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Modeling Endogenous Technological Change for Climate Policy Analysis

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RESOURCES FOR THE FUTURE

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Abstract

The approach used to model technological change in a climate policy model is a critical determinant of its results. We provide an overview of the different approaches used in the literature, with an emphasis on recent developments regarding endogenous technological change, research and development, and learning. Detailed examination sheds light on the salient features of each approach, including strengths, limitations, and policy implications. Key issues include proper accounting for the opportunity costs of climate-related knowledge generation, treatment of knowledge spillovers and appropriability, and the empirical basis for parameterizing technological relationships. No single approach appears to dominate on all these dimensions, and different approaches may be preferred depending on the purpose of the analysis, be it positive or normative.

Key Words: exogenous, technology, R&D, learning, induced

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Introduction

One of the most complex and salient questions remaining in climate change policy modeling is the appropriate treatment of technological change (TC). The approach to modeling TC is widely considered to be one of the most important determinants of the results of climate policy analyses; that is, the level of emissions abatement that can be achieved at a given cost. In this context, TC can be understood as the increase in outputs (including abatement) possible with a given level of inputs (including emissions) through the processes of invention, innovation, and diffusion. Unfortunately, the complex mechanisms by which these processes work are not captured easily in modeling frameworks, creating significant difficulties for modelers attempting to determine the effects of climate policies that inevitably are intertwined with TC in energy supply and demand technologies.

In climate change policy models, endogenous technology change (ETC) implies incorporating a feedback mechanism by which policy changes the direction, and possibly the overall level, of TC toward carbon-saving technology change. This feedback occurs through channels such as energy prices, research and development (R&D), or learning through past experience. This contrasts with exogenous assumptions about the rate of overall and carbon-saving TC, which are unresponsive to policy. This paper addresses several specific questions. What are the major assumptions regarding TC in climate policy models and, more specifically, currently how is TC made endogenous? What are the advantages and disadvantages of these approaches? And finally, what can we learn from these approaches?

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Exogenous Technological Change

Until recently, the most widespread method of treating TC in climate policy modeling was to consider it an exogenous variable—simply an autonomous function of time. Specifically, technology has been specified as two distinct functions of time. One follows the overall progress of the economy, typically representing a Hicks-neutral productivity gain. The other captures the potential for TC to proceed in an energy-saving manner. In some models, this is referred to as autonomous energy-efficiency improvement (AEEI) and reflects a bias in the direction of productivity improvements within a sector toward more energy-efficient (or perhaps carbon-efficient) production (e.g., McCracken et al. (1999); Nordhaus (1994)). In other disaggregated models, energy-saving progress also can be implemented by increasing the Hicks-neutral productivity of a more energy-efficient sector or technology or by adding a new technology to the menu of available technologies at a given point in time. Autonomous energy-efficiency improvement has the primary advantage of simplicity, whereby modeling effort can be directed to other areas, model nonlinearities and multiple equilibria are less likely to occur, and sensitivity analysis can be accomplished readily with different AEEI values.[1]

Related to both approaches is the use of backstop technologies, or energy sources that are already known, but not yet commercialized widely. It often is assumed that a backstop technology is available in an unlimited supply at a constant, but relatively high, marginal cost. If the price of energy inclusive of carbon policy becomes high enough, the backstop technology will penetrate the market and prevent the price of energy from rising further. Modelers often assume that the cost of the backstop technology is decreasing with time at its own autonomous rate. Some models have more than one backstop technology, such as the GREEN model (Burniaux et al. 1992). Examples of backstop technologies include advanced solar power, renewable transportation fuels, nuclear fusion, and advanced fossil-fuel generation technologies

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[1] While models with exogenous TC cannot capture directly the responsiveness of technology to climate policies, they can employ sensitivity analysis to evaluate how modeling results would be influenced if technology evolved differently under alternative policy scenarios.

such as shale oil (Loschel 2002). When backstop technology prices are assumed to be a function of time, they represent another way of incorporating exogenous TC.

Finally, in some econometric models with flexible functional forms there may be multiple trends determining the overall level and bias of technological change. For example, Jorgenson and Wilcoxen (1993) include five parameters describing technological change—two describing the overall level (a_t and b_t) and three describing biases (the vector b_{pt}):

$$\begin{aligned}\ln q = \alpha_0 + \ln p'\alpha_p + \alpha_t g(t) + \tfrac{1}{2}\ln p'\beta_{pp}\ln p \\ + \ln p'\beta_{pt} g(t) + \tfrac{1}{2}\beta_{tt} g^2(t)\end{aligned}, \quad (1)$$

where q is unit cost, p is a vector of input prices, $g(t)$ is a time trend, and the α's and β's are parameters. Here, overall productivity growth is given by the negative derivative of this expression with respect to time, or

$$-\frac{\partial \ln q}{\partial t} = -\left(\alpha_t + \ln p'\beta_{pt} + \beta_{tt} g(t)\right) g'(t). \quad (2)$$

The presence of prices in this formula leads some to view this as a model of price-induced TC. However, it is useful to note that the actual cost function at a given point in time does not depend at all on historic prices—today's production possibilities depend on current prices and the passage of time only. Therefore, this is not ETC in the sense that the choice of technically feasible options has changed due to historic policies including prices (or anything else). Thus, even though the observed rate of TC appears endogenous, the underlying technology possibilities are not.

There is a wide literature, however, acknowledging that TC is not a completely autonomous phenomenon and that it is the result of various other processes, such as input and output prices, economy-of-scale effects, private and public investment in R&D, and learning (e.g., see Oravetz and Dowlatabadi (1995); Newell (1999); Jaffe, Newell, and Stavins (2003); Grubb, Kohler, and Anderson (2002); and Azar and Dowlatabadi (1999)). This extensive literature of ETC includes an edited book (Grubler et al. 2002), and four special journal issues (*Resource and Energy Economics*, 2003, vol, 25; *Energy Economics*, 2004, vol. 26; *Ecological Economics*, 2005, vol. 54; and *The Energy Journal*, 2006). Some of these studies, such as

Oravetz and Dowlatabadi, emphasize that modeling TC using AEEI is not entirely consistent with empirical evidence. Others criticize the use of AEEI as neglecting the causes that affect the evolution of technologies, leading to distorted and inappropriate model results.[2]

Endogenous Technological Change

The development of alternatives to exogenous TC reflects, in part, demand by policymakers for normative ("what ought to be") analyses of climate change policies that appropriately model technological change. However, the line between positive ("what is") and normative analysis often is blurred in many studies that include ETC, despite the different requirements of each. This blurring arises, in part, because the literature indicates that important positive questions have yet to be answered unequivocally. Among these is the basic question of exactly what drives technological change and, therefore, what ETC ought to capture and why.

One line of intuition is that ETC represents a constraint that, when relaxed, yields lower costs for reducing emissions. A number of studies find this result when ETC is coupled with the possibility that TC is undersupplied due to innovation market failures. In this case, modeling TC endogenously implies optimal carbon-mitigation policies with more near-term abatement and lower abatement costs than similar ETC models (Grubb, Köhler, and Anderson 2002). In contrast, other studies implicitly or explicitly assume that TC in the base case is (roughly) optimal; therefore, allowing it to change in response to policy changes might not affect mitigation costs very much if other relative prices do not change very much—an envelope theorem result.[3] Throughout the literature, studies have used markedly different specifications to attain their results, and there is no clear consensus on the most appropriate methodology (Weyant and Olavson 1999). Although difficult to categorize neatly, the most commonly used approaches model ETC in one of three ways: direct price-induced, R&D-induced, and learning-induced.

