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ENTICE-BR: THE EFFECTS OF BACKSTOP TECHNOLOGY R&D ON CLIMATE POLICY MODELS

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ABSTRACT

Recent attempts to endogenize technology in climate policy models have produced mixed results. Models including alternative technologies find large gains from induced technological change. However, technological progress in these models comes through learning-by-doing, which ignores the potential opportunity costs of technological change. Models using R&D spending as the driver of technological change address this. However, since these models typically include only a single representative energy technology, substitution across technologies is not possible. This paper addresses these shortcomings by including policy-induced energy R&D in a model with a backstop energy technology. I show that, while induced technological change is important, larger welfare gains come from simply adding an alternative technology to the model. As in models with a single technology, opportunity costs of research limit the role induced innovation can play. Moreover, since the backstop technology improves welfare even without climate policy, accurate policy analysis depends on a carefully constructed baseline simulation.

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Much debate over climate change policy revolves around the potential costs of such policies. Many economists argue that policy prescriptions such as those proposed by the Kyoto Protocol do too much, too quickly. Advocates of more stringent policies often point to the potential of new technologies to reduce the costs of complying with such stringent regulations. As much research has shown, environmental policies can be expected to induce technological change that makes reducing emissions less costly.[1] Nonetheless, until recently, most climate policy models did not explicitly link policy to technological improvements.

Recent attempts to endogenize technological change in climate models have produced varying results. In general, models predicting strong impacts of induced technological change (ITC) include several alternative technologies, and model technological improvements through learning-by-doing. Most models finding a limited role for ITC include only a single energy technology, and assume technological improvements result from increases in energy research and development (R&D) spending.

Each modeling strategy has potential drawbacks. While assuming that technology evolves via learning-by-doing may fit historical correlations between installed capacity and the cost of energy technologies, it treats such learning as a black box. As a result, learning-by-doing models do not address the costs of acquiring new knowledge. This is important because new energy R&D may crowd out other forms of R&D. Since the social rates of return to R&D are high, such crowding out has important macroeconomic effects. Models including energy R&D, such as Popp (2003) and Goulder and Schneider (1999), find that crowding out of other R&D limits the potential contributions of ITC.

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[1] See, for example, Lanjouw and Mody (1996), Jaffe and Palmer (1997), Newell, Jaffe, and Stavins (1999), and Popp (2002).

Alternatively, models that only include a representative energy technology allow for technology to increase energy efficiency, but do not offer the opportunity for new, carbon-free energy sources to develop. Such technologies, which are assumed abundant, and thus available at constant marginal cost, are commonly referred to as *backstop technologies*. Currently, the high costs of technologies such as wind and solar energy limit their potential contribution to energy consumption. However, one would expect climate policies to induce research lowering these costs. For example, Popp (2002) shows a dramatic increase in solar energy patents during the energy crisis of the 1970s. Because these energy technologies allow production to continue without increased carbon emissions, research that lowers the costs of such technologies could substantially lower the cost of achieving carbon emissions reductions.

To address these concerns, in this paper I introduce a model including both a backstop technology and ITC provided via research and development. The paper extends the ENTICE model (Popp 2003) to include research on both energy efficiency and a carbon-free backstop technology. I find that adding a backstop technology to the model does lower the costs of climate policies, and does increase the potential contribution of ITC. As in Popp (2003), the opportunity costs of R&D limit the role that ITC can play. In fact, the biggest gains come not from ITC, but from simply adding a backstop to the model. That is, even without ITC, the presence of a backstop technology lowers the costs of reducing carbon emissions. Moreover, some consumption of backstop energy technologies occurs even without climate policy. When considering the gains from policy, one should only consider the marginal changes in usage of the backstop technology that result. Thus, capturing a baseline scenario that accurately includes alternative energy sources is important.

I. Literature Review

Despite the growing evidence that environmental policy influences the direction of technological change, few climate change models directly incorporate links between policy and technology. Even fewer include a backstop technology. Models that include innovation typically do so in one of two ways. *Bottom-up* models include a detailed specification of energy systems, and usually include both traditional fossil fuels and alternative energy technologies. However, these models typically do not include detailed modeling of the overall macroeconomy, and typically model induced technological change in a learning-by-doing framework, in which the costs of various technologies decrease with experience. Examples include Grübler and Messner (1998), Manne and Richels (2002), and Messner (1997). Because these models endogenize technology through learning-by-doing, rather than purposeful R&D investment, they miss the potential opportunity costs that may result when energy R&D crowds out other inventive activity. As Popp (2003) shows, ignoring potential crowding out significantly overstates the potential role of induced technological change.

