

International Technology Spillovers in Climate-Economy Models: two possible approaches

Enrica De Cian

May, 2006

In this paper I analyze two possible methodologies of modeling international technology spillovers in a climate-economy CGE model. Technological change, by affecting productivity, energy and carbon intensity, eventually influences the amount of CO_2 emissions, the costs and the timing of the policies targeted at their reduction. Technological change is here defined so as to include also the diffusion and adoption phase. Moreover, in an increasingly integrated world, new products and technologies developed in one region will eventually diffuse internationally. The two approaches described in this paper are based on two mechanisms used to model technological change in climate models: learning curves, total factor productivity and the autonomous energy efficient improvement parameter. The first approach seems more appropriate to represent international technology spillovers in models with endogenous technological change in the energy sectors, because learning curve are normally used for energy technologies. The second methodology suits better multi-sector and multi-country models such as CGEs in which trade flows are endogenously computed. In this paper I consider the international spillovers mediated by international trade in capital goods. Both methods will be based on a preliminary assessments of the presence and the magnitude of international spillovers. The type of econometric analysis required is also illustrated.

1 Introduction

Technological change has become a relevant component of long-term climate change policies. Anthropogenic CO_2 emissions are the product of population, economic activity per capita, energy use of economic activity and the carbon intensity of energy used. In a growing world economy, reducing economic activity does not seem an appealing strategy. The other two options available are reducing the energy intensity and/or the carbon intensity of economic activities. The economic and environmental gains of these behaviors are not under discussion: the issue is at what costs. Technological change plays a key role in making these strategy more attractive from an economic perspective. Technological change

refers to the whole process of invention, development or innovation and diffusion or adoption of new products, pieces of equipment and processes.

The development of more advanced and cleaner technologies needs R&D expenditure, capital investments and knowledge accumulation. World R&D activity is concentrated in the OECD countries, whereas the developing countries are lagged behind. To put things into perspective, the major future polluters, China, India and Brazil have low capacities of affording R&D expenditure and costly investments. This implies less technological progress where it would be needed the most. The lack of domestic knowledge accumulation may be partially compensated by the international technology spillovers that stems from trade. The process of diffusion plays an important role in spreading the benefits of technological change from innovating to non innovating countries. Technology diffusion can take place through international trade in capital goods such as machinery and equipments. It is part of the process of technological change as it represents a stage of further commercialization and adoption of the new technologies developed in the OECD. The diffusion process is reflected in the purchase of new goods and imports are the purchase of foreign goods.

Technological change has received increasing interests from climate-economy modelers, the reason being the significant effect it has on the timing and the costs of climate change mitigation (Loschel, 2002; Carraro, Gerlagh, van der Zwaan, 2003). From a theoretical perspective, endogenous growth theory has also emphasized the role of technological progress in the long-term sustained growth (Arrow, 1962; Romer, 1986, 1990). In this literature technological progress is determined endogenously by either R&D investments or technology spillovers such as learning-by-doing and R&D externalities. Spillovers are deeply related to the nature of technology and knowledge as partially public goods. So far modelers have focused on cluster-technologies, intra-firms and intra-industry spillovers. Fewer are the attempts in modeling international technology diffusion.

Two research questions drive this study: first, how trade openness and international spillovers influence domestic technological progress. Second, whether the resulting technological change is energy and carbon saving or using. The ultimate goal is to understand the implications of international technology spillovers in a computable general equilibrium model. CGE models have become one tool used to analyze the economic impacts of climate policies. Moreover, being multi-sector and multi-country models, they particularly suit the study of international trade, technology diffusion and their interactions across sectors and countries. To this end, a better understanding and modeling of technological change and its diffusion is required. This study will look at the magnitude and the implications of technology spillovers mediated by international trade in capital goods.¹ In particular it looks at how imports machinery and equipments can affect those variables that are related to the production of CO_2 : productivity, energy and carbon intensity.

First an econometric assessment will evaluate the presence and the strength

¹I am also thinking about an extension to FDI.

of such linkages. The resulting estimates will provide some guidelines for the representation of international technology spillovers in a CGE model. This paper presents two modeling approaches that are based on the mechanisms used to represent technological change in CGE models: a learning curve approach and one based on the technological parameters TFP and AEEI.

The resulting framework could then be used to analyze the effects of climate and trade policies in the presence of international technology spillovers. Such a model could capture further interactions between trade and climate policies. Trade policies such as trade liberalization in capital goods could have the side effect of promoting the diffusion of emission-saving technologies and thus to make technology progress available to the non innovating countries. Which sectors are to be liberalized first may become then important for the degree of technology diffusion. The study will be organized in three parts:

1. Theoretical background
2. Empirical analysis
3. Modeling

2 Theoretical background

The topic of international technology spillovers and their implications on productivity, energy and carbon intensity is at the crossroad between different literatures. This first part will present a selective review, highlighting the concepts that are important for the study of international technology spillovers and technological change in climate-economic models.

2.1 Some definitions

Technical change is defined as a change in the techniques of production at the firm or industry level that results both from R&D and from learning by doing (innovation). Technological change is the application of new knowledge of scientific engineering agronomic principles of techniques of production across a broad spectrum of economic activity (Binswanger and Ruttan, 1978). However, the current literature does not rely on this terminology very strictly and the two terms are often used interchangeably. The Schumpeterian distinction of technological progress into the three stages of invention, innovation and diffusion is now widely recognized.

Induced technical change was first introduced by Hicks (1932) to define the development and the diffusion of any new technology due to a change in relative factor prices. The price change can be due to both policy changes and economic condition variations. In climate-models this term usually refers to the effect of a price change due to climate policies such as carbon taxes. Endogenous technical change is used more in a modeling context to indicate technical or technological changes that are determined inside the model (Grossman and Helpman, 2001;

Sijm, 2004). Technological change is neutral if it shifts the unit isoquant inward without affecting the shape. Technological change is biased toward an input if there is a change in the slope of the isoquant.² Binswanger and Ruttan (1978) define input bias as the rate of change in the factor share at constant prices, where the factor share $Si(t)$ is defined as the value of an input over total costs :

$$Si(t) = Pi(t)Vi(t)/P(t)Q(t)$$

$$\text{Biases} = \dot{Si}(t)/Si(t) = \widehat{Pi} + \widehat{Vi} - \widehat{P} - \widehat{Q} = d\log(Vi(t)/Q(t)) - d\log(P(t)/Pi(t))$$

$$\begin{cases} \dot{Si}(t)/Si(t) \geq 0 & \text{i-using} \\ \dot{Si}(t)/Si(t) \leq 0 & \text{i-saving} \\ \dot{Si}(t)/Si(t) = 0 & \text{i-neutral} \end{cases}$$

In words technological change is i-saving if the input share decreases at constant factor prices. The presence of spillovers is deeply related to the nature of technology and knowledge as partially public goods. Technological spillover, or knowledge spillover, is defined as technological progress available at a lower than the original cost paid by the inventor (Griliches, 1979). Weyant and Olavson (1999) define spillovers as any positive externality that results from purposeful investments in technological innovation or development. They describe different forms and level of spillovers. Technological spillovers can be direct or disembodied (pure knowledge spillovers concerning the impacts of R&D of others) and indirect, that is embodied in new capital goods; they can be intertemporal, that is occurring over time with experience accumulation. They are also called learning by doing spillovers. As for the level, spillovers can take place across firms, industries or national boundaries.

2.2 Technological change and climate change

Whether technological progress is modeled as exogenous or endogenous matters for the cost effectiveness of climate policies. Simulations of CO_2 stabilization scenarios with different types of model have shown how the presence of endogenous technological change affects the availability, the timing and the cost of climate policies.³

Technological change can affect CO_2 emissions and reduction through several channels. Kaya's identity decomposes CO_2 emissions into its major determinants

$$CO_2 = \frac{GDP}{POP} * \frac{energy}{GDP} * \frac{CO_2}{energy} * POP \quad (1)$$

²For further definitions of biased technological change see appendix A.

³For a review of these studies see Loschel(2002), Edenhofer et al. (2005), Carraro, Gerlagh and van der Zwaan (2003).

For a given level of output, CO_2 reduction can come from lower:

- energy use per se;
- energy use per unit of output;
- CO_2 emissions per unit of energy;

For a given level of output, carbon emissions can be reduced by substituting energy for other inputs (energy saving), by reducing the energy used per unit of output (energy efficiency gains) or by curbing carbon emissions per unit of energy used (carbon intensity gains).