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[2] This is related to the Lucas (1976) critique in that AEEI is not a "deep" structural parameter and it is unlikely to remain stable as policymakers change their behavior.

[3] Such results include Nordhaus (2002), Goulder and Schneider (1999), Goulder and Mathai (2000), Sue Wing (2003), and Smulders and de Nooij (2003).

Direct price-induced TC implies that changes in relative prices can spur innovation to reduce the use of the more expensive input (e.g., energy) in accordance with the Hicks-induced innovation hypothesis. Research and development-induced TC allows for R&D investment to influence the rate and direction of technological change. It often involves an explicit knowledge capital stock. There is considerable diversity in R&D-based approaches to modeling TC, which for the sake of convenience we categorize into neoclassical growth extensions and multi-sector general-equilibrium approaches. Model structure is the dominant factor in this further division, as different model structures tend to lend themselves to different R&D-based endogenizing approaches. Finally, learning-induced TC allows for the unit cost of a particular technology to be a decreasing function of the experience with that technology. Learning-by-doing (LBD) is the most commonly employed method used in this approach, where the unit cost of a technology is typically modeled as a decreasing function of its cumulative output. Table 1 summarizes the modeling of TC in a sample of climate change policy models to demonstrate the variety of approaches.

The aim of this paper is not to evaluate critically any particular model's method or findings, but rather to elucidate the common avenues of modeling ETC and to examine briefly the implications and limitations of each. Instead of a comprehensive review of the ETC modeling literature, we restrict our review to select papers that illustrate key concepts of ETC modeling methodology.[4] The paper is organized as follows. Section two examines direct price-induced ETC; section three examines R&D-induced ETC; section four examines learning-induced ETC; and section five brings together our conclusions with a discussion of the implications of the choice of ETC modeling structure for climate change policy-modeling results.

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[4] For surveys of the literature and other overviews of modeling methodology, see Loschel (2002); Clarke and Weyant (2002); Grubb, Köhler, and Anderson (2002); Azar and Dowlatabadi (1999); Grübler, Nakicenovic, and Victor (1999); Goulder (2004); Weyant (2004); Smulders (2005); Vollebergh and Kemfert (2005); Edenhofer et al. (2006); Köhler et al. (2006); Popp (2006); Sue Wing and Popp (2006); Sue Wing (2006); Weyant and Olavson (1999); and Edmonds, Roop , and Scott (2000).

Direct Price-Induced TC

Direct price-induced TC is a relatively straightforward method of endogenizing TC with conceptual roots dating back to Hicks (1932), who suggested:

> A change in the relative prices of the factors is itself a spur to invention and to inventions of a particular kind – directed at economizing the use of a factor which has become relatively expensive. (Hicks 1932: 124-125)

Later empirical studies established a solid foundation for Hicks' induced-innovation hypothesis and it is widely recognized now as an important consideration in the understanding of TC (Ruttan 2002). This empirical evidence has been bolstered further recently with studies such as Newell, Jaffe, and Stavins (1999), who find that historical energy-price increases account for one-quarter to one-half of the observed improvements in energy efficiency for a sample of consumer durables from 1958–1993. Popp (2002) finds that patenting in energy-related fields increases in response to increased energy prices.

In the context of climate policy modeling, if the price of energy rises, price-induced TC will lead to greater energy efficiency, often through a productivity parameter that is tied to prices or through earlier diffusion of energy-efficient technologies. The exact pathway through which this occurs depends greatly on the model structure. There are only a few examples of direct price-induced TC used in climate policy models due to the somewhat ad hoc or reduced form nature of specifying the relationship between price and TC. It is most common for models that use price-induced TC to use an AEEI parameter or a LBD approach as well, as will be discussed in more detail in section four.

In the ICAM3 model, the expectation that the price of energy will rise induces TC, as does LBD (Dowlatabadi 1998). In the U.S. Energy Information Administration's NEMS model, price-induced TC is included in several modules, including the residential and commercial modules, while LBD is included in others, such as the industrial and electricity modules. In the NEMS residential module, price-induced TC is included to allow for earlier diffusion of energy-efficient technologies if fuel prices increase significantly and remain high over a multi-year period. Specifically, this earlier diffusion is accomplished by shifting the date of introduction into the market by up to 10 years if there is a doubling of prices from the base-year price that holds for three years. The length of the shift is a function of the price in comparison to the base-year price. The NEMS commercial module has an analogous structure for the diffusion of advanced commercial equipment (EIA 2003).

The empirical evidence suggests that the price-inducement form of TC does have merit as a partial explanation; higher energy prices clearly are associated with faster improvements in energy efficiency (Newell (1999); Popp (2002)). However, the reduced-form approach largely has been passed over for the R&D- or learning-induced TC methodologies. We now turn to those approaches in more detail.

R&D-Induced TC

R&D-induced TC is one of the most common approaches used to endogenize TC, and a variety of models have been developed along these lines. The theoretical basis for much recent work using this approach can be traced to the early work of Kamien and Schwartz (1968) and Binswanger and Ruttan (1978) and to the new endogenous-growth literature (Aghion and Howitt 1998; Romer 1990; Lucas 1988; Grossman and Helpman 1994). It has been reinforced recently by direct application of microeconomic empirical evidence, such as by Popp (2001, 2002) and Fischer and Newell (2005). The critical element of R&D-induced TC is a modeling structure that treats innovation as the result of explicit investment in R&D. There are a myriad of pathways for this process, but these pathways tend to include a stock of knowledge and a flow of R&D investment into that stock of knowledge. Either directly or indirectly, that stock of knowledge influences TC.

In R&D models, knowledge is treated implicitly in varying degrees as rival or non-rival and appropriable or non-excludable. Knowledge is non-rival if one person's use of knowledge does not diminish the ability of others to use it. Knowledge is fully appropriable if firms have the ability to capture all the social benefits derived from knowledge gained through R&D investment. In many R&D models, knowledge is not treated as fully appropriable, in that firms cannot treat knowledge they create as an entirely private good.[5] In both cases, knowledge generates free spillovers to other firms, which in some models are the primary driver of economic growth.[6] These spillovers are a common element in many R&D models, but even within this subset of models with spillovers, there are considerable differences in how knowledge influences productivity. These structural differences often can be attributed to the asking of different questions, although sometimes they highlight differences of opinion in how TC functions.

Neoclassical Growth Extensions

Climate change policy models with ETC often are based on the neoclassical growth framework, with an aggregate economywide production or cost function based on inputs of capital, labor, and other inputs that capture both emissions and emissions-control activities. Many of these approaches to modeling ETC build directly on endogenous growth theory, particularly the models of Romer (1990), Aghion and Howitt (1998), Acemoglu (1998, 2001), and Kily (1999). Following endogenous growth theory, a common approach to endogenizing TC is the inclusion of a knowledge stock directly in the economywide production function. A variation of this used specifically for climate policy applications has a knowledge stock explicitly included in an emissions-abatement cost function rather than the aggregate production function. In another variation, some models forgo the production function and focus instead on the emission-output ratio or carbon-output ratio by making these ratios a function of the knowledge stock. Others use a "blueprint" approach, where R&D creates discrete blueprints and technology changes over time with each new generation of blueprints. Each of these variations will be discussed below.