In comparison, *top-down* models focus on the links between environmental policy and macroeconomic performance. Endogenous technological change in these models typically comes through accumulated investment in research and development (R&D). Examples include Popp (2003), Buonanno *et al.* (2003), Nordhaus (2002), and Goulder and Schneider (1999). In these models, potential crowding out between energy and other types of R&D limit the potential of induced technological change.[2] The importance of crowding out is explored in Popp (2003). That paper includes three simulations with ITC: one with complete crowding out of other R&D, one with partial crowding out, and one with no crowding out. In the base case, with partial

(50%) crowding out of other R&D from new energy R&D, ITC improves welfare by 9.4%. This falls as low as 1.9% with full crowding out, and increases to as much as 45.3% without crowding out.[3]

While these models present a more realistic view of the nature of R&D markets, they do not provide realistic alternatives of energy technologies. Only Goulder and Schneider include non-fossil fuel alternative energy sources. However, as Gerlagh and van der Zwaan (2003) note, Goulder and Schneider assume that fossil and non-fossil fuel energy sources are complements, rather than substitutes. This limits the potential role that fuel-switching may play. Recent work by Gerlagh and van der Zwaan addresses this shortcoming by including a backstop technology in a top-down modeling framework. Van der Zwaan *et al*. (2002) introduces the DEMETER model, in which induced technological change affects the non-fossil fuel input via learning-by-doing that lowers its costs. This work, as well as Gerlagh and van der Zwaan (2003), finds greater potential for ITC than other top-down models. However, since technology improves via learning-by-doing, the potential opportunity costs of R&D are ignored. Thus, it isn't clear whether the gains they observe result from the addition of a backstop technology, or from the assumption of learning-by-doing.[4] In comparison, this paper includes both a backstop technology and technological progress through R&D. Thus, I am able to explore the role that crowding out may play in limiting the gains from ITC. I find that, while adding alternative

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[2] The exception is Buonanno *et al*. (2003), which include a single stock of R&D that improves both total factor productivity and energy efficiency. Not surprisingly, this complementary (although unrealistic) relationship between energy R&D and other R&D leads to large welfare gains from induced technological change.

[3] Macro level data from the U.S. support the notion of partial crowding out. For example, a regression of non-energy R&D on energy R&D provides the following results:
(standard errors in parenthesis):

$$\underset{(4762.59)}{\textit{non-energy R\&D} = -9320.351478} \; \underset{(1.09)}{-0.41}\,\textit{energy R\&D} + \underset{(0.73)}{19.82}\,GDP + \varepsilon$$

[4] A recent working paper by Gerlagh and Lise (2003) modifies the DEMETER model to include both learning-by-doing and R&D spending. However, that model only includes the energy sector, and thus does not allow for potential macroeconomic feedbacks of climate policy.

technologies to the model is important, crowding out effects still limit the potential gains from ITC.

II. The Model

This paper extends the ENTICE model of climate change policy (Popp 2003) by adding a backstop technology. Below I present key equations in the revised ENTICE model, referred to as ENTICE-BR to note the inclusion of backstop R&D. Appendix A includes a complete list of all equations in the model.

ENTICE is a modified version of the DICE model (Nordhaus 1994, Nordhaus and Boyer 2000) that includes endogenous links between climate policy and energy innovation. Like DICE, ENTICE is a dynamic growth model of the global economy that includes links between economic activity, carbon emissions, and the climate. It includes fossil fuels as an input to production, as in the more detailed RICE model (Nordhaus and Yang 1996, Nordhaus and Boyer 2000). However, ENTICE retains the global framework of the DICE model, rather than dividing the world into separate regions. Given the limited empirical information available on international diffusion of environmental technologies, calibrating a regional model is left for future research.

In both the DICE and ENTICE models, the goal of the model is to maximize per capita utility, equation (1), subject to the economic constraints below [equations (2)-(11)].[5]

(1) $$\max V = \sum_{t=0}^{T} U_t[c_t, L_t]R_t$$

[5] Environmental equations remain unchanged from the DICE model, and are not presented here. They are included in an appendix available from the author.

