2007; Jamasab, 2007; Söderholm and Klassen, 2007). However, estimates of parameters controlling the learning processes vary significantly across available studies. Here, averages of existing values are used, as reported in Table 1. The value chosen for the LbD parameter is lower than those typically estimated in single factor experience curves, since here technological progress results in part from dedicated R&D investment. This more conservative approach reduces the role of "autonomous" learning, which has been seen as overly optimistic and leading to excessively low costs of transition towards low carbon economies.

Backstop technologies substitute linearly for nuclear power in the electricity sector, and for oil in the non-electricity sector. Once backstop technologies become competitive thanks to dedicated R&D investment and pilot deployments, their uptake is assumed to be gradual rather than immediate and complete. These penetration limits are a reflection of inertia in the system, as presumably the large deployment of backstops would require investment in infrastructures and wide reorganisation of economic activity. The upper limit on penetration is set equivalent to 5% of the total consumption in the previous period by technologies other than the backstop, plus the electricity produced by the backstop in the electricity sector, and 7% in the non electricity sector.

Spillovers in knowledge and experience

In addition to the international LbD spillovers mentioned above, WITCH also features international spillovers in knowledge for energy efficiency improvements. The amount of spillovers entering each world region is assumed to depend both on a pool of freely available world knowledge and on the ability of each country to benefit from it. In turn, this absorption capacity depends on the domestic knowledge stock, which is built up through domestic R&D according to a standard perpetual capital accumulation rule. The region then combines knowledge acquired from abroad with the domestic knowledge stock to produce new technologies at home. For details, see Bosetti, Carraro et al. (2008).

The detailed characterization of endogenous technical change in the energy sector allow us to depict both policies aimed at internalizing the innovation externality (regions invest less in energy R&D than it is optimal from a global perspective) as well as those dealing with the climate externality, independently or in combination. This allows checking for potential mutual interactions of overlapping policies. However, it should be noted that important additional externalities such as appropriability and knowledge protection issues are not captured given the macro-economic structure of the model.