[5] There are exceptions. Some studies, such as Goulder and Schneider (1999) and Nordhaus (2002) explicitly treat the knowledge stock in two parts: appropriable knowledge and non-excludable knowledge.

[6] As discussed in Clarke and Weyant (2002) and Jaffe, Newell, and Stavins (2005), the public-good nature of knowledge leads to innovation market imperfections, although these are not always modeled explicitly in climate change policy models.

Knowledge in Economywide Production Functions

Models that endogenize TC by including a factor augmenting knowledge capital stock directly in the economywide production function typically follow the endogenous growth literature. In one example of this approach, Buonanno et al. (2003) extend the aggregate production function of the Nordhaus and Yang (1996) RICE model to create the ETC-RICE model. ETC-RICE has the following production function for each country:

$$Q = AK_R^{\beta}(L^{\gamma}K^{1-\gamma}), \tag{3}$$

where Q is economic output, A allows for exogenous TC, K_R is knowledge capital, L is labor, K is physical capital, and β and γ are parameters. With a specification of this form, R&D efforts increase K_R and raise the productivity of all output. If the elasticity of knowledge β is positive, this specification results in increasing returns to scale; if $\beta - \gamma$ is positive (i.e., $\beta+1-\gamma > 1$), it results in increasing returns to scale in non-fixed inputs.[7] Just as in the Nordhaus and Yang (1996) RICE, a model of this type has the economic agent (social planner) choose the optimal level of investment—and now the R&D effort as well. Just as in RICE, the cost of R&D is subtracted from the left-hand side of the DICE model's output balance equation (where consumption equals output less investment and production costs). By itself, this inclusion of ETC does not allow any energy-saving benefits from R&D and no particular market failure is modeled in this specification. We will address the implications of this modeling methodology in Buonanno, Carraro, and Galeotti (2003) below after a discussion of their further modeling of induced-TC through adjustments to the emissions-output ratio.

A second, and more complex, example of including a factor augmenting knowledge stock is in the climate policy model in Smulders and de Nooij (2003). Smulders and de Nooij endogenize both the rate and direction of TC. Economic growth is driven by endogenous factor augmenting TC, as follows. Final output (Y) is modeled as a constant elasticity of substitution (CES) production function of augmented labor (L) and augmented energy (resources) (R):

[7] Increasing returns to scale in non-fixed inputs can lead to an unbounded control problem and the absence of a competitive equilibrium.

$$Y = A \cdot \Phi(A_L L, A_R R), \tag{4}$$

where A is exogenous Hicks-neutral TC. A_L and A_R are endogenous factor augmentation (technology) levels for labor and energy services respectively. They are defined for $i = L, R$ as

$$A_i = \int_0^1 q_{ik} \left(\frac{x_{ik}}{S_i} \right)^{1-\beta} \mathrm{d}k , \tag{5}$$

where q_{ik} is the quality level of intermediate goods of type k, x_{ik} is the use of intermediate goods ("capital") of type k for the production of type i services, S_i is the use (or, in equilibrium, the supply) of raw input i. The number of intermediate goods in each sector is normalized to unity. The market for intermediate goods is characterized by monopolistic competition.

ETC is modeled in this framework by assuming that each intermediate goods producer improves the quality of the good by investing in R&D. The rate of change in the quality of the good is given by

$$\dot{q}_{ik} = [\xi Q_i D_i^{1-\omega_i}] D_{ik}^{\omega_i} , \tag{6}$$

where D_{ik} is the flow of resources spent on R&D by the firm, D_i is the flow of sector-wide investment for input i, ξ is a scaling parameter, ω_i is the share of innovation returns for intermediate good k to input i that accrue to the inventing firm (an appropriability parameter), and Q_i is the current aggregate quality level (a proxy for a knowledge stock or level of technology). Q_i is given simply as follows (for $i=L,R$)

$$Q_i = \int_0^1 q_{ik} dk . \tag{7}$$

Each intermediate goods producer chooses D_{ik} to maximize the net present value of the firm. Given this specification, there are two innovation spillovers. The first is that each individual firm builds on the knowledge accumulated by all firms in the sector, as given by Q_i. The second is due to ω representing the share of returns to innovation that are not appropriated, implying that quality development efforts are more productive when other firms in the sector are more active. In other words, each firm ignores how his or her investment benefits both other firms now (through the aggregate investment term D_i) and other firms in the future (through the accumulated stock term Q_i). Thus, two market failures are modeled in this specification.

Smulders and de Nooij's modeling framework allows for policy analysis examining the short- and long-run growth implications of energy conservation policies but does not address questions of economic welfare. They find that energy-conservation policy will lead to reduced net per capita income levels due to the direct costs of the policy outweighing the offsetting effect of induced innovation. Nonetheless, the ETC framework does reduce the cost of a policy, although non-energy R&D activities may be crowded out, with no increase in total R&D. In fact, a theoretical result based on this model structure is that induced innovation will never more than offset the initial policy-induced decline in per capita income levels, obviating the possibility of "win-win situations."[8] As a general proposition, ETC should induce higher long-run output only if spillovers are relatively high in carbon-saving innovation compared to other areas that would receive R&D effort. This appears not to be the case in Smulders and de Nooij's model.

Knowledge in Greenhouse Gas-Intensity Ratios

Rather than endogenizing technical change directly in the production function, another pathway used in the literature is to allow the emissions- or carbon-intensity ratio to be a function of knowledge. In particular, the original Nordhaus (1994) DICE model has been extended to endogenize TC in this manner.

In the original DICE model, carbon intensity is affected by the substitution of capital and labor for carbon energy. This is modified in the R&DICE model in Nordhaus (2002), so that carbon intensity is determined by an induced innovation function or innovation-possibility frontier.

The innovation-possibility frontier takes the following form in the R&DICE model:

$$\dot{\sigma}_t / \sigma_t = \Psi_1 R_t^{\Psi_2} - \Psi_3, \tag{8}$$

[8] This result does not hold in other model frameworks (e.g., Fischer and Newell 2005).

where σ_t is the industrial carbon energy/output ratio at year t (implying $\dot{\sigma}_t/\sigma_t$ is the rate of change of the carbon energy-output ratio), R_t is the R&D inputs into the carbon-energy sector in year t, and the Ψ_i are parameters (calibrated assuming optimized R&D in the past). A few other modifications were made from the original DICE model. Capital, labor, and the interest rate are exogenously assumed, giving an exogenously determined level of output. Emissions in this model are a function of the exogenously determined output and the endogenous carbon-output ratio σ_t.

In the R&DICE model, the cost of R&D and cost of carbon energy also are subtracted from consumption in the DICE model's output balance equation (where consumption equals output less investment and production costs). Here, the cost of research is multiplied by four to reflect a generic innovation market failure; that is, that the social opportunity cost of R&D exceeds its private cost due to crowding out. By implication, in equilibrium the rate of return to carbon energy R&D also exceeds the return to ordinary standard investment by a factor of four in the base case.