In this equation, U_t represents utility at time t, c_t is per capita consumption, L_t represents population, and is also the measure of labor inputs. R_t is a discount factor to represent the rate of time preference.[6]

The objective function, (1), is maximized subject to the following constraints. First, production is defined. Below, Q_t represents output produced at time t. Overall technological progress comes through changes in total factor productivity, A_t. Inputs include labor, L_t, the physical capital stock, K_t, and effective energy units, E_t. Effective energy units are a measure of the productive capabilities of three possible energy inputs: fossil fuels, F_t, a carbon-free backstop technology, B_t, and knowledge pertaining to energy efficiency, $H_{E,t}$. $p_{F.t}$ and $p_{B,t}$ represent the cost of fossil fuels and the backstop fuel, respectively. Note that both prices vary over time. The cost of these fuels are subtracted from total output in the ENTICE-BR model:[7]

(2) $$Q_t = A_t K_t^{\gamma} L_t^{1-\gamma-\beta} E_t^{\beta} - p_{F,t} F_t - p_{B,t} B_t$$

Labor is determined by exogenous population growth. The capital stock, K_t, equals the sum of current investment, I_t, and the previous capital stock, adjusted for depreciation, δ:

(3) $$K_t = I_t + (1-\delta)K_{t-1}.$$

[6] As many economists have recently noted, discount rates that seem appropriate for single-generation projects may be inappropriate for long term projects that span several generations. Although there is no consensus on how to deal with this problem, a constantly declining discount factor is consistent with suggestions that a lower discount rate should be used for the distant future. Thus, following Nordhaus, the pure rate of social time preference, R, declines over time to capture uncertainty over future conditions, and is given by $R(t) = \prod_{v=0}^{t} \left[1 + R_0 e^{-g_r t}\right]^{10}$, where g_R is a parameter defining the growth of R over time. Portney and Weyant (1999) provide a good review of the current debate on discounting for long-term environmental projects.

[7] Energy consumption, represented by fossil fuel usage, F, is measured in tons of carbon. The price of fossil fuels is thus the price per ton of carbon. Backstop energy units are converted to represent the equivalence of one ton of carbon-based energy.

A. The Energy Sector

Effective energy units, E_t, uses a nested constant elasticity of substitution (CES) framework to aggregate the contributions of fossil fuels, the backstop energy source, and knowledge pertaining to energy efficiency. Popp (2003) uses a similar framework in the ENTICE model without backstop energy. The second nest, between fossil fuels and the backstop technology, is introduced in van der Zwaan *et al*. (2002). One advantage of using this functional form is that it provides a more realistic evolution of the backstop technology over time. By modeling the backstop and fossil fuels are imperfect substitutes, it allows for the possibility of "niche markets" for the backstop technology even when the price of the backstop exceeds fossil fuel prices. In each nest, the ease of substitution is represented by ρ_i. The case of perfect substitution is $\rho_i = 1$. The elasticity of substitution is $1/(1-\rho_i)$. Given this, effective energy units are modeled as:

$$(4) \qquad E_t = \left[\alpha_H H_{E,t}^{\rho_H} + \left(\left(\frac{F_t}{\alpha_\Phi \Phi_t} \right)^{\rho_B} + B_t^{\rho_B} \right)^{\rho_H / \rho_B} \right]^{1/\rho_H}$$

Equation (4) states that the total energy requirements for production must be met either by the use of fossil fuel or by technological advances that substitute for fossil fuels. Note that technology enters equation (4) in one of two ways. $H_{E,t}$ represents technological advances that replace fuels in production, and can thus be thought of as improvements to energy efficiency. This stock of knowledge responds endogenously to changes in policy, through an invention possibilities frontier that is described below. α_H is a scaling factor that determines the level of energy savings resulting from new knowledge. Technology also enters exogenously through Φ_t, which represents exogenous changes in the ratio of carbon emissions per unit of carbon services.

Φ_t decreases over time as defined below, where g_t^z is the (negative) growth rate of Φ_t per decade, and δ^z is the rate of decline of this growth rate.

(5) $$\Phi_t = \exp\left[\left(\frac{g_t^z}{\delta^z}\right)\left(1-\exp\left(-\delta^z t\right)\right)\right]$$

The parameters defining Φ_t are first calibrated to match the emissions path of the DICE model in a model without R&D. α_Φ represents the percentage of this exogenous technological change that remains once R&D is added to the ENTICE model.