The first dimension (energy use) is mostly related to socio-economic forces such as population, output growth and economic activity while the last two depend more on techno-economic forces (Bosetti et al., 2005). Technological change (TC) can have an impact on CO_2 emissions through the three dimensions described above (Galeotti and Carraro, 2003):

- On the supply side, TC may affect the energy efficiency of existing technologies;
- TC can reduce the cost of low-carbon emitting technologies, making them more competitive;
- TC can improve energy efficiency in the end-use sector through product and process innovation;
- TC, by increasing productive, can trigger a positive effect on the scale of the economy.

2.3 Endogenous growth theory, trade and international technology spillovers

The new growth theory has started looking into the black-box of the Hicksian-neutral technological progress. The endogenous growth theory has emphasized the role of learning by doing and knowledge externalities (Arrow, 1962; Romer, 1986); the theory on endogenous technical change departs from the assumption of competitive markets and introduces monopolistic competition where investment in research and development is a profit-driven activity (Romer, 1990; Grossman and Helpman, 2001). Either there is continuous innovation that increases the quality or the quantity of existing goods, or there are knowledge-technological externalities coming along with the process of capital and knowledge accumulation that prevent the decreasing marginal returns on capital to set in.

Grossman and Helpman (2001) develop a model of endogenous technological change suitable for the study of the relationship between endogenous growth and international trade. They consider research as an economic activity driven by economic incentives. There is a manufacturing sector that produce the final good for consumption using the intermediates developed by the innovation

sector. In this context productivity growth (output per unit of primary inputs) is represented by the number⁴ of intermediate varieties. A country grows more when it devotes more resources to the innovation sector, which is defined as the creation of new intermediates varieties. Research helps building up the stock of public knowledge that reduces the effective input-requirements per unit of output.

Trade can have an impact on domestic productivity, energy and carbon intensity through several channels (Grossman and Helpman, 2001):

- Pure knowledge effect: a wider transmission of knowledge increases the stock of global knowledge;
- Communication and imitation opportunities are enhanced;
- Competition between innovators that eliminates duplication of research;
- Increased market size: this implies more profits and thus more R&D spending but also competition with a higher number of varieties and thus lower profits;
- Enhanced availability of intermediates inputs and capital equipments;
- Reallocation of resources across sectors and structural change.

When the first three linkages are activated, countries can benefit from a form of increasing returns to scale because they pool their effort in developing a global stock of knowledge that can feed invention and innovation in all participating countries. Knowledge is the input of the innovation process and of technical change. International trade can increase the availability of the input of technical progress. International flows of workers, the exchange of engineers and information may ease the acquisition of new methods of production. Labor mobility disseminates the knowledge that workers have acquired in different firms and thus change the endowment of human capital. The stock of human capital affects the absorptive capacity, that is the ability of assimilating and adapting foreign technologies. Trade increases the mobility in cleaner capital and in cleaner goods. If countries are integrated through trade, participation in the world economy gives access to a larger variety of inputs, machineries and capital equipments. International trade enlarged the scale of economic activity, but it also has a structural effect. Trade induces changes in the profitability of certain sectors and eventually it can induce a change in the energy mix (Copeland and Taylor, 2003).

The impact of higher growth on the emissions is not straightforward. A key factor is whether this further trade and growth process is energy saving or energy using. In the endogenous growth theory higher growth requires more resources to be shifted from the traditional sectors toward research activities.

⁴In the quality-ladder variant, productivity is increasing in the quality of inputs. However, the major results do not change.

The latter are typically human-capital-intensive and thus a structural change in this direction can be expected to reduce the energy intensity of the economy.

Another important channel of international transmission of knowledge and technology has been opened by the rapid diffusion of multinational enterprises (MNEs) and the resulting foreign direct investments. Aitken and Harrison (1999) summarize the major channels by which FDI could affect domestic productivity: introduction of new products and processes, imitation and competition.

Technology spillovers are neither automatic nor costless but they require adoption capabilities, e.g. human capital and indigenous research capacity. The absorptive capacity of a country is related to its economic, human and technological development. However, not all types of transfers require the same effort. Material transfers (e.g. seeds and machineries) do not require particular abilities. Design transfers (e.g. blueprints, formulas and handbooks) need more engineering capacity. Capacity transfers (e.g. scientific knowledge, technical capacity or capability) can be benefit from only in the presence of skills and competencies to evaluate and use technical information. They often require tacit knowledge about production processes that cannot be transferred with capital equipment (Binswanger and Ruttan, 1978). Potentialities of reducing these barriers come especially from those transactions that involve human contact and personal relations. CDM and JI mechanism may be an example since they also aim at consolidating capacity building in the developing countries and in the transition-economies. Trade barriers can also hinder technology diffusion. In this context, trade liberalization acquires a further role and which sectors are liberalized first may have implications in term of the degree of technology diffusion.

The presence of international trade may also influence the way domestic policies work. For example, induced technological change where climate policies are more stringent may lead to higher investment in clean capital and cleaner methods and processes of production. Countries committed to climate change may eventually gain a comparative advantage in cleaner machineries and equipments. In a open trading system, this relatively abundance in clean capital would affect the pattern of trade and could lead to an expansion of the clean capital intensive good (composition effect). Moreover, the relative price change induced by climate policies could increase the profitability of cleaner production techniques (technique effect) (Copeland and Taylor, 2003). Through trade less developed countries can benefit and use these cleaner technologies. Trade acts like a further possibility of production and thus allows countries to specialize in the sector where they have a comparative advantage but then to buy goods outside their production possibilities. If more technology-advanced goods are produced in developed countries, developing countries still can import them and reap the benefits of foreign innovation and technological progress.

Trade in different classes of goods leads to different degree of knowledge spillovers because technology intensity varies across sectors, leading to different degrees of embodied technology. Next section deals with technology-intensive capital goods.

2.3.1 Trade in capital goods

Endogenous growth theory views technology as a stock of knowledge. Being technological change the application of new knowledge to production processes, the cumulative production of capital goods can approximate technological progress (Arrow, 1962). The development of new capital goods and the use of new equipment and machineries in the manufacturing and in the industrial sector are considered the major sources of technological progress (Jaffe, Newell and Stavins, 2005). Trade in these goods is thus expected to generate indirect international spillovers of the technology embodied in them. In fact, the use of capital goods implies the acquisition of the knowledge that actually enable the use of these goods. Thus, trade in capital goods can be taken as a proxy of international technology spillovers.

The literature on trade and growth has emphasized the role of equipment and machinery imports. DeLong and Summers (1991) found that equipment investments have a higher impact on growth than non equipment investments. Mazumdar (2001) differentiated between domestic and imported equipment, finding a stronger impact for imported capital goods. The intuition is that more spillovers are likely to stem from goods that are relatively intensive in R&D. As shown in table 1, OECD countries concentrate most of their R&D expenditure on machinery and equipment.

ISIC REV. 3	1999
Total business sector 1-99	100
Food products, beverages and tobacco 15-16	1.3
Textiles, textile products, leather and footwear 17-19	0.4
Chemical, rubber, plastics and fuel products 23-25	15.9
Machinery and equipment 29-33	35

Table 1: Business R&D expenditure by sector. Source: OECD STAN statistics, 2005

Table two shows that the composition of bilateral exports from OECD to the bigger developing countries, China, India and Brazil, is concentrated on machinery and equipment, which accounts for about 40% of total bilateral trade flows.

ISIC REV. 3	1999
Food products, beverages and tobacco 15-16	2.104
Textiles, textile products, leather and footwear 17-19	5.07
Chemical, rubber, plastics and fuel products 23-25	19.49
Machinery and equipment 29-33	40.04

Table 2: Bilateral export flows between OECD and China, India, Brazil all together. Source: OECD STAN Bilateral Trade Database, 2005

Table three provides the same information of table two but in terms of percentage composition with respect to the total stock of trade defined as the cumulative trade exports from 1988 to 2003.