Nordhaus (2002) compares this ETC specification with the specification in DICE (where carbon intensity only is affected by mitigation efforts substituting abatement for consumption). His primary conclusion is that induced innovation is likely to be less powerful of a factor in reducing emissions than substitution. This result is related directly to the calibration that assumes the returns to R&D equal its opportunity costs.

Returning to the ETC-RICE model, in addition to endogenizing aggregate productivity growth (ETC as described earlier), Buonanno et al. (2003) take an approach similar to Nordhaus to endogenizing emission intensity, making it a function of that same knowledge stock K_R. They term this "induced TC" and their formulation is

$$\frac{E}{Q} = [\sigma + \chi e^{-\alpha K_R}](1-\mu), \tag{9}$$

where E is emissions, Q is output, α is the elasticity by which knowledge reduces the E/Q ratio, σ is an exogenous parameter describing the value to which the E/Q ratio tends to asymptotically as the stock of knowledge increases, χ is a scaling coefficient, and μ is the rate of abatement effort. A positive value for the scaling coefficient χ indicates that R&D efforts will result in emissions-saving TC. The knowledge stock increases with R&D investment and depreciates at an exogenous rate over time. Importantly, there is no potential for climate-friendly R&D to compete with or crowd out other, aggregate R&D—this knowledge stock is exactly the same variable that influences overall productivity.

Buonanno et al. also incorporate ETC in third way, where they allow for spillovers from an international knowledge stock of R&D to other regions' productivity (modeled by an additional spillover term of K_W^{ε}, equal to the sum of knowledge in other regions, multiplied by the left-hand side in equation (3)). An interesting result is that the total cost of achieving Kyoto targets rises when "induced TC" is modeled versus "endogenous TC" only and rises again when international spillovers are added. While this result runs counter to our intuition that additional avenues (such as R&D or foreign R&D) to mitigate could only lower costs, we believe it reflects difficulties in calibrating parameters. For example, holding R&D and direct abatement expenditures constant delivers different (and presumably sometimes higher) emissions as the "induced TC" and spillover features are added to the model—a consequence of the fact that one stock variable is governing all three phenomena. At the same time, the Nash game being played by different regions may be affected by these changes, complicating the results.

Blueprint Approach

Van Zon and Yetkiner (2003) take an approach similar to Smulders and de Nooij (2003), only intermediate goods are based on discrete "blueprints" with a fixed quality instead of allowing continuous improvement. While both are based on the new endogenous growth literature, and the Romer (1990) model in particular, the blueprints model is closer to the Romer formulation. A basic premise is that there is an R&D sector that uses specialized R&D labor (L_A) to create discrete blueprints for intermediate goods, the productivity of which does not change after invention. The change over time in the number of blueprints $\dot{A}$ is modeled as

$$\dot{A} = \delta A L_A , \tag{10}$$

where δ is the productivity of the R&D process and A is the number of blueprints, implying that the existing stock of blueprints increases the productivity of R&D for blueprints. Final output (Y)

is modeled as a function of non-R&D labor input (L_Y) and capital services received from each "effective" intermediate good (x_i^{e}), defined below. The production function is thus defined as:

$$Y = L_Y^{1-\alpha} \int_0^A (x_i^{\mathrm{e}})^\alpha \, \mathrm{d}i \tag{11}$$

where α is a parameter. The supply of intermediate goods is then modeled through a two-step process.

First, the quantity of each effective intermediate good x_i^{e} is a function of capital (x_i), energy (e_i) (both determined each period), and a total factor productivity parameter (λ_i) (fixed over time for blueprint i) through the Cobb-Douglas production function:

$$x_i^e = \lambda_i (x_i)^\beta (e_i)^{1-\beta}, \tag{12}$$

where β is a parameter.

Second, new blueprints are being added each period based on the R&D described above (which proceeds faster when L_A is larger). New blueprints with $i = A$ (i.e., the newest intermediate good) have a total factor productivity is given by

$$\lambda_A = \lambda_0 A^\zeta, \tag{13}$$

where λ_0 is the total factor productivity of the first intermediate, and ζ is the corresponding factor of proportion, which implicitly measures the quality improvements of the latest intermediates.

With this model, van Zon and Yetkiner find that an energy tax that is recycled in the form of an R&D subsidy may increase long-run growth, through R&D-induced TC. This result stems from a market-failure in the R&D market: firms do not consider the effect that current R&D has on increasing the value of the next R&D investment. In addition, they find that in order to have energy-efficiency growth and output growth with rising energy prices, both an R&D policy and an energy policy are needed.

Knowledge in Abatement Cost Functions

In a variation on several of the approaches described above, some model structures are based on an economywide carbon-abatement cost function, rather than on a production function.

While the abatement cost function can be derived from a production function, in explicitly modeling the abatement cost function, TC is dealt with somewhat differently.

Goulder and Mathai (2000) create a set of optimizing equilibrium models with knowledge accumulation that directly reduces abatement costs. One set of models uses a cost-effectiveness criterion and solves for the time path of abatement and R&D investment to minimize the present value abatement costs of achieving a concentration target under different TC assumptions. The second set of models uses a cost–benefit criterion and solves for the time path of abatement and R&D investment that minimizes present value social costs (including climate damages) under different TC assumptions.

Into each of these frameworks, they separately incorporate both R&D and LBD, which govern the rate of knowledge accumulation; the LBD specification will be discussed in Section 4. All innovation market failures are assumed to already have been corrected by public policy, so there is no appropriability problem in their model.

In the cost-effectiveness R&D-based model, the social planner's objective function covers each time period *t* from the present into the infinite future, as follows

$$\min_{A_t, I_t} \int_0^\infty (C(A_t, H_t) + p(I_t)I_t)e^{-rt}\,dt\,, \tag{14}$$

where $C(\cdot)$ is the cost function, A_t is the level of abatement at time t, H_t is the stock of knowledge, $p(\cdot)$ is the real price of investment resources, and I_t is investment in knowledge (i.e., R&D expenditure). This minimization problem is subject to a constraint governing the change in the concentration of CO_2 in the atmosphere (the concentration target), as well as a constraint governing the change in the knowledge stock.

In this second constraint, the accumulation of knowledge ($\dot{H}_t$) is given by

$$\dot{H}_t = \alpha_t H_t + \Psi(I_t, H_t)\,, \tag{15}$$

where α is the rate of autonomous TC (an AEEI term), and Ψ is the knowledge accumulation function. The initial knowledge stock (H_0) is initialized to unity. Goulder and Mathai also assume that the knowledge accumulation function Ψ has the following properties: $\Psi(\cdot) > 0$, $\Psi_I(\cdot) > 0$, and $\Psi_H(\cdot) < 0$.

In this formulation, R&D investment increases the knowledge stock and thereby reduces future abatement costs. On the other hand, R&D investment also adds to the costs that the social planner is attempting to minimize. A key theoretical result out of the cost-effectiveness framework is that the presence of R&D-induced TC implies a reduction in near-term abatement and an increase in later abatement (i.e., a "steeper" optimal time path of abatement), a result that contrasts with claims (typically driven by assumptions about learning, discussed later) that endogenizing TC leads to more aggressive near-term action. Under both frameworks, Goulder and Mathai also find that including R&D in their model formulation lowers the time path of the carbon tax, since the carbon tax relatively is more effective in reducing emissions with ETC than without. At the same time, in the cost–benefit framework this implies a higher overall optimal level of abatement, since emissions reductions relatively are less expensive. Similarly, it implies higher overall welfare for society (i.e., lower overall costs, including climate damages).