This remaining technological change is retained so that emissions in the baseline (no policy) simulation with R&D replicate the results of the DICE model without R&D. The R&D modeled in ENTICE-BR captures purposeful short-term efforts to improve energy efficiency or lower the costs of the backstop technology. However, such R&D is not the only way in which carbon intensity falls over time. Examples of other potential influences on carbon intensity include changes in consumption patterns and switching to less carbon intensive fuels (e.g. from coal to oil to natural gas) over time. Because the DICE model and its variants are a one-sector macroeconomic growth model, such changes are not explicitly modeled. Since Nordhaus calibrates exogenous technological change based on historical rates of decarbonization, it is impossible to separate out these effects from the effects of R&D in his rate of exogenous technological change. As a result, long-run emissions simulated without any exogenous decline in carbon-intensity are unrealistically high.[8]

Because differences in the costs of fossil fuels and the backstop technology will affect their relative usage, defining the costs of each is important. Following Nordhaus and Boyer

[8] Fortunately, sensitivity analysis suggests that the percentage of exogenous technological change remaining does not affect the net economic impact of induced technological change. The intuition is that it is the level of R&D induced between an exogenous and endogenous R&D simulation that affects this difference. Changing the scaling

(2000), the price of carbon is the sum of the marginal cost of carbon extraction, $q_{F,t}$, and a markup that captures the difference between consumer prices and the marginal costs of extraction. Nordhaus notes that this markup includes transportation costs, distribution costs, and current taxes. For ENTICE, I use a weighted average of regional markups from RICE, weighting by each region's share of total carbon consumption in the base year. This value equals 163.29.

(6) $P_{F,t} = q_{F,t} + 163.29$

Following Nordhaus, the marginal cost function, $q_{F,t}$, takes the following form:

(7) $$q_{F,t} = 113 + 700[CumC_t / CumC^*]^4$$

$CumC_t$ represents cumulative carbon extraction up to year t, and $CumC^*$ represents the maximum possible extraction. In this equation, the marginal cost independent of exhaustion is \$113 per ton. Marginal costs increase as extraction increases. Note that the price equation is extremely convex – the carbon price equation is relatively elastic in the short run.[9]

Backstop technologies are, by definition, technologies for which scarcity is not a concern. Thus, cumulative extraction does not affect the price of the backstop technology. Rather, the price falls over time as technology advances. Defining $H_{B,t}$ as the stock of knowledge pertaining to the backstop, and using η to represent the relationship between new knowledge and prices, the backstop price is:

(8) $$p_{B,t} = \frac{P_{B,0}}{H_{B,t}^{\eta}}$$

factor only changes the *level* of emissions in each simulation, but not the *difference* between them. This is discussed more thoroughly in the sensitivity analysis presented in Popp (2003).

[9] A more detailed discussion of the derivation of these parameters can be found in Nordhaus and Boyer (2000).

This specification is similar to that used in experience curves, (see for example, Ibenholt, 2002). In this specification, $1\text{-}2^{-\eta}$ provides the cost reduction that occurs from a doubling of the knowledge stock. This calculation is commonly referred to as the *progress ratio*.

B. Modeling Technological Change

Technological change enters the model through the two knowledge stocks defined above. Technological advances can improve energy efficiency ($H_{E,t}$) or lower the costs of using the backstop technology ($H_{B,t}$). Similar to a physical capital stock, these knowledge stocks are created by the accumulation of previous research and development (R&D) in the manner described below.

$$H_{i,t} = h(R_{i,t}) + \left(1 - \delta_H\right) \cdot H_{i,t-1}, \qquad i = E,B \tag{9}$$

Equation (9) states that the stock of knowledge, $H_{E,t}$, increases due to increases in R&D net depreciation of old knowledge. The function $h(R_{i,t})$ is the *innovation possibility frontier*. It models the process by which energy R&D, $R_{i,t}$, creates new knowledge. The parameter δ_H allows for the possibility of knowledge decay over time.[10]

To define the innovation possibility frontier, I begin with the assumption that there are diminishing returns to energy R&D over time. The assumption implies that since energy R&D is specialized within a given field, it becomes more and more difficult to find new inventions as the knowledge frontier moves out. Popp (2002) provides supporting evidence. Thus, any functional form for the innovation possibility frontier must have the following properties. First, the derivative of h with respect to R should be positive, but the second derivative should be negative, so that there are diminishing returns to research *at any given time*. In addition, the derivative

[10] Sensitivity to the decay rate is explored in Popp (2003). As in the base model in that paper, I assume a zero decay rate here, as this best replicates the expected patterns of energy R&D and energy savings in the base model.