OECD Exports stock (1988-2003)	Brazil	China	India
Machinery and equipment nec (29 ISIC-REV.3)	17.10	19.00	18.24
Electronic equipment (30-33 ISIC-REV.3)	23.96	23.70	14.97
Motor vehicles and parts (34 ISIC-REV.3)	9.32	4.52	2.98
Transport equipment nec (35 ISIC-REV.3)	7.76	4.91	4.98

Table 3: Bilateral export stock OECD-China,India,Brazil.
Source: OECD STAN Bilateral Trade Database, 2005

The major suppliers of capital goods are the bigger innovators. These figures are consistent with the study of Eaton and Kortum (2001) who found a positive correlation between R&D intensity and specialization in machinery and equipments and in the production and export of these goods. Trade in machinery and equipment can be expected to be a major channel of embodied spillovers from developed countries, where capital goods are improved, to the developing ones, where most of these goods are imported. Developing countries, the major polluters, have the least capacity of affording R&D expenditure and costly investments. International technological diffusion can at least reduced this divide by contributing to accumulate capital, knowledge and the resulting technological externalities. Imports of capital goods increase the stock of knowledge (technology). Imports of machinery and equipments in the developing countries from rich countries, where the technology embodied in these capital goods moves forward, may eventually trigger technological progress in the importing countries. Some studies did find that, in the presence of endogenous technological change, cleaner technologies developed in industrialized countries in response to climate policy spread to countries not committed to emissions reduction (Loschel, 2002).

The degree of technological spillovers is related to the level of capital imports, which in turns depends on country specific trade policies.

2.4 Climate-economy-CGE models and technological change

2.4.1 Sources of endogenous technical change

Two mechanisms have been used to model endogenous technical change: R&D investments and R&D externalities or learning by doing (LBD). R&D expenditure and LBD capture two different types of learning process. Whereas R&D investments are profit-driven and therefore costly, LBD is free as it occurs with capital accumulation and experience. The idea of knowledge accumulation as an unintentional process was developed by Arrow (1962): the accumulation of knowledge is a by-product of the manufacturing of capital goods. This allows the presence of knowledge in constant-return-to-scale world. Romer (1986) instead considered the firm as rationally investing in R&D, creating private knowledge,

appropriable by the firm only, and public knowledge, freely is available to everybody. In principle both types of learning coexists, providing a more complete description of technological change as a process determined by both intentional and unintentional learning.

The R&D approach treats knowledge as a distinct input in the production function, with its own accumulation equation depending on depreciation and R&D expenditures. R&D generates spillovers that break diminishing returns and thus allow sustained growth. A production function with both R&D investments and externalities can be specified as in Goulder and Schneider (1999):

$$Y_t = A(Re_t)F_t(K_t, L_t, Ri_t) \text{ where } Ri_{t+1} = (1 - \delta)Ri_t + Ii_t \quad (2)$$

Re is the externality from which firms benefit freely whereas Ri is the appropriable knowledge.

The notion of LBD has been developed further by the learning curve literature. This approach relates the investment costs of a technology to the production and manufacturing of the technology, to R&D stock or expenditure and/or to the use of the technology (IEA, 2000). These three factors give rise to three different concepts of learning: learning by doing, learning by searching and learning by using. Cumulative installed capacity can be considered a proxy for the experience accumulated during the production and the manufacturing of the technology and thus of learning by doing. Cumulative R&D expenditure can approximate the stock of knowledge and thus learning by searching for a certain technology. Investment costs of a technology can be a decreasing function of the cumulative installed capacity, LBD, only or of the cumulative R&D expenditure as well, LBD and LBS, giving rise respectively to a 1-factor and 2-factors learning curve.

The speed of learning by doing can be measured by the learning rate, defined as the percentage improvement of a new technology, usually the percentage cost change that occurs with the doubling of the cumulative capacity (Soderholm and Sundqvist, 2003). A learning rate of 0.2 means that when the cumulative capacity doubles the cost of the technology declines by 20 percent. A learning curve with LBD looks like

$$C_{it} = a(CC_{it})^{-b} \quad (3)$$

where a is the specific unit cost at unit cumulative capacity ($t = 0$), b is the learning index, CC_{it} is cumulative capacity of a technology at time t and C_{it} is the unit investment cost at time t of technology i . A learning curve in a specific technology can be integrated in a production function where $(CC_{it})^{-b}$ is assumed to represent its state of knowledge at time t in sector i (Soderholm and Sundqvist, 2003). For example, assuming a neutral technical change coefficient proportional to the cumulative capacity, $A_{it} = \beta^{-1}(CC_{it})^{-b}$, a production function with LBD could be formulated in the following way:

$$Y_{it} = \beta^{-1}(CCit)^{-b}F(Kit, Lit, Eit) \quad (4)$$

Since experience is a cumulative variable, knowledge at time t is likely to underestimate the total weight of experience. The productivity parameter A_{it} can be better approximated by the new capacity installed at time t , $NCit$, normalized with respect to the average learning acquired up to that point, $\sum(aCCit^{-b})$ (Gerlagh et al., 2000):

$$A_{it} = \beta^{-1}(NCit / \sum(aCCit^{-b}))$$

and thus

$$Y_{it} = \beta^{-1}NCit / \sum(aCCit^{-b})F(Kit, Lit, Eit)$$

Both the R&D externalities⁵ and the learning curve approaches can be seen as an application of the Helpman and Krugman (1985) model of economies of scale with external effects. This model allows for increasing return to scale at the industry level whereas individual firms preserve constant return to scale. The production function can be seen as composed of two blocs: $F(vi, Ei) = F(vi)B(Ei)$ where $F(vi)$ is a standard constant return to scale production function and $B(Ei)$ is a factor amplifying the productivity of $F(vi)$. Vi are inputs and Ei can represent sectoral, country or international elements. For example, it can represent international spillovers. In this setting, firms set prices according to marginal costs $p = C(wvi, q)$, but the effective cost is $p = c(wvi, q)/B(Ei)$. In the two approaches considered in this section

$$B(Ei) = \begin{cases} \beta^{-1}(CCit)^{-b} & \text{with LBD} \\ A(Re_t) & \text{with R\&D externalities} \end{cases}$$

Helpman and Krugman have shown that there exist further gains from trade if the magnitude of the external effect E_i under free trade is bigger than under autarky.

2.4.2 Technological change in climate-economy models: the state of the art

Economy-energy-environmental models have become the standard tool to quantify the economic impacts of climate policy. Top-down models are aggregate representation of the general economy and hence are more suitable for describing the macro-economic implications of climate and trade policies. Top-down models can be of two types: neoclassical growth models or computable general equilibrium (CGE). Growth models solve the economy equilibrium using

⁵This framework cannot account for R&D investments that, being profit driven, need a market structure different from perfect competition, as mention in section 2.3.

intertemporal optimization. They can easily be extended to include intertemporal dynamics such as R&D investments and endogenous technological change (ETC). These models typically have one country and one sector and are not very suitable for the study of trade-related issues such as international technology spillovers.

Computable general equilibrium models (CGEs) account for interactions across different markets and they compute international trade flows endogenously. Yet, in these multi-sector models it is more difficult to represent intertemporal optimization problems and long run dynamics such as investments. There are two ways of specifying long-term dynamics: recursively or intertemporally. Recursive CGE computes static equilibria at each point in time that are then linked in a long run recursive-path by specifying growth dynamics in between time steps (Edenhofer et al., 2005). Dynamic CGEs compute the equilibrium by maximizing the total discount sum of utility and profits over the overall time horizon. In a recursive model future choices will depend on the past, but not the vice versa. A dynamic model is forward-looking and the optimal allocation today depends on future opportunities as well.

CGEs have represented technological progress using different approaches reviewed in Carraro et al. (2002), Jaffe, Newell and Stavins (2002), Weyant and Olavson (1999) and Loschel, (2002). Most CGE models, especially when including a large number of countries and sectors, assume a given overall productivity (TFP) and include an exogenous time-trend in the energy-input coefficient. This parameter, called autonomous improvement in the energy efficiency parameter (AEEI) captures the non-price induced technical change in terms of energy-intensity improvements. The justification of a declining coefficient on energy inputs is the stylized fact that energy intensity tends to fall with economic growth and development (Paltsev et al., 2005). A production function with AEEI looks like (Sue Wing, 2005)

$$Y(t) = A(t)F(VA(t), \gamma(t)E(t))$$

$$\frac{\partial \gamma(t)/\partial t}{\gamma(t)} = AEEI \leq 0$$

where $VA(t)$ is a composite of value-added e.g. labor and capital and $E(t)$ is an energy composite. However, there has been an increasing interest in the representation of endogenous technological change also in CGE models. The previous section reviews the major mechanisms that can be used to this purpose. Whereas the LBD approach has been applied mostly in bottom-up models, top-down CGE models tend to implement ETC via R&D. Goulder and Schneider (1999), in one-country-dynamic CGE model, have introduced an industry that produce R&D services. R&D investments are costly, but at the same time they increase the stock of knowledge and generate a positive externality. A firm benefits from the R&D externality in its industry, which in turns depends on the industry-wide level of expenditure on R&D. This is an example with

ETC in all sectors. Kemfert (2005) has a the dynamic CGE model, WIAGEM, where R&D investments directly change energy productivity. Technical change is induced by climate policies and only cooperating countries invest in R&D. Non-cooperating countries also benefit from the accumulated knowledge capital via spillovers generated by capital flows.