Multi-Sector General Equilibrium Approaches

Multi-sector general equilibrium models differ from the previous approaches in that the economy is disaggregated into distinct sectors and the economic activity within and between sectors is modeled. The strength of the approach is that it may provide additional insights on the effects of interactions between sectors, such as spillovers—or crowding out—from R&D. The cost is that general equilibrium models tend to be data intensive and computationally demanding. We focus here on approaches that include explicit ETC.[9]

Just as in several of the models discussed above, some general equilibrium models explicitly endogenize TC through the inclusion of knowledge capital in the production function, albeit at a sectoral, rather than economywide, level. One notable example is Goulder and Schneider (1999). Goulder and Schneider develop a partial equilibrium analytical framework and

[9] This is in contrast to macroeconometric approaches, such as Carraro and Galeotti (1997). Carraro and Galeotti decompose capital into "energy-saving" or "energy consuming" stocks, with the idea that policies affect the incentives of firms to invest in R&D in each of these types of capital. Carraro and Galeotti (1997) infer technical progress econometrically by examining the dynamics of other variables. Specifically, a latent variable structural equation is used to extract information about TC without having an exact representation of TC.

then implement some of the resulting insights in a numerical general equilibrium model that endogenizes TC, with a particular emphasis on spillover effects.

Specifically, in their general equilibrium model, Goulder and Schneider divide the knowledge stock into appropriable knowledge (H) and non-excludable knowledge ($\bar{H}$). The non-excludable knowledge represents the spillover knowledge enjoyed by all firms in each industry (but not across industries). A scaling factor, $\gamma(\bar{H})$, is then used to determine the effect of $\bar{H}$ on output in the CES production function for a representative firm in each industry:

$$Q = \gamma(\bar{H})(\alpha_H H^{\rho} + \alpha_G G^{\rho})^{1/\rho}, \tag{16}$$

where Q is output, G is an aggregate of all other production inputs (labor, ordinary capital, and several intermediate inputs), and the α's and ρ are parameters. There are four intermediate goods industries (conventional energy, alternative energy, energy-intensive materials, and other materials), and three industries that produce final goods or services (new physical capital investment, R&D service goods, and general consumption goods). The scaling factor $\gamma(\bar{H})$ is an increasing function of non-excludable knowledge that levels off to a constant in the long run in order to allow for steady-state growth. Note that this production function implies that for each representative firm, R&D will influence output both through the firm's input of appropriable knowledge and the spillovers from non-excludable knowledge generated in the industry.

In particular, Goulder and Schneider assume that appropriable knowledge capital accumulates linearly with R&D expenditure:

$$H_{t+1} = H_t + \varepsilon R_t, \tag{17}$$

where R_t is the real expenditure on R&D at time t,[10] and ε is a constant governing the rate at which R&D services increase the appropriable knowledge stock. Note that this specification implies that appropriable knowledge capital does not depreciate (a departure from how the physical capital stock is treated). Goulder and Schneider find that the qualitative results do not depend greatly on the specification in (17) but rather depend on the initial differences across

[10] Goulder and Schneider (1999) assume a single representative firm for each industry, so R_t is also the industry-wide expenditure on R&D at time t.

industries in the marginal social returns to R&D due to asymmetries in both spillovers and the tax treatment of R&D.

Spillovers derived from the production of non-excludable knowledge $\bar{H}$ are a critical component driving the model results, as can be seen by the scaling factor $\gamma(\bar{H})$ in the firm's production function in equation (16). Non-excludable knowledge is assumed to accumulate in the same manner as appropriable knowledge

$$\overline{H}_{t+1} = \overline{H}_t + \beta \overline{R}_t \,, \tag{18}$$

where $\overline{R}_t$ is the industry-wide expenditure on R&D at time *t* (i.e., $\overline{R}_t = R_t$), and β is a parameter governing the magnitude of potential spillovers ($\beta = 0$ represents the case of no spillovers). Firms are assumed to have perfect foresight and make investment decisions in physical capital and R&D to maximize the present value of the firm. Model runs are made with different assumptions about pre-existing distortions in the R&D market, which depend on the array and magnitude of knowledge spillovers (e.g., value of β in different industries), as well as the industrial allocation and scope of prior subsidies to R&D. Goulder and Schneider apply the model to assess the consequences of carbon tax and R&D subsidy policies with and without these prior distortions.

Goulder and Schneider find that the presence of ETC in their model leads to lower costs of achieving a given abatement target, but higher gross costs of a given carbon tax (i.e., costs before netting out climate benefits). In fact, both costs and benefits of a given carbon tax are higher relative to their model with only exogenous TC (where H is exogenous and $\beta = 0$), due to more extensive carbon abatement, for the economy responds more elastically to price shocks from the policy. With environmental benefits included, Goulder and Schneider find greater net benefits of this higher abatement level for a given carbon tax when ETC is present. This outcome can be reinforced or muted if there are prior distortions in R&D markets, depending on the type of distortions.

One important feature underlying these results is a crowding out effect where expansion of knowledge generation in one sector comes at a cost to other sectors due to the limited pool of knowledge-generating resources (i.e., there is a positive and increasing opportunity cost to R&D). A carbon-tax policy serves to spur R&D in the alternative energy sector, but discourages

R&D in non-energy and conventional energy sectors due both to slower growth of output in those industries and the limited pool of knowledge-generating resources.[11]

On the other hand, the knowledge spillover effects, whereby policy-induced R&D has social returns above private returns, provide additional benefits from a climate policy above the environmental benefits. However, the presence of ETC with spillovers does not imply the possibility of zero-cost carbon abatement, unless the spillovers overwhelm the crowding out effect, a largely empirical question. In a separate model run, Goulder and Schneider find that private R&D subsidies only play a role when TC is endogenous, and their effect is found to be contingent on the size of the knowledge spillovers (the β parameter), as one would expect.

Sue Wing (2003) incorporates ETC into a complex general equilibrium model, building off several of the concepts in Goulder and Schneider (1999) and some of the other papers discussed above. At the core of Sue Wing's model is a recursive, dynamic general equilibrium model in which a representative agent maximizes welfare. Producing industries maximize profits subject to the technologies of production and consumption, the economy's endowments of primary factors and natural resources, and existing taxes and distortions. The agent leases the services of the endowed factors of production to the industries to produce commodities, which provides the income used to pay for consumption, investment, and R&D.