$\partial^2 H/\partial R \partial H$ should be negative, so that there are diminishing returns to research *across time periods*. One functional form that satisfies these assumptions is a constant elasticity relationship between research and knowledge:

$$(10) \qquad h(R_{i,t}) = aR^{b_i}_{i,t}H^{\phi_i}_{i,t}, \qquad i = E,B$$

A similar innovation possibilities frontier is often used in the endogenous growth literature.[11] Equation (10) satisfies the two assumptions regarding diminishing returns to R&D as long as both b_i and ϕ_i are between 0 and 1.

Because of the public goods nature of knowledge, the role of market failures in R&D must be considered. Virtually all empirical studies of R&D find that the social returns to R&D are greater than the private returns to R&D.[12] Since firms will invest until the private rates of return to R&D are equal to the rates of returns on other investments, underinvestment in R&D will occur. To model the positive externalities that result from the creation of new knowledge, the return on R&D investment is constrained to be four times that of investment in physical capital.[13] Omitting such market failures implicitly assumes that government policies, such as R&D subsidies, will sufficiently augment private R&D efforts to correct market failures. Popp (2003) shows that such an assumption nearly doubles the potential gains from ITC.

Finally, we need to account for the opportunity cost of R&D. This is important because empirical work suggests that at least some energy R&D will replace other forms of R&D. Research activities are carried out by highly-trained scientists and engineers. Since years of

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[11] See, for example, Jones (1995) and Porter and Stern (2000). Romer's (1990) original specification of the endogenous growth model is a special case of this where $\phi = 1$. By setting $\phi = 1$, Romer generates increasing returns to knowledge over time. While this may be appropriate for macro-level R&D, for more specific R&D in a given field, it is reasonable to assume that the returns fall over time as the pool of potential ideas in the field dries up (see, for example, Griliches (1989, p. 317)).

[12] There is a large body of empirical work that verifies the social returns to R&D are greater than the private returns. Examples include Griliches (1995), Hall (1995), Jaffe (1986), Mansfield (1977, 1996), and Pakes (1985).

[13] This is done by calculating the marginal products of physical capital investment and energy R&D, and constraining the latter to be four times higher than the former.

training are needed to enter the field, the supply of scientists and engineers available at any one time is inelastic – it cannot quickly increase when new research needs arise. For example, Goolsbee (1998) finds that one of the chief beneficiaries of R&D tax subsidies are scientists and engineers, who receive larger wages when subsidies are increased.

To proceed, note that all output is devoted to either consumption, investment in physical capital, or R&D:

(11) $$Q_t = C_t + I_t + R_{E,t} + R_{B,t}$$

However, this simple accounting ignores the potential effects of crowding out. The opportunity cost of a dollar of energy R&D is that one less dollar is available for any of three possible activities: consumption, physical investment, or investment in other R&D.[14] The opportunity costs of the first two are simply valued at one dollar. However, since the social rate of return on R&D is four times higher that of other investment, losing a dollar of other R&D has the same effect as losing four dollars of other investment. Thus, the cost of any research that crowds out other research is four dollars.

To implement this, four dollars of private investment are subtracted from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock is:

(3') $$K_t = \{I_t - 4{*}crowdout{*}(R_{E,t} + R_{B,t})\} + (1-\delta)K_{t-1},$$

where *crowdout* represents the percentage of other R&D crowded out by energy R&D. Based on footnote 3, in the base case I assume new energy R&D crowds out 50% of other R&D.

[14] Here, I am referring to R&D designed to increase productivity in other sectors. Accounting for the opportunity cost of this research is important, since it is not explicitly included in the model.

C. Calibration

Calibration of the R&D sector of the ENTICE-BR model is based on results from the empirical literature on induced innovation. This section focuses on calibration of the backstop technology and its associated R&D. Details of calibration of energy efficiency R&D are discussed both in Popp (2003) and appendix B of this paper.

To begin, initial values for backstop R&D and backstop energy consumption are needed. Based on data in Anderson (1997), the initial value of backstop energy research, is set to equal 10 percent of energy efficiency R&D, or 1 billion dollars.[15] Following van der Zwaan *et al*. (2002), who use results from Nakicenovic *et al*. (1998), 4 percent of all energy consumption in 1995 comes from the backstop technology, for an initial value of 0.25 equivalent tons of carbon.