There are some CGE models that have implemented ETC using learning curves. DEMETER (Gerlagh et al., 2003) is a dynamic CGE with a bottom up feature in the energy sector. This model has only one region and thus do not allow for the presence of spillovers across countries. This model introduce ETC via learning curves only in the energy sector, where there are two technologies: fossil fuel-based and carbon free technology. Total production is determined by a nest-CES with two inputs: a capital-labor composite and energy composite. The Hicksian technical progress in the production function and the energy efficient index of the energy composite are exogenous. ETC is implemented by introducing a learning rate in the productivity parameter of the production function of the two energy inputs. The productivity parameter is taken as exogenous by the firm: hence, despite the presence of learning spillovers, firms preserve a constant return to scale production function. Kverndokk et al. (2004) use a two-sectors (electricity and non electricity) dynamic CGE with LBD. They distinguish between traditional and advanced technologies: the latter are more expensive but subject to higher LBD. As in DEMETER ETC is introduced only in the electricity sector.

In principle it would be more appropriate to have ETC in all industries as both energy demanders and suppliers can experience productivity growth and energy efficiency improvements. However, as it emerges from this brief model review, most models have limited the endogenous technological component to the energy sector.

2.5 Accounting for international technology spillovers in a CGE model

Spillovers can take place across technologies, firms, sectors and countries (Sijm, 2004; Weyant and Olavson, 1999). So far modelers have focused on the first three types. Goulder and Schneider (1999) have introduced intra-industry spillovers from R&D. Each firms invests in R&D, contributing to the accumulation of the stock of knowledge that is enjoyed by all firms in a sector. Kverndokk et al. (2004) include sectoral spillovers that stem from LBD. They are confined to the energy sector. However, the interest in international spillovers is becoming stronger. Countries are more and more integrated and the need of explicitly modeling technology diffusion in climate model is increasing. Grubb et al. (2002) explore the impact of climate policies under different spillovers scenario and they did find that technology diffusion has an impact on CO_2 emissions. However their study assumes rather than quantifying international technology spillovers. Kemfert (2005) is one of the first attempts to account endogenously for international technology spillovers across countries via capital flows. Buonanno et al. (2001) simulated the presence of international tech-

nology spillovers by introducing an exogenous stock of world knowledge in the production function and in the emission-output ratio equation. The value-added of CGE models is that this exogenous stock could be made endogenous. The way intra-firms and intra-sectors spillovers have been introduced may provide an example for how to model international spillovers. Next two sections will describe two possible ways of dealing with international technology spillovers.

2.5.1 Via learning curves

Technical change can be endogenized by specifying learning curves. In a CGE, international technology spillovers can be accounted for by linking the learning curves to the trade flows endogenously computed by the model. The most spillover-conducive channel is trade in capital goods: machinery and equipment. As mentioned above, the stock of capital goods is a proxy of the knowledge they embodied. For the time being trade exposure will be represented by an unspecified variable, TEt . The underlining intuition is that higher exposure to trade amplifies the ability and the speed of learning. As illustrated in section 2.3.1, an increase in the inflow of goods, services and investments often requires the diffusion of technical information and the acquisition of new capacities and notions. The evidence about imports and FDI affecting domestic productivity is increasing: it might be the case that international technology spillovers also translate into cost reduction. A suggestion about how to actually implement this idea comes from the two-factors learning curves. They try to disentangle the effect of cumulative capacity from other factors that can influence cost reduction, namely R&D investments. A two-factors learning curve could include learning by trading instead of learning by searching in the following way:

$$C_{it} = aCC_{it}^bTEt^d \text{ where } b < 0 \quad (5)$$

Or a three-factors learning curve, including all three types of learning, could be specified:

$$C_{it} = aCC_{it}^bTEt^dR\&Dt^e \quad (6)$$

The relationship between cost reduction and LBD occurs over time: therefore there are other factors taking place during that period of time that may influence how LBD interacts with costs. For example, changes in trade and/or FDI flows. This specification tries to capture this interaction.

For the two-factor learning curves with cumulative capacity and R&D two learning rates have been defined

$$\text{LBD} = 1-2^b \text{ rate of learning by doing}$$

$$\text{LBS} = 1-2^e \text{ rate of learning by searching}$$

Similarly the rate of learning by trading rate (LBT) can be introduced

$$\text{LBT} = 1 - 2^{-d}$$

where LBT is defined as the percentage cost reduction with doubling in trade exposure. These definitions of learning rates assumes that the other variable remains constant: while the capacity double, R&D (or TE) does not change. This is not a very realistic assumption. If instead I allow for simultaneous changes in the trade variable, a LBD rate accounting for contemporaneous trade influences can be defined as follow:

$$1 - 2^{-b} \Delta T E t^d \text{ where } \Delta T E t = T E t + i / T E t$$

$$\text{if } \Delta T E t \leq 1 \text{ then } L R \leq 1 - 2^{-b}$$

$$\text{if } \Delta T E t \geq 1 \text{ then } L R \geq 1 - 2^{-b}$$

where $i = t + i - t$ is the time interval in which capacity doubles.

The intuition is that greater exposure to trade will benefit the learning process. This is in line with the condition of gains from trade in the Helpman and Krugman model briefly described at the end of section 2.4.1: the external effect, in this case the learning rate, under free trade should be bigger.

A production function with endogenous technical change and international spillovers would look like

$$Y_{it} = \beta (C C_i t)^b T E t^d F(K_{it}, L_{it}, E_{it})$$

The implementation of learning curve in a CGE model is complicated by the presence of many sectors. LBD can be introduced both in the energy sector and in the non-energy sectors. By introducing sector-specific learning curves technical change is endogenized in a specific sector. As Edenhofer and al. (2005) pointed out, there is a distinction between endogenous energy-technical change and overall technical change, usually measures by the total factor productivity (TFP) of the economy and by changes in Hicksian-neutral coefficient. Most CGE climate-models introduce ETC in the energy sector leaving the overall TFP exogenous. ETC only in the energy sector is not able to capture the technological progress of the whole economy and it would omit the linkages with the productivity growth in the other sectors. However, it can be argued that technological change in the energy sector affects the all economy to the extent that energy is an input to all economic activities. Moreover, the energy sector has had a leading role in causing anthropogenic climate change and it is now

the key player in its mitigation.

Alternatively, learning curves could be introduced also in the other sectors. The use of sector-specific learning curves could account for the heterogeneity of the learning process across sectors, for which there is some empirical evidence (Loschel, 2002). However, the presence of many sectors may make this attempt cumbersome. This approach seems more suitable for models in which technological change is endogenized only in the energy sector. Next section will consider another option that seems more feasible for CGE models with many sectors.

2.5.2 Via productivity and energy efficiency parameters

A more direct way to introduce international technology spillovers is to link the TFP and the AEEI parameters to trade variables. Most CGE models represent the production side of the economy using nested constant elasticity of substitution (CES) technologies with constant return to scale (CRST). This assumption allows to represent the firm's problem by using the dual theory of cost minimization and it allows for biased technological change. Typically at the top nest an energy composite can be substituted for a value-added aggregate. Within both the energy and value-added aggregate further substitution among more specific inputs can occur. The nested structure gives flexibility in allowing for different elasticities between different inputs. The focus here is on the bias toward the energy aggregate as a whole; for this reason the attention is confined to the top nested level, as if there were two aggregate inputs.