A major difference between Sue Wing's model and previous models is that Sue Wing further separates out several of the factors influencing innovation to gain insight into the general equilibrium effects of inducing innovation in one sector and its consequences for the cost of carbon policies. Conceptually, Sue Wing describes his approach in terms of two commodities: a "clean" commodity (C) and a "dirty" commodity (D). There is one industry for each, and both commodities are used as input to production. Each industry i has a production function at time t given by

$$Y_i(t) = \phi[v_i(t), Q_i(t)], \tag{19}$$

[11] Goulder and Schneider (1999) model the entire pool of knowledge-generating resources as inelastic, but in the long run it may be more elastic, for example through increases in the pool of R&D labor.

where $Y_i(t)$ is each industry's output after adjustment for knowledge services, ϕ is a nested CES function, $v_i(t)$ reflects "intangible knowledge services," and Q_{ti} is each industry's nested CES production function (in terms of intermediate goods and other factors of production). Technical change is the effect of $v_i(t)$ on each industry's production function (shifting the envelope of possibilities for substituting clean inputs for dirty inputs). Intangible knowledge services allocated to each industry, $v_i(t)$, are modeled as a function of the rate of return to R&D investment (also a function of the prices of output in a given sector), as follows:

$$v_i(t) = \vartheta(p_i(t), \overline{H}(t)), \qquad (20)$$

where $p_i(t)$ is the price of output from each industry, and $\overline{H}(t)$ is the aggregate knowledge stock over all industries. The function ϑ is assumed to be increasing with both prices and the knowledge stock. This formulation allows for the inter-sectoral distribution of knowledge services to be shifted by changing relative prices, even if the stock of knowledge remains constant. The aggregate knowledge stock accumulates over time as a function of economywide R&D investment:

$$\dot{\overline{H}}(t) = \varpi(\overline{R}(t), \overline{H}(t)), \qquad (21)$$

where $\overline{R}(t)$ is the economywide R&D investment. The function ϖ is assumed to be increasing with $\overline{R}(t)$ and decreasing with $\overline{H}(t)$, implying diminishing returns to knowledge. Finally, R&D investment is determined by a fixed marginal propensity to save and the relative cost of tangible and intangible investment.

Using this formulation of ETC within a numerical general equilibrium model, Sue Wing (2003) finds that a carbon tax reduces aggregate R&D, slowing the rate of TC and the growth in output. Given his fixed-saving rule and absence of knowledge spillovers, this follows from having a less efficient, smaller economy. However, the relative price effects of a carbon tax lead to considerable reallocation of knowledge services, enabling the economy to adjust to the carbon tax in a more elastic manner, reducing the total costs of the carbon tax. Sue Wing finds that this effect of ETC is substantial due to shifting of knowledge services.

Summary and Distinctions

This overview of approaches to modeling R&D-induced TC, while by no means comprehensive, captures the potential pathways through which TC has been endogenized as a function of R&D. Other recent studies with explicit R&D-induced TC include Popp (2004); Bollen, Manders, and Veenendaal (2004); Schneider and Goulder (1997); and Grubb, Chapuis, and Duong (1995).

Given the great diversity of model structures with R&D-induced TC, some important distinctions are warranted to clarify the approaches and explain certain implications of the modeling methodologies. First, it is important whether R&D activity has been chosen optimally in the calibrated base case or whether it is subject to potentially correctable distortions. The models above differ in whether there are prior distortions in the R&D market, what type of distortions these are, and the potential for policy interventions to partially correct or exacerbate the distortions with corresponding welfare benefits and costs.

Another important distinction is the elasticity of the supply, or opportunity cost, of additional R&D. If there is a relatively inelastic supply of R&D (e.g., capable engineers and scientists), more effort on climate mitigation R&D reduces the ability of other firms or sectors to perform R&D, effectively crowding out R&D activity. This R&D crowding out behavior is evident in several models, where a subsidy or tax policy that induces energy-saving R&D will decrease R&D in other sectors of the economy, potentially decreasing aggregate economic output (e.g., Nordhaus (2002); Goulder and Schneider (1999); and Sue Wing (2003)). This implies that the cost of a carbon constraint could be more or less costly with the inclusion of ETC (versus presumptively leading to lower costs).

On the flip side of crowding out, there are spillover effects, or the degree to which R&D by any specific sector or firm is non-excludable. In other words, it is the degree to which firms, in equilibrium, fail to capture the full benefits of their R&D choices. With spillovers, we have a preexisting market failure (i.e., social returns above private returns) that may be partially corrected by an emissions policy and more directly by an R&D policy. Spillovers have been used in various ways in the papers described above, but in nearly all cases, more spillovers tend to imply a lower cost of achieving a given carbon constraint due to a partial correction of the R&D market imperfection.

There clearly exists a tension between spillovers and crowding out, with the former pointing to greater cost savings when ETC is included and the latter dampening or even overturning that effect. In many models, the degree to which spillovers and crowding out arise is a complex interaction among underlying assumptions about model structure and distortions in the R&D market; the direction and magnitude of effects only can be gleaned by simulating the model. Yet, these assumptions have important ramifications for the total cost of a climate policy as well as the conclusions drawn about the degree to which previous estimates based on exogenous technology assumptions are biased.

It is worth noting that spillover effects are considered the dual of appropriability issues (Clarke and Weyant 2002). The divergence between private returns and social returns arises because of an inability to appropriate gains outside the firm. If a firm successfully can appropriate the profits of R&D expenditure, it will have more incentive to undertake R&D and the social returns of that R&D will converge with the private returns. The opposite also holds: If firms appropriate less of the profits of their R&D, they will be less likely to undertake R&D and the R&D they do undertake will have high social returns due to unappropriated spillover effects.

Whether models are couched in terms of spillovers or appropriability, it is important to keep in mind that R&D market failures generally are hard to correct. A recent paper by Otto et al. (2006) points out that while a climate policy focused in part on technological change can have lower costs than one only focused on mitigation, a policy that solved the general R&D market failure would have huge gains. However, such policies are hard to come by in practice.

Regardless, the relative price of energy clearly has a role in influencing the direction of TC even if effects on the overall level of R&D are limited, and even if the effect on costs is ambiguous.[12] Higher prices of inputs to production create an incentive to improve technology to

[12] It potentially also could boost the rate of productivity growth (e.g., Jorgenson and Wilcoxen 1993), but absent a market failure in the model (whether explicit or implicit), this should not increase welfare.

economize on the use of such inputs. In the case of energy, this would imply that a carbon policy encourages R&D investment directed at lowering the costs of such a policy. For example, Sue Wing (2003) hypothesizes that relative prices affect how the “knowledge services” from the knowledge capital are allocated throughout the economy. This concept of ETC has strong implications for the way innovation is reallocated under a carbon policy in its attempt to reduce policy costs.

Learning-Induced TC

Learning-induced TC approaches tend to be quite different than R&D-induced approaches. In this section, the history and concepts behind learning will be discussed first, followed by a brief discussion of some approaches.

A long-recognized concept, technological learning first was quantified by Wright (1936) for the aircraft industry. He noted that unit labor costs in airframe manufacturing declined with accumulated experience, as measured by cumulative output. In economics, the concept is often described as learning-by-doing and generally is defined as the decrease in costs to manufacturers as a function of cumulative output, or “learning-by-using,” and the decrease in costs (and/or increase in benefits) to consumers as a function of the use of a technology (Arrow 1962; Rosenberg 1982).[13] Learning-by-doing commonly is measured in the form of “learning” or “experience” curves in terms of how much unit costs decline as a function of experience or production. Frequently, such curves are estimated in log-log form.