To determine the initial price of the backstop technology, two issues arise. First is that a wide range of possible prices exist. For example, the cost of wind energy varies depending on local conditions. In ideal conditions, the price of electricity from wind is nearing competitive levels. Burtraw *et al.* (1999) report the cost of wind energy to be 44% higher than that of energy from fossil fuels. This yields an initial price of $400 per carbon ton equivalent (CTE) of backstop energy. Gerlagh and Lise (2003) report prices for alternative energy sources ranging from 2 to 5 times that of fossil fuels. Using the upper range of this as a second alternative, I consider an initial price of $1200 as a second option. Second, because fossil-fuels and the backstop are imperfect substitutes, their relative prices determine the elasticity of substitution between energy sources. Unfortunately, the resulting elasticity of substitution using the prices

[15] The $10 billion figure for energy efficiency R&D is discussed in Popp (2003), and represents two percent of all R&D done in OECD countries in 1995.

mentioned above yield very high elasticities of substitution.[16] Thus, I also consider a starting price of \$2000 CTE. This provides more reasonable elasticities of backstop energy R&D, as the resulting elasticity of substitution is similar to that for energy efficiency R&D.[17]

Next, a value for η, which relates human capital to backstop price decreases, is chosen. Again, no good empirical estimates exist. Results for two values, 0.4 and 1.0, are presented. These yield progress ratios of 24 and 50 percent respectively. A 50 percent progress means that a doubling of the knowledge stock reduces the backstop price by 50 percent. More importantly, under realistic base case R&D scenarios, the share of energy consumption resulting time paths for backstop energy R&D are comparable to other studies. Such rapid progress is comparable to changes in patenting and prices during the past 20 years. The 24 percent progress ratio yields slightly lower shares of backstop energy than comparable scenarios. However, as shown in the results section, the marginal returns to R&D are more realistic. Thus, a 24 percent progress ratio is used for the base case.

Finally, the parameters of the inventions possibilities frontier are chosen as before. Key goals of the calibration include:

- Based on Popp (2002), the elasticity of energy R&D with respect to changes in energy prices is inelastic, with a target value of 0.35.
- As noted earlier, there are diminishing returns to energy R&D. Thus, the inducement effect of energy prices will fall over time.
- Both the response of energy R&D to price changes and the energy savings resulting from these new technologies occur quickly. Popp (2002) finds that mean lag for the

[16] This is important because, as shown later, high elasticities of substitution result in unrealistically high levels of policy-induced R&D.
[17] Although high, keep in mind that, for the elasticity of substitution, what matters is the price of the last backstop energy unit consumed. One would expect this to be higher than prices for technologies in ideal environments.

effect of energy prices on energy patenting is 3.7 years, and the median lag is 4.9. In addition, the energy savings resulting from new patents occur quickly. Popp (2001) finds that it takes just three years for a new energy patent to have its maximum effect on energy consumption. Since the responses are fairly quick, and since each time period in the ENTICE model represents one decade, I assume that the full effects of price changes on energy R&D occur within each decade.

To preserve these assumptions for energy efficiency R&D, the parameters *a* and *b* for energy efficiency R&D change slightly in simulations with and without a backstop technology, so that base case R&D is comparable in each. Table 1 lists the parameter values used for each assumption regarding the initial backstop price and the progress ratio.

III. Policy Simulations

With the completed ENTICE-BR model in hand, I proceed to simulate the results of imposing a carbon emissions policy on the global economy. There are two main questions to be explored: (1) what impact does adding a backstop technology (and its associated R&D) have on the model, and (2) does the role of induced technological change increase when a backstop is considered? The results suggest that the role of ITC does increase somewhat when a backstop is considered, but the largest welfare gains come not from endogenizing technological change, but rather from simply adding the backstop in the first place.

Results are considered for three possible scenarios, with three separate simulations contained with each scenario. The three scenarios are:

1) a business as usual (BAU) case that includes no policy constraints,

2) an optimal policy scenario in which the marginal costs of carbon abatement equal the marginal environmental benefits of reduced carbon emissions, and
3) a more restrictive command-and-control policy in which emissions are restricted to 1995 levels.[18]

Within each policy scenario, I consider three separate simulations:

1) ENTICE: this is the model from Popp (2003) that endogenizes energy R&D but does not include a backstop technology,
2) ENTICE-B: a backstop technology is added, but with a constant price over time, and
3) ENTICE-BR: a backstop technology is added, along with R&D that lowers the backstop price over time.