A production function accounting for both neutral and biased technological change can be represented using augmenting coefficients:

$$Q = F(\phi_v(t)V_v(t), \phi_e(t)V_e(t)) \quad (7)$$

where $\phi_i(t)$ are the input-specific augmentation factors, V_e is a composite energy input and V_v represent the value-added aggregate. Assuming that $\phi_i(t) = A(t) * \varphi_i(t)$ and that $F(\cdot)$ is homogeneous of degree one in both arguments, the neutral component, the TFP or Hicksian-neutral technical change, can be factored out

$$Q = A(t)F[\varphi_v(t)V_v(t), \varphi_e(t)V_e(t)] \quad (8)$$

Measuring TFP, $\frac{A(t)}{A(t)}$, as output over capital and labor adjusted for their share on output, as most of the literature on international spillovers did, is not totally appropriate if the production function includes intermediate or inputs other than labor and capital. A multi-factor productivity measure should be used

$$TFP = d\log Q/dt - (s_v * d\log V_v + s_e * d\log V_e)$$

where $s_i = P_i * V_i/Q$

The use of TFP as a measure of productivity and technological change is based on the neoclassical growth theory where this parameter is typically exogenous and it is determined residually as the difference between output growth and the weighted average of factors accumulation. The endogenous growth theory and the theory of endogenous technical change show that important determinants of TFP are the process of innovation and inventions, also denoted as R&D activities. Several empirical studies find a significant relationship between TFP and several measures of R&D activities (Griliches, 1998; Coe and Helpman, 1995). In this framework another measure of productivity can be derived by the production function used in the endogenous growth theory. Productivity growth can be define as follow: ⁶

$$TFP = \frac{\dot{A}(t)}{A(t)} = \frac{\dot{N}(t)}{N(t)} = g * R\&D \quad (9)$$

where R&D can be the R&D expenditure, as in the lab-equipment version of the Romer model (Acemoglu, 2006), R&D employment (Romer, 1990) or the number of blueprints (Grossman and Helpman, 1991). Coe and Helpman (1995) did show that when the R&D sector is a relative small share on GDP, most of the variation in TFP is generated by R&D differences. This measure also has its own drawbacks. Intangible inputs such as knowledge are difficult to measure and are likely to be underestimated by R&D proxies.

Consider a CES specification of equation⁷ (7)

$$Q = [\sum (\alpha_i (\phi_i * V_i)^\rho)]^{1/\rho}$$

where Q is output, V_i are inputs (in this specific context i= v,e) and $\rho = (\sigma-1)/\sigma$

⁶There are different specifications of endogenous growth theory, but they all share the Dixit-Stiglitz formulation and they all lead to a similar aggregate production function of the form:

$$Y = \frac{N(t)}{1-\beta} K^{1-\beta} L^\beta$$

where N(t) is total number of inputs available and it is growing at a rate g such that

$$N(t) = N(0) * e^{g * R\&D}$$

Under this specification

$$A(t) = \frac{N(t)}{1-\beta}$$

$$TFP = \frac{\dot{A}(t)}{A(t)} = \frac{\dot{N}(t)}{N(t)} = g * R\&D$$

⁷For clarity the time index is omitted. However, prices, augmentation and technology coefficients, inputs and outputs are all time-dependent.

where σ is the elasticity of substitution between inputs. Cost minimization subject to this production function gives rise to the CES unit cost function

$$C_i(1, P_i) = [\sum (\alpha_i * P_i / \phi_i)^{1-\sigma}]^{1/(1-\sigma)}$$

where P_i is the price of input i . Using Shephard's lemma the demand function of each input can be derived

$$\frac{V_i}{Q} = [\alpha_i * \frac{P_q}{P_i} * \phi_i]^\sigma \quad (10)$$

Without loss of generality ϕ_i can be decomposed into the Hicksian neutral technological progress, $A(t)$ and the input-specific bias $\varphi_i(t)$, which in the case of energy is also called AEEI. The unit cost function becomes

$$C_i(1, P_i) = (1/A) [\sum (\alpha_i * P_i / \varphi_i)^{1-\sigma}]^{1/(1-\sigma)}$$

and the demand function can be expressed as

$$\frac{V_i}{Q} = \frac{1}{A} [\alpha_i * \frac{P_q}{P_i} * \varphi_i]^\sigma \quad (11)$$

If $\varphi_i = 1$ then $\phi_i = A$ and technological progress is i -neutral; if $\varphi_i \geq 1$, it is i -saving.

Recalling the definition of Binswanger and Ruttan of bias technological change, energy bias is the rate of change in the shares of the energy input over production at constant prices :

$$BIAS = \frac{\partial Se / \partial t}{Se}$$

where $Se = P_e V_e / P_q Q$ is the share of the value of energy input over total costs

$$BIAS = d \log(P_e V_e / P_q Q) \quad (12)$$

Technical change is energy-saving if

$$d \log(P_e V_e / P_q Q) \leq 0$$

or if

$$d \log(V_e / Q) \leq 0$$

controlling for prices.

The structure of technological progress, A , and of the energy bias, φ_e , needs to be specified. The idea is to make these two parameters an endogenous function of trade openness. Human capital and a time trend are also included. Following Fisher-Vanden et al. (2004) and Gerlag(2006), an exponential form is assumed

$$A(t) = \exp(t + M(t) + H(t)) \quad (13)$$

$$\varphi_e(t) = \exp(t + M(t) + H(t)) \quad (14)$$

where t is a time trend, M represents trade openness and H is a variable for human capital.

The assumption behind these specifications is that TFP and AEEI are determined by the same variables. In other word, the process of technical change is driven by some forces that I am trying to identify. They way it affects each input can differ, generating the notion of biased technical change.

3 Empirical analysis

Both approaches outlined in the previous section require an econometric assessment of the presence of international technology spillovers. In particular I need to evaluate the impact of trade openness on the measure of technological change described in section 2.5, total factor productivity (TFP), AEEI and on learning rates (Mc Donald and Schrattenholzer, 2001 and 2003). The attention will be on trade in capital goods (equipment and machinery), though an extension to include foreign direct investments (FDI) would be worthwhile, if data are available. Next sections review the previous empirical studies in this field and then illustrate the type of econometric analysis needed by both approaches outlined in the previous section.

3.1 Empirical evidence on international technology spillovers: literature review

The empirical evidence on international technology spillovers has focused on the relationship between total factor productivity (TFP) and:

- Imports in capital goods
- Patent innovations, domestic and foreign R&D
- FDI

Keller (2004) reviews the empirical evidence on all these three types of linkages. Most of the literature has dealt with technological diffusion related to

imports (Coe and Helpman, 1995; Coe, Helpman and Hoffmaister, 1997 De-Long and Summers, 1991). Relating TFP to capital import captures the so called embodied knowledge spillovers or indirect benefits. Sue Wing, Seifert and Moreno (2005) disaggregate the variable capital goods using two digit level data to study the impact on TFP of different types of capitals. Not all capital categories lead to the same degree of technological diffusion: specialized industrial machinery (72 according to the classification Standard International Trade Classification (SITC), Revision 2) has a stronger impact on TFP compared to the other types of capital.

The relationship between TFP and patent or R&D data captures the direct benefit from R&D or disembodied knowledge spillovers (van Meijl, 1995; Coe and Helpman, 1995).

The evidence on FDI is more mixed. Empirical studies on this subject tend to be more country and sector specific, depending on the availability of micro data. One common result is the positive correlation between FDI and firms's productivity. In line with the theoretical prescriptions of the Melitz's model, firms that engage in FDI tend to be more productive. A study on the energy intensity in China found foreign-owned firms to have a lower energy intensity (Fisher-Vandend, Jefferson, Liu and Tao, 2004). Lane and Milesi-Ferretti (1999) show that trade openness and FDI are positive correlated.

As for the learning curve approach, there are no empirical attempts to quantify the effects of international technology spillovers mediated by trade on the learning process. Any assessment would be a new contribution.

3.2 LC approach

The idea is to estimate directly the impact of trade on the learning rate, following the approach developed by Soderholm and Sundqvist (2003). Taking log of the learning curve defined in equation 5 we obtain a linear relation

$$\log(Cit) = a_i + \beta * \log(CCit) + \delta * \log(TEt) + U_{it} \quad (15)$$

from which we can obtain an estimate of the learning index b (β) and of the trade-sensitivity parameter d (δ). This type of regression has been used to estimate technology-specific learning rates (e.g. wind turbin, solar PV cells and panels) (McDonald and Schrattenholzer, 2003). I conclude in section 2.5.1 that learning curves are more likely to be used to endogenize technological change in the energy sector. To this end energy data at sectoral level (for a defined energy sector rather than for a specific technology) are needed:

- A proxy of the total unit cost in the energy sector. The major cost element in this category are capital investments, fuel costs and maintenance and operation (Gerlag et al., 2003). The GTAP database has detailed information about sectoral costs. The OECD STAND Industrial Database contains long time-series on many industrial variables for OECD countries.