Historically, learning curves have been observed in many industries and are a well-established empirical concept (Azar and Dowlatabadi 1999; Grübler, Nakicenovic, and Victor 1999; Loschel 2002). They implicitly take into account in a reduced form all the parameters that influence the total costs of a product as it moves through the development stages toward becoming a mature technology. These parameters include those that govern production improvements, product development, and decreases in process input costs (Neij 1997). Learning

[13] Note that “learning-by-searching” (based on cumulative R&D expenditures) also has been used in the literature, but it is essentially R&D-induced TC.

curves have the advantage of employing an empirically validated concept to endogenize TC in a relatively straightforward manner.

Learning also may introduce “path dependencies,” as is considered critical by some analysts (e.g., Grubb, Köhler, and Anderson (2002); Ruttan (2002)). A process is considered path-dependent when the sequence of historical events predicates future possibilities, possibly leading to an irreversible “lock-in” of a particular technology pathway (Clarke and Weyant 2002). Including learning as TC can create a path dependency through its very nature as a self-reinforcing process: the more experience is accumulated with one technology, the lower its cost and the more competitive the technology is, leading to even more accumulated experience relative to other choices. This has been described as a “virtuous cycle” (Grubb 1997).

The primary disadvantage to learning-induced TC is its reduced-form nature—it can be inserted mechanically into a model, but it is difficult to quantitatively identify the determinants of LBD—or even be confident about the causality. The ease with which learning curves can be estimated gives a false sense of comfort and precision that may belie the R&D or other resources that went into the technology development (Clarke and Weyant 2002). For instance, it may be that the part of the underlying force driving learning curves is R&D, through the following scenario: when production costs drop, the potential competitiveness of the product increases, increasing the rate of return on additional R&D, inducing more R&D, which lowers the costs further and at the same time spurs more production. In this case, there are unaccounted for R&D costs that a reduced-form LBD approach does not capture.

Sue Wing (2001) expresses two additional reservations about learning-induced TC. First, he finds a lack of empirical data on the relative rates of learning in several advanced energy technologies, making model parameterization difficult. Second, he sees a disregard for the general equilibrium effects of learning-induced productivity improvements that may influence final results in models that include learning. For instance, if there is LBD in carbon-free energy technologies, with lower costs, demand will increase, leading to a shift from carbon-intensive energy technologies. This would tend to lower the demand for carbon-intensive energy technologies, lowering their price (if supply is upward sloping) and changing the relative price ratio between carbon-free and carbon-intensive energy so that it is less favorable than it once was. This would serve to slow the market penetration of carbon-free energy technologies.

Specific Approaches

Despite its disadvantages, the empirical tractability of learning curves has led to the use of learning-induced TC throughout the literature, particularly in disaggregated "bottom-up" models. Disaggregated models are well-suited for incorporating learning because of their rich technology specificity, which more easily lends itself to a learning curve for each technology. Some more aggregated models also use learning, but it is not as common. One reason is that learning tends to be thought of as a technology-specific phenomenon and therefore is harder to apply in the typical aggregation of a "top-down" model.

The most common way to capture learning-induced TC in climate policy models is based on an exponential relation between unit cost and cumulative output:

$$C(K) = \alpha K^{-\beta}, \tag{23}$$

where C is the unit cost of a technology, K is the cumulative installed capacity (or cumulative output), α is the cost of the first unit (a normalization parameter), and β is the learning elasticity. This implies that a doubling of experience will reduce specific costs by a factor of $2^{-\beta}$, also known as the progress rate. This formulation only requires the output and cost history to parameterize the learning function. However, the non-convexity of the problem solution has been an algorithmic hurdle to incorporating this learning function in some optimization frameworks (Grübler and Messner 1998). Manne and Barreto (2004) explore some of these issues and suggest potential solutions.

A common result of including ETC through LBD is that the carbon tax needed to attain a specific CO_2 concentration target tends to be lower than in models without LBD or with LBD turned off. This result is intuitive—with LBD modeled as described above, no R&D expenditure is needed and any additional capacity of carbon-free energy technologies will lower the costs of that technology in the future, leading to more emissions reductions per dollar of further investment.

Another commonly observed result of incorporating LBD in climate policy models is that the optimal abatement path to reach a given concentration target involves increased near-term abatement and less abatement later (Grübler and Messner 1998). This result occurs because increased near-term abatement encourages earlier LBD in low-carbon technologies, which lowers the long-term costs of abatement.[14]

Other studies suggest that there are actually two factors. On one hand, there is the added value to near-term technology investment due to LBD, as just mentioned. On the other hand, LBD also leads to lower costs of future abatement, which implies that abatement should be delayed. The net result of the two opposing effects may be theoretically ambiguous, but numerical simulations by Manne and Richels (2004) suggest that the slope of the abatement curve over time actually may be steeper with LBD included, contrary to previous findings, such as those of Grübler and Messner (1998) described above. Goulder and Mathai (2000) also find an ambiguous result, with only a weak effect of ETC on the optimal abatement path.

To model LBD, Goulder and Mathai (2000) adjust their formulation of knowledge accumulation given above in (15), by replacing the R&D investment (I) with the level of abatement (A):

$$\dot{H}_t = \alpha H_t + \Psi(A_t, H_t), \tag{24}$$

where again $\dot{H}$ is the accumulation of knowledge, α is a parameter, and Ψ is a function of abatement and the knowledge stock, with the same characteristics as Ψ in equation (15). With this specification, current abatement acts as a learning investment in knowledge, analogous to R&D investment. The result is similar to many other LBD studies in that both the optimal carbon tax is lower at all points in time and that there may be considerably more total abatement for any given carbon tax. Analogously, for any given path of abatement, the necessary carbon tax is

[14] Note this runs counter to a common argument that a gradual increase in near-term abatement is optimal in order to avoid premature obsolescence of the existing capital stock and allow more time for low-cost substitutes to be developed.

lower. However, as mentioned above, the effect of LBD on the slope of the optimal path of abatement is ambiguous.

A hybrid approach that includes both LBD- and R&D-based TC has been used in a few studies. For example, Fischer and Newell (2005) model the knowledge stock (an input into the cost function for a particular industry) as a constant elasticity of substitution function of cumulative R&D, H_t, and cumulative output, Q_t, as follows:

$$K_t(Q_t, H_t) = \left(\frac{Q_t}{Q_1}\right)^{k_1}\left(\frac{H_t}{H_1}\right)^{k_2}, \tag{25}$$

where k_1 and k_2 are parameters. They take considerable care in basing technological parameter values in their model on econometric studies of technological change and other evidence. A somewhat similar formulation also is used in Bahn and Kypreos (2003), who add a “two-factor” learning curve to the MERGE model (see Manne and Richels (2004)).

Many other climate change policy-modeling studies have included some form of learning-induced TC, usually with a variant of (22), including: Grübler and Messner (1998); Seebregts (1999); Gritsevskyi and Nakicenovic (2000); van der Zwann et al. (2002); Anderson and Bird (1992); Papathanasiou and Anderson (2001); Castelnuovo and Galeotti (2003); Gerlagh and Lise (2003); Gerlagh and van der Zwann (2003); Jacoby, Reilly, and McFarland (2003); Messner (1997); and Mulder, de Groot, and Hofkes (2003). The NEMS industrial and electricity modules also include LBD (EIA 2003).