Furthermore, for each of the two policy simulations, I re-run the ENTICE-BR model with R&D fixed at BAU levels. Comparing this to the full ITC run provides the gains resulting from ITC under each of the two policies. I calculate the *net economic impact* of a policy as the present value of consumption under the policy minus the present value of consumption in the base case, in which carbon emissions are uncontrolled.

A. Business as Usual

One goal of this paper is to ascertain the impact of adding a backstop technology to the ENTCIE model. Thus, before examining the effect of the backstop technology under various policy scenarios, it is important to consider how the presence of a backstop technology alters the baseline simulation. Two important considerations are the rate at which the backstop price falls

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[18] The more restrictive policy is included because most climate policies proposed in the policy arena aim for far greater restrictions than called for in an optimizing economic model. For example, the Kyoto Protocol requires industrialized country emissions to be reduced by 5 to 8 percent below 1990 levels. Since the DICE model is global, capturing regional differences, such as the lack of restrictions on developing countries, is not possible. Thus, I use a slightly higher global emissions constraint to allow for higher emissions from developing countries.

and the contribution that the backstop technology plays in energy markets. Figures 1 and 2 illustrate each, respectively. For reference in the next section, values for the optimal policy simulation are also included in Figure 2.[19]

Considering costs first, note that these fall from 4 to 8% by 2025, 8 to 20% by 2055, and 14 to 30% by 2105. With a low initial price, the backstop price falls below the price of fossil fuels by 2065. To compare this to other projections, van der Zwaan *et al*. (2002) project cost decreases of 12% by 2025, and 40% by 2105. Messner (1997) projects cost decreases ranging from 35% to 60% for solar thermal to 45% to 58% for wind between 1990 and 2050. A study by the IEA (2002) predicts cost decreases of 30-40% for solar thermal and wind between 2000 and 2030. One reason why ENTICE-BR predicts slightly lower cost savings than these other studies is that it is the only one in which technological advances are explicitly modeled through R&D. As a result, it is the only model explicitly considering the opportunity costs of obtaining these advances.

Comparing the contribution of the backstop technology to total energy consumption, we find that, even without policy, the backstop contributes between 5 and 13% in 2025, 6 to 29% in 2055, and 8 to 64% in 2105.[20] In comparison, van der Zwaan *et al*. (2002) predict a share of about 7% by 2025, 12% by 2055, and 30% by 2105.[21] By 2050, Messner (1997) predicts shares of just 1% for solar and wind in a static model, and shares of 19% and 10% respectively under learning-by-doing. The EIA International Energy Outlook (2003) projects that hydropower and other renewable resources will contribute 7.8% of energy consumption by 2025. Thus, the short-

[19] Changes in price for the optimal policy scenario are not included, as they are very small (less than 1%).

[20] Although these ranges seem large, the big difference is between the low price scenario and the other two. The share of the backstop technology rises quickly in the low price scenario because the backstop price falls below the fossil fuel price by 2065. This scenario is likely overly optimistic about the potential contribution of a backstop technology, but is presented to illustrate the model's sensitivity to a range of assumptions.

[21] These figures are approximate, as they are extrapolated from figures in van der Zwaan *et al*. (2002).

run projections of the ENTICE-BR model are similar to other studies, and the long-run projections are slightly more conservative.

B. Optimal Policy

Because the DICE model and its variants incorporate environmental damages into the model, it is possible to calculate an optimal carbon policy, in which the marginal costs of carbon abatement equal the marginal benefits of lower emissions. Typically, simulations involving these models find that the optimal policy is to go slow. Since carbon emissions remain in the atmosphere for several hundred years, the marginal damages resulting from any new emissions are modest. Thus, gradually phasing in carbon reduction lowers the opportunity cost of reducing emissions without having much impact on the global climate. As an example, Nordhaus and Boyer (2000) calculate an optimal carbon tax in 2005 of $9.13 per ton. In comparison, restricting emissions to 1990 levels would require a carbon tax of $52.48.

Table 2 and Figure 3 summarize the welfare gains for the optimal policy scenario. Figure 3 illustrates the welfare gain for each of the three backstop price assumptions. Here, the comparison is between an optimal policy and BAU simulation with similar assumptions about the backstop technology. The welfare gains for the medium and high price scenario are comparable. Simply adding a backstop at a constant price enhances welfare by nearly 15%, and considering R&D that lowers the backstop price increases welfare by another 6-8%. In both cases, simple factor substitution is most important, as the major gains come from a model without a backstop technology. Gains are higher in the low price scenario, both with and without R&D, as the low initial price enables the backstop technology to become competitive even under a policy of moderate carbon taxes. Thus, the share of renewable energy increase more dramatically. As a result, adding both a backstop and backstop R&D increases welfare by over

60%, although again the largest gains come from simply adding a backstop technology to the model.