- Total energy installed capacity or installed capacity in respectively clean and carbon technologies. Common proxies used for $CCit$ in specific technologies are the cumulative capacity installed, cumulative production or cumulative sales (McDonald and Schrattenholzer, 2000). To define such a measure for the whole energy sector is more difficult: it requires an approximative aggregation of the capacity of all technologies being in use. Kverndokk et al., 2004 measured accumulated experience in the electricity sector with its aggregate accumulated production. Data on these variables should be available for both OECD and non-OECD countries (Extended Energy Balance, IEA/OECD).
- Bilateral trade in capital goods at two digit-level. Detailed aggregate data are available at the OECD STAN Bilateral Trade Database. Input-output tables may provide some information about the types of capital imports flowing into the energy sector. Alternatively, capital imports in the energy sector could be approximated by those categories that are known to be used mostly in the energy sector, such as power-generating machinery and equipments (71 according to the SITC classification system). However, the productivity variable in a specific sector such as energy may be affected not just by sectoral but also by aggregate capital imports. Both total and energy-specific capital imports should be tried as independent variables

Another issue is whether to use trade flows, capital imports at time t , or stock, cumulative capital imports up to time t . The use of trade flows would capture only simultaneous effects, which in a learning process are likely to be small. The use of a stock (or a lag) variable instead would go beyond contemporaneous effects. In a learning process, experience starts exerting its influence with some lag with respect to the time of acquisition. To capture the delayed effects of experience, a stock of cumulative knowledge should be tried. The regression 15 using stocks would look like:

$$\log(Cit) = a_i + \beta * \log CCit + \delta * \log(\sum(TEt)) + Uit \quad (16)$$

Further issues that must be considered is the presence of multicollinearity, as it can be the case that cumulative capacity already includes the capital imported, and endogeneity of cumulative capacity. This empirical analysis could also represent a test of the sufficient condition of gains from trade in a model with externalities external to the firm. In this context, the externality is represented by LBD. A positive δ would indicate a positive contribution of trade to costs reduction and thus to the learning process.

3.3 TFP approach⁸

The framework developed in section 2.5.2 provides some equations that can be used to estimate the presence and the bias of international technology spillovers. In log terms, equation (13) yields an equation that can be taken to the data

⁸I am currently working on this empirical analysis

$$\log A_{jt} = \beta_1 t + \beta_2 M_{jt} + \beta_3 H_{jt} + \alpha_j + u_{jt} \quad (17)$$

where j is a sector or a country index.

This regression focuses on the Hicksian-neutral technical change. From the perspective of climate change what matters is whether technological change and technological spillovers are energy and carbon saving.

Taking the natural log of (11) for $i = e$, an estimable equation for the energy bias can be derived

$$\log \frac{V_e}{Q} = \log \frac{1}{A} + \sigma [\log \alpha_e + \log \frac{P_q}{P_e} + \log \varphi_e] \quad (18)$$

Plugging the definition for $\varphi_e(t)$ into (18) an estimable equation for energy bias can be obtained

$$\log \left(\frac{V_e}{Q} \right)_{jt} = \gamma_0 + \gamma_1 \log A_{jt} + \gamma_2 \log (P_q/P_e)_{jt} + \gamma_3 t + \gamma_4 M_{jt} + \gamma_5 H_{jt} + \beta_j + v_{jt} \quad (19)$$

where $\gamma_o = \sigma [\log \alpha_e]$. By the definition of energy bias given above, technological progress is energy-saving if $\gamma_3 \leq 0$.

The assumption behind these specifications is that TFP and AEEI are determined by the same variables. In other word, the process of technical change is driven by some forces that I am trying to identify. They way it affects each input can differ, generating the notion of biased technical change.

If the production function distinguishes between non carbon and carbon energy inputs, here represented by CO_2 emission, a similar regression could evaluate whether technical progress is carbon-saving or not.

$$\log \left(\frac{CO_2}{E} \right)_{jt} = \beta_0 + \beta_1 \log A_{jt} + \beta_2 \log (P_q/P_e)_{jt} + \beta_3 t + \beta_4 M_{jt} + \beta_5 H_{jt} + \alpha_j + u_{jt} \quad (20)$$

where $\beta_o = \sigma [\log \alpha_C]$.

The estimation of these equations will provide a test for the hypothesis of trade as a channel of international technology spillovers that contributed to the process of technological change. If the empirical findings are significant, international technology spillovers can then be modeled by linking the productivity parameter $A(t)$ and the energy-efficiency coefficient $\varphi_e(t)$ directly to trade flows or stocks. This could be done at sectoral level, using econometric estimations of the effect of trade variables on TFP and on energy intensity.

3.3.1 Data requirements

Data at sectoral level are not available for a significant number of countries, therefore this analysis will be carried out at aggregate-country level. A panel of 49 (19 non OECD and 30 OECD) countries over the period 1990-2003 is the starting sample. The major sources of the data are OECD and IEA statistics and the World Development Indicators of the World Bank.

Trade openness is measured by the flow of capital imports from the OECD countries as a total in US\$ dollar.⁹ Capital goods are carriers of the knowledge they embodied and thus it seems reasonable to think about technologically sophisticated goods as a channel for international transmission, as illustrated in section 2.3.1. Since technological spillovers may take time to exert any effect both lag and cumulative imports should be tried as independent variables. Different types of capital goods will be used. Machinery and equipment (ISIC - REV 3, 29-33), machinery and equipment n.e.c. (ISIC - REV 3, 29), electrical machinery and apparatus (ISIC - REV 3, 31), motor vehicles, trailers and semi-trailers (ISIC - REV 3, 34) and other transport equipment (ISIC - REV 3, 35). Equation 5 only accounts for spillovers that occurs indirectly through trade (also called indirect or embodied spillovers). This channel could interact with the level of R&D activities in the exporting countries, in this case the OECD countries: to capture this effect a further term $Mjt * R\&D_{oecd}$ is included. Higher R&D in machinery and equipments should lead to bigger spillovers. The OECD STAN industry dataset contains R&D expenditure in OECD countries by sector, allowing the possibility of interacting each type of capital good with its R&D expenditure share.

Human capital is included because it influences the absorptive capacity of a country. It seems that the measure of human capital that is most correlated with growth is the net secondary school enrollment ratio of male. However, these type of data are available up to 1999 (Barro&Lee database) and on a five-year base. The World Development Indicators have more recent data, up to 2002, but not homogeneously for all countries. Better data are available for the gross secondary school enrollment ratio. Another variable that can be used to account for higher level education is the number of scientific and technical journal articles.

Two measures of energy intensity will be used: aggregate energy intensity (measured in thousand of tonnes of oil equivalent (Ktoe) per PPP international US dollars of GDP) and per capita energy intensity (kilogram of oil equivalent (Kgoe) per PPP international US dollars of GDP). Energy use is measured as total final consumption of the total of all energy sources. The term final consumption (equal to the sum of end-use sectors' consumption) implies that energy used for transformation and for own use of the energy producing industries is excluded. Final consumption reflects for the most part deliveries to industry and the energy use in the transportation sector.

⁹The decision of focusing only on OECD exports of capital goods is due to the fact that R&D activities are concentrated in these countries. Spillovers are expected to be generated by the most innovating countries.

Data on energy prices are by type of product. Ideally it would be preferable to have an index for the real end use energy price. Such a measure is available only for OECD countries. The equations above will be estimated for the subsample of OECD countries using a real index of energy prices for industry and households available from IEA.

For the non OECD countries I need to construct a weighted average price using as weights the share of each product over the total final use (a sort of energy CPI). The most used sources of energy in the end-use sector are electricity, petroleum products and either gas or coal. Therefore the price index could focus on these three types:

$$EPI = (COAL/TFC)P_{coal} + (PETROPR/TFC)P_{pp} + (ELE/TFC)P_{ele}$$

or

$$EPI = (PETROPR/TFC)P_{pp} + (GAS/TFC)P_{gas} + (ELE/TFC)P_{ele}$$

Another option could be to include the world oil price, which probably plays a significant role but would not explain any cross-country variation. As for carbon price, it is not available for the time period under analysis, which spans from 1990 to 2003, when a carbon market did not exist yet.

Energy intensity is related to the structure of an economy: the larger the share of energy-intensive activities, the bigger this ratio. Changes in sectoral composition of total output should be controlled for. The World Development indicators contains data on the percentage of GDP produced by different sectors (agriculture, industry, manufacturing, services).

As mentioned above a measure of multi-factor productivity accounting for the presence of energy inputs should be used. However, the measurement of the energy share can be problematic as it requires data on energy prices. Moreover, this share is likely to vary over time. Alternatively, following the endogenous growth theory approach outlined above, the productivity parameter $A(t)$ can be approximated by a R&D variable. The stock of real expenditure, the number of patents (both for residents and non residents) and the number of workers in the R&D sector will be tried.