Conclusion

Given the considerable variety of approaches used to include ETC in climate policy models, it is clear that there is no agreement in the literature regarding a “correct” approach. All of the approaches discussed in this paper have their limitations, and all are approximations that miss some important phenomena underlying the complex relationship of TC with the results of climate policy models. Perhaps more importantly, all struggle with an inherent lack of empirical data to calibrate model parameters convincingly. Below are some key insights from this review for consideration by both modelers and users of model results. Our focus has been on R&D- and learning-based approaches (versus price-induced), as most recent developments in endogenizing TC fall into these categories.

Three main points are worth emphasizing with regard to R&D-based approaches: 1) they are most easily used in more aggregate models; 2) they engender a tension between spillovers and crowding out; and 3) the empirical evidence underlying many of the relationships in R&D-based approaches remains somewhat weak. Each of these points will be addressed in turn.

First, R&D-based approaches lend themselves more easily to highly aggregated, forward-looking models with an explicit production function. In this approach, R&D is treated as an investment in a knowledge stock, which is an input into production similar to physical capital. Among aggregate models, those that consider the profit-maximization condition of firms tend to have an easier time incorporating R&D because they more easily incorporate the divergence between social returns and private returns.[15]

Regardless of the model structure, the treatment of both crowding out and spillover assumptions are highly important. Several studies have spillovers that scale the output of the production function and find that the optimal carbon policy is different when spillovers are included. Spillovers have important consequences for measuring welfare effects because they represent a source of potential welfare improvements (i.e., a market failure).

A considerable difficulty in endogenizing TC based on R&D lies in determining the values of the key parameters. This also is more broadly true of many of the relationships theorized in the model structures described in this paper, which have not been fully empirically validated (if at all). Choosing a functional specification that fits best within any given model, but at the same time is empirically valid, is not an easy task. Nor is it an easy task to consider both public R&D and private R&D. Few, if any, models attempt to address both explicitly due to the difficulties in modeling and measuring each—yet there are likely to be interactions between the two that are important to climate policy.

[15] See Fischer and Newell (2005), who explicitly address the divergence in first-order conditions between social and firm-level optimization regarding knowledge investments.

Distinct from the explicit R&D pathway, many LBD-based models have sought to include an association between falling unit production costs and cumulative output or experience with a technology. Three main points are worth emphasizing with regard to these learning approaches: 1) they are most readily used in technology-rich models; 2) they capture an apparent empirical regularity; and 3) there are questions about extrapolating these approaches to new technologies and causality.

First, in models replete with technological specificity, adding in learning appears to be a natural way to include ETC. At the technology level, empirical evidence supports the idea of a learning effect. Moreover, including this effect appears to have important implications for climate policy, such as lower costs of achieving a given carbon-mitigation target. In some cases, adding learning also changes the slope of the optimal abatement path for a given concentration target, implying more near-term reductions, although recent work has indicated that the effect of learning on the slope of the abatement is ambiguous.

However, LBD-based TC also has substantial problems. There is always the question of the validity of extrapolating historical evidence of learning in past technologies to new technologies. In addition, learning is a "black box," leading to questions of the causality of the reduced costs. For example, is the process of learning influenced by additional R&D investment, and, if so, is that R&D investment counted as a cost of the policy? Similarly, does learning in one technology come at the cost of learning in other technologies, and, if so, is this opportunity cost captured in the model?

Some efforts have been made to marry the R&D and learning approaches through learning-by-searching, where costs drop as an function of R&D expenditures (e.g., Bahn and Kyproes (2003)), but this specification suffers from many of the same issues that the more commonly employed LBD approach does. One of these issues is that there may be difficulties in finding a globally optimal solution, since the path-dependent nature of learning may lead to multiple optima. In addition, much as in the case of the R&D approach, there are difficulties in finding empirically robust values for the essential learning parameters, which have a large effect on results.

Despite these difficulties, with only a few exceptions most studies find that the ramifications and insights elucidated by incorporating ETC are important quantitatively. The methodology used to incorporate ETC ought to depend on the goal of the study: positive or normative. For positive analysis, models can be formulated in a variety of ways to generate predictions of prices and quantities that are as accurate as possible. In normative studies, it is much more important to have as transparent an accounting of opportunity costs as possible, and R&D-based TC has some advantages in this regard.

Modelers should consider the strengths and limitations of each approach to endogenizing technological change and experiment with the approaches that best correspond to the purpose and structure of the model, keeping in mind the possible biases inherent in choosing one approach over another. Users of model results should be aware of the substantial implications that these subtle assumptions can have on model results. Perhaps most importantly, users looking to draw normative conclusions about the costs and benefits of alternate policies need to be particularly aware of the degree to which models have been ground-truthed against historic facts and trends and ensure that opportunity costs have been accounted for properly. While exceptionally promising, there is a sense that our ability to model the phenomena technological change has outstripped our ability to validate the models empirically, making this an area where policymakers and other normative users need to be particularly careful.

Tables

Table 1. Technological Change Characteristics in Selected Climate Policy Models

Model	*Type*	*Representation of technological change*	*Reference*
SGM	CGE	EX	McCracken et al. (1999)
DICE/RICE	IAM	EX	Nordhaus (1994)
ETC-RICE	IAM	R&D	Buonanno, Carraro, and Galeotti (2003)
GEM-E3	CGE	EX	Capros et al. (1997)
DGEM	CGE/ME	EX	Jorgenson and Wilcoxen (1993)
GOULD-MATHAI	CF	LBD/R&D	Goulder and Mathai (2000)
GOULD-SCHNDR	CGE	R&D	Goulder and Schneider (1999)
GREEN	CGE	EX	Burniaux et al. (1992)
ICAM3	IAM	LBD/PR	Dowlatabadi (1998)
IMAGE	IAM	EX/PR	Alcamo, Kreileman, and Leemans (1998)
MARKAL	ES	LBD	Barreto and Kypreos (1999)
MESSAGE	ES	LBD	Grübler and Messner (1998)
MIT-EPPA	CGE	EX/PR/LBD	Jacoby, Reilly, and McFarland (2003)
Sue Wing-EPPA	CGE	R&D	Sue Wing (2001)
PACE	CGE	EX	Böhringer (1998)
POLES	ES	LBD	Kouvaritakis, Soria, and Isoard (2000)
R&DICE	IAM	R&D	Nordhaus (2002)
WARM	CGE/ME	R&D	Carraro and Galeotti (1997)
E3ME	ME	R&D	Barker and Köhler (1998)
G-CUBED	CGE	EX	McKibbin and Wilcoxen (1993)
PIZER	CGE/IAM	EX	Pizer (1999)
MACRO	CGE/IAM	EX	Manne and Richels (1992)
SMULDERS	CGE	R&D	Smulders and Nooij (2003)
NEMS	ES	EX/PR/LBD	EIA (2003)

Acronyms:

Models: CGE, macroeconomic computable general equilibrium model; ES, disaggregated energy technology and system model; IAM, integrated assessment model; ME, macroeconometric model; CF, cost-function model

Technological Change: EX (exogenous); LBD (learning-by-doing); PR (price-induced); R&D (research and development)

Source: Grubb, Kohler, and Anderson (2002); Loschel (2002); and authors.

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