The econometric analysis as outlined above will provide the effects of imports on TFP, which is an aggregate measure of technical progress. It includes fast-growing sectors as well slow-growing sectors. To be integrated in a CGE model this aggregate elasticity needs to be converted into the sectoral parameters, using some factors of conversion such as value-added based productivity measures that reflect an industry capacity to contribute to economic-wide growth (OECD, 2001). Alternatively sectoral data on imports and productivity growth should be used. Another option could be to consider the effect of total imports in capital goods on sectoral productivity, such as productivity, energy and carbon intensity in the energy sector.

4 Conclusions

This paper explores the issue of integrating international technology spillovers in a climate CGE model. In an increasingly integrated world, international technology spillovers are an important stage of the process of technological change. Two possible approaches are considered, based on two mechanisms used to represent technological change: learning curves and TFP and AEEI. First, I illustrate how they could be implemented from a theoretical point of view. Then, the preliminary econometric analysis is outlined. The major conclusion is that both approaches could potentially be followed, although the learning curve method seems to be limited to models with endogenous technical change only in the energy sector. The other approach instead can be applied to the all economy or to all sectors. However, data to obtain sectoral estimates are not available and therefore aggregate estimates need to be converted into sectoral coefficients. I think that both ways are worth further research. At the moment I am working on the second one.

References

- [1] IEA International Energy Agency. Experience curves for energy technology policy. Technical report, IEA, Paris, 2000.
- [2] Syed Ahmad. On the theory of induced invention. *The Economic Journal*, 76(302):344–357, June 1966.
- [3] B.J. Aitken and A.E. Harrison. Do domestic firms benefit from direct foreign investment? evidence from venezuela. *The American Economic Review*, 89(3):605–618, June 1999.
- [4] C. Azar and H. Dowlatabadi. A review of the treatment of technological change in energy economic models. *Annual Review of Energy and the Environment*, 24:513– 544, 1999.
- [5] Hans P. Binswanger. The measurement of technical change biases with many factors of production. *The American Economic Review*, 64(6):964–976, December 1974.
- [6] H.P. Binswanger and V.W. Ruttan. *Induced Innovation: Technology, Institutions and Development*. John Hopkins University Press. Baltimore, MD, 1978.
- [7] V. Bosetti, M. Galeotti, and C. Carraro. *The Dynamic of Carbon and Energy Intensity in a Model of Endogenous Technical Change*, volume 6 of *Nota di Lavoro*. Fondazione Eni Enrico Matteo, Milan, 2005.
- [8] Paolo Buonanno, Carlo Carraro, and Marzio Galeotti. Endogenous induced technical change and the costs of kyoto. *Nota di Lavoro* 64, Feem, Milan, 2001.

- [9] Gavin Cameron, James Proudman, and Stephen Redding. Redding, technological convergence, r&d, trade and productivity growth. *European Economic Review*, 49(3):775–807, April 2005.
- [10] Carlo Carraro, R. Gerlagh, and van der Zwaan B. Endogenous technical change in environmental macroeconomics. *Resource and Energy Economics*, 25:1–10, 2003.
- [11] Caselli and Wilson. Importing technology. July 2003.
- [12] David T. Coe and Elhanan Helpman. International r&d spillovers. *European Economic Review*, 39:859–87, 1995.
- [13] David T. Coe, Elhanan Helpman, and W. Hoffmaister Alexander. North-south r&d spillovers. *Economic Journal*, 107:134–49, 1997.
- [14] B.R. Copeland and M. Scott Taylor. *Trade and the Environment*, volume 1. Princeton University Press, 2003.
- [15] Ben-David Dan and H. Papell David. International trade and structural change. *NBER Working Paper Series*, (6096), July 1997.
- [16] J. Bradford DeLong and H. Summers Lawrence. Equipment investment and economic growth. *The Quarterly Journal of Economics*, 106(2):445–502, 1991.
- [17] J. Eaton and S. Kortum. International technology diffusion: Theory and measurement. *International Economic Review*, 40(3):537–570, 1999.
- [18] J. Eaton and S. Kortum. Trade in capital goods. *European Economic Review*, Forthcoming 2001.
- [19] O. Edenhofer, Kai Lessmann, Claudia Kemfert, Michael Grubb, and Jonathan Koehler. Induced technological change: Exploring its implications for the economics of atmospheric stabilization. synthesis report from the innovation modelling comparison project. *Submit to the Energy Journal*, August 2005.
- [20] Wilfred J. Ethier. National and international returns to scale in the modern theory of international trade. *The American Economic Review*, 72(3):389–405, June 1982.
- [21] R. Gerlagh and B. van der Zwaan. Gross world product and consumption in a global warming model with endogenous technological change. *Resource and Energy Economics*, 25:35–57, 2003.
- [22] Rolf Golombek and Michael Hoel. Climate policy under technology spillovers. *Environmental and Resource Economics*, 31:201–227, 2005.

- [23] L. H. Goulder and S.H. Schneider. Induced technological change and the attractiveness of CO_2 abatement policies. *Resource and Energy Economics*, 21(3-4):211–253, 1999.
- [24] Zvi Griliches. Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 10(1):92/116, Spring 1979.
- [25] Zvi Griliches. Productivity, r&d, and the data constraint. *The American Economic Review*, 84(1):1–23, March 1994.
- [26] Gene M. Grossman and Elhanan Helpman. *Innovation and Growth*. Cambridge MA, 7 edition, 2001.
- [27] Michael J. Grubb, Chris Hope, and Roger Fouquet. Climatic implications of the kyoto protocol: the contribution of international spillovers. *Climatic Change*, (54):11–28, 2002.
- [28] Arnulf Grubler, Nebojsa Nakicenovic, and David G. Victor. Dynamics of energy technologies and global change. *Energy Policy*, 27(5):247–280, 1999.
- [29] Walid Hejazi and A. Edward Safarian. Trade, foreign direct investment, and r&d spillovers. *Journal of International Business Studies*, 30(3):491–511, 1999.
- [30] Elhanan Helpman, Marc J. Melitz, and Stephen R. Yeaple. Export versus fdi with heterogeneous firms. *American Economy Review*, 94(1):300–316, 1994.
- [31] Adam B. Jaffe, G. Newell Richard, and N. Stavins Robert. A tale of two market failures: technology and environmental policy. *Ecological Economics*, 54:164–171, 2005.
- [32] D.W. Jorgenson and B.M.Frumeni. The role of energy in productivity growth. In JW Kendrick, editor, *International Comparisons of Productivity and Causes of Slowdown*. Cambridge MA, 1984.
- [33] M.I. Kamien and L. Schwartz N. Induced factor augmenting technical progress from a microeconomic viewpoint. *Econometrica*, 37(4):668–684, October 1969.
- [34] W. Keller. International technology diffusion. *Journal of economic literature*, 42(3):752–782, 2004.
- [35] Claudia Kemfert. An integrated assessment model of economy-energy-climate-the model wiagem. integrated assessment. *An international Journal*, 3(4):281/289, 2002.
- [36] Claudia Kemfert. Induced technological change in a multi-regional, multi-sectoral, integrated assessment model (wiagem) impact assessment of climate policy strategies. *Ecological Economics*, 54:293–305, 2005.

- [37] Arrow J. Kenneth. The economic implications of learning by doing. *The Review of Economic Studies*, 29(3):155–173, June 1962.
- [38] J. Koehler, Carlo Carraro, Michael Grubb, David Popp, and N.Nakifenovif. Modelling endogenous technical change in climate-economy models. *Prepared for the IMCP Special issue of the Energy Journal*, 2005.
- [39] S. Kverndokk, KE Rosendahl, and TF Rutherford. Climate policies and induced technological change: impacts and timing of technology subsidies. Memorandum 05/2004, Oslo University, Department of Economics, April 2004.
- [40] S. Kverndokk, K.E. Rosendhal, and T.F. Rutheford. Climate policies and induced technological change: Impacts and timing of technology subsidies. 2004.
- [41] Philip R. Lane and Gian Maria Milesi-Ferretti. The external wealth of nations: Measures of foreign assets and liabilities for industrial and developing countries. CEPR Discussion Papers 2231, C.E.P.R. Discussion Papers, September 1999. available at <http://ideas.repec.org/p/cpr/ceprdp/2231.html>.
- [42] Andreas Loschel. Technological change in economic models of environmental policy: a survey. *Ecological Economics*, 43:105–126, 2002.
- [43] Joy Mazumdar. Imported machinery and growth in ldc's. *Journal of Development Economics*, (65):209–224, September 2001.
- [44] Alan McDonald and Schrattenholzer Leo. Learning curves and technology assessment. *International Journal of Technology Management (IJTM)*, 23(7/8), 2002.
- [45] Alan McDonald and Leo Schrattenholzer. Learning rates for energy technologies. *Energy Policy*, 29:255–261, march 2001.
- [46] OECD. Measuring productivity. measurement of aggregate and industry-level productivity growth. Oecd manual, OECD, Paris, 2001.
- [47] Sergey Paltsev and al. The mit emissions prediction and policy analysis model.(eppa)model version 4. Report 125, MIT Joint Program on Science and Policy of Climate Change, Cambridge, 2005.
- [48] David Popp. Induced innovation and energy prices. *The American Economic Review*, 92(1):160–180, March 2002.
- [49] J. P.Sjim. Technological change and spillovers in climate policy modeling. Ecn report ecn-c-04-073, Energy Research Centre of the Netherlands, 2004.
- [50] Paul M. Romer. Increasing return to scale and long-run growth. *Journal of Political Economy*, 94:1002–1037, 1986.

- [51] Paul M. Romer. Endogenous technological change. *Journal of Political Economy*, 98:S71–S102, 1990.
- [52] Vernon W. Ruttan. *Technology, Growth, and Development: An Induced Innovation Perspective*. New York, Oxford University Press, 2001.
- [53] P. Soderholm and Sundqvist T. Learning curve analysis for energy technologies: Theoretical and econometric issues. Environmentally compatible energy strategy project, International Institute of Applied System Analysis (IIASA), Austria, 2003.
- [54] R. Summers and Alan Heston. The penn world table (mark 5): An expanded set of international comparisons, 1950-1988. *The Quarterly Journal of Economics*, 106(2):327–368, May 1991.
- [55] Hans van Meijl and van Tongeren Frank. Endogenous international technology spillovers and biased technical change in the gtap model. *GTAP Technical Paper No. 15*, January 1999.
- [56] J. Weyant and T. Olavson. Issues in modeling induced technological change in energy, environment and climate policy. *Environmental Modeling and Assessment*, 4:67–85, 1999.
- [57] Ian Sue Wing. Induced technical change and the cost of climate policy. *MIT Joint Program on the Science and Policy of Global Change*, (102), September 2003.
- [58] Ian Sue Wing. Representing induced technological change in models for climate policy analysis. Joint Program Program on the Science and Policy of Climate Change, 2005.
- [59] Ian Sue Wing and Richard S. Eckaus. Explaining long-run changes in the energy intensity of the u.s. economy. *MIT Joint Program on the Science and Policy of Global Change*, September 2004.
- [60] Ian Sue Wing and S. Eckaus Richard. The decline in u.s. energy intensity:its origins and implications for long-run CO_2 emission projections.

A Technical change and biases: three definitions

A production function accounting for both neutral and biased technological change can be represented using augmenting coefficients or inputs expressed in the per effective unit. Using augmentation coefficients:

$$Q = F(\phi_v(t)V_v(t), \phi_e(t)V_e(t)) \quad (21)$$

where $\phi_i(t)$ are the input-specific augmentation factors, V_e is a composite energy input and V_v represent the value-added aggregate. Assuming that $\phi_i(t) = A(t) *$

$\varphi_i(t)$ and that $F(\cdot)$ is homogeneous of degree one in both arguments, the neutral component, the TFP or Hicksian-neutral technological change, can be factored out

$$Q = A(t)F(\varphi_v(t)V_v(t), \varphi_e(t)V_e(t))$$

At constant prices technical biases is defined as (Kamien and Schwartz, 1969)

$$\frac{V_v \dot{V}_v(t)}{V_v(t)} - \frac{V_e \dot{V}_e(t)}{V_e(t)} = d\log(V_v(t)/V_e(t)) = (1 - \sigma) \left[\frac{\varphi_e \dot{\varphi}_e(t)}{\varphi_e(t)} - \frac{\varphi_v \dot{\varphi}_v(t)}{\varphi_v(t)} \right]$$

where σ is the elasticity of substitution between the two composite inputs. For low values of $\sigma, \sigma < 1$

$$\begin{cases} d\log(V_v(t)/V_e(t)) \geq 0 & \text{E-saving} \\ d\log(V_v(t)/V_e(t)) \leq 0 & \text{E-using} \end{cases}$$

The intuition is that if technical progress affects the augmentation of an input more than proportionally, it reduces the effective amount needed for producing a certain quantity of output.

Let us assume that $\varphi_v(t) = 1$ so that $\frac{V_v \dot{V}_v(t)}{V_v(t)} = \frac{A \dot{A}(t)}{A(t)} = TFP$

$$Q = AF(V_v(t), \varphi_e(t)V_e(t))$$

In this case the energy bias can be defined as: $TFP - AEEI$, where

$$AEEI = \frac{\varphi_e \dot{\varphi}_e(t)}{\varphi_e(t)}$$

Technical change is energy-saving if $TFP - AEEI \leq 0$.

The other way of including technical change in the production function is using effective inputs:

$$Q = F(\phi_v(t)V_v(t), \phi_e(t)V_e(t)) \quad (22)$$

where $\phi_i(t)$ are the input-specific augmentation factors, V_e is a composite energy input and V_v represent the value-added aggregate. Assuming that $\phi_i(t) = A(t)/\gamma_i(t)$, the production function can be expressed in effective inputs and Hicksian-neutral technical change can be factored out:

$$Q = A(t)F(V_v(t)/\gamma_v(t), V_e(t)/\gamma_e(t))$$

At constant prices technical biases is defined as (Kamien and Schwartz, 1969)

$$\frac{V_v \dot{(t)}}{V_v(t)} - \frac{V_e \dot{(t)}}{V_e(t)} = (1 - \sigma) \left[\frac{\dot{\gamma}_v}{\gamma_v} - \frac{\dot{\gamma}_e}{\gamma_e} \right]$$

where σ is the elasticity of substitution between the two composite inputs. For low values of σ , $\sigma < 1$

$$\begin{cases} (1 - \sigma) \left[\frac{\dot{\gamma}_v(t)}{\gamma_v(t)} - \frac{\dot{\gamma}_e(t)}{\gamma_e(t)} \right] \geq 0 & \text{E-saving} \\ (1 - \sigma) \left[\frac{\dot{\gamma}_v(t)}{\gamma_v(t)} - \frac{\dot{\gamma}_e(t)}{\gamma_e(t)} \right] \leq 0 & \text{E-using} \end{cases}$$

The lower $\gamma_i(t)$, the higher the output for a given level of input $V_i(t)$. If $\gamma_v(t)$ is growing at a lower rate than $\gamma_e(t)$, it means that to produce the same output we need a lower quantity of $V_v(t)$ relative to $V_e(t)$. In the factor augmentation expression technological progress enter multiplicatively meaning that the higher the augmentation coefficient, the higher the output for a given level of inputs.

The two definitions are equivalents because

$$\varphi_i = \frac{1}{\gamma_i}$$

which implies that

$$\begin{aligned} \frac{\dot{\varphi}_i(t)}{\varphi_i(t)} &= -\frac{\dot{\gamma}_i(t)}{\gamma_i(t)} \\ (1 - \sigma) \left[\frac{\dot{\gamma}_v(t)}{\gamma_v(t)} - \frac{\dot{\gamma}_e(t)}{\gamma_e(t)} \right] &= (1 - \sigma) \left[\frac{\dot{\varphi}_e(t)}{\varphi_e(t)} - \frac{\dot{\varphi}_v(t)}{\varphi_v(t)} \right] \end{aligned}$$

When there are more than two inputs, a measure of bias that accounts for factor prices is the rate of change in the factor share, where the factor share is defined as the value of an input over total costs (Binswanger and Ruttan, 1978):

$$\begin{aligned} Si(t) &= Pi(t)V_i(t)/P(t)Q(t) \\ \text{biases} &= \dot{Si}(t)/Si(t) = \widehat{Pi} + \widehat{Vi} - \widehat{P} - \widehat{Q} = d\log(V_i(t)/Q(t)) - d\log(P(t)/Pi(t)) \end{aligned}$$

$$\begin{cases} \dot{Si}(t)/Si(t) \geq 0 & \text{i-using} \\ \dot{Si}(t)/Si(t) \leq 0 & \text{i-saving} \\ \dot{Si}(t)/Si(t) = 0 & \text{i-neutral} \end{cases}$$