Table 2 provides more detail, and presents two separate welfare comparisons. First, the number in each cell on the left provides the welfare gain compared to a BAU simulation with no backstop technology. For example, with a medium backstop price, adding a backstop increases welfare by $4.87 billion compared to the BAU without a backstop, and adding a backstop with R&D increases welfare by $9.36 billion compared to the BAU without a backstop. These numbers illustrate the important effects of simply adding a backstop to a model. However, it is not right to say that the welfare gains from an optimal policy are $11.67 trillion when backstop R&D is added, because the appropriate comparison is across scenarios with similar assumptions under the policy and in the BAU scenario. Thus, reading across, one obtains the gain from an optimal policy under each of the three simulations, as presented in Figure 3. This is calculated as the difference between welfare gains from the no backstop base in the BAU and optimal scenarios. For example, with a medium backstop price, welfare increases by $1.88 trillion with no backstop, by $2.15 trillion with a constant price backstop, and by $2.31 trillion with a backstop and backstop R&D. The fifth column shows that simply adding a backstop increases welfare by 14.2%, and adding backstop R&D increases welfare an additional 8.6%

Finally, to show the gains from induced R&D, Table 2 also presents results for a policy simulation that holds both energy R&D and the backstop R&D at BAU levels. Comparing the welfare gains here to the gains with endogenous R&D shows that induced innovation improves welfare by 6.8% in the medium backstop price case. This is lower than the 9.4% increase found in Popp (2003) in a model without a backstop. Note that, in each case, the welfare gains from an optimal policy in an exogenous R&D model are nearly identical to the welfare gains for a model with a backstop technology without R&D. When ignoring the additional R&D induced by climate policy, the gains from innovation are offset by the opportunity costs of R&D. Moreover, the relative prices between the backstop and fossil fuels help determine the value of policy-induced R&D. Although the gain from ITC is similar for the medium and high price case, it is twice as high in the low price case.

To help evaluate the R&D parameter assumptions, Table 3 presents the value of an additional $1 billion of energy R&D and backstop energy R&D for each set of assumptions under an optimal policy regime. For energy efficiency R&D, an additional billion dollars increases welfare by nearly $5 billion. This nearly 5:1 ratio is consistent with the notion that the social returns to R&D should be significant, due to the public goods nature of research, and is similar to results in Popp (2003). For backstop R&D, only the returns for the high price assumption and 24% progress ratio are near same figure. For all other sets of backstop R&D assumptions, the returns to backstop R&D are higher. As a result, I focus on the high price assumption in detailed discussion of the results below. In most cases, the pattern of results do not differ substantially across backstop price assumptions. Those differences that do exist are discussed in the sensitivity analysis presented in section IV.

Table 4 summarizes key variables for the base scenario. The table shows results for the base ENTICE model, as well as for runs with a backstop technology and with backstop R&D. Simulations denoting exogenous R&D eliminate the effects of policy-induced R&D by constraining R&D in the policy scenarios to the levels of the BAU scenario. Turning first to R&D, note that the patterns for both energy R&D and backstop R&D are similar to the patterns found for energy R&D in Popp (2003). Adding backstop R&D to the model results in a small decrease in other energy R&D. However, this change occurs in both the BAU and policy scenarios, so the elasticity of energy R&D across the scenarios remains similar.[22] Based on the results of Popp (2002), the model is calibrated so that the elasticity of energy in the base ENTICE model equals 0.35 in 2005. Because diminishing returns to energy research reduce the inducement effect over time, the elasticity of energy R&D falls over time.[23] Thus, diminishing returns to research have the effect of lowering energy R&D somewhat in the long-run. For backstop energy R&D, the resulting elasticity is somewhat higher, although it too falls in the long-run due to diminishing returns.

Turning to emissions, note that neither ITC nor the presence of a backstop technology has a significant impact on emissions reduction. In fact, emissions are initially somewhat higher when a backstop is considered. Figure 4 presents the emissions control rates over time for the first 100 years. Control rates (and also carbon taxes) do increase slightly when a backstop is introduced. However, they are higher when backstop R&D is exogenous, rather than endogenous. The intuition here is that additional policy-induced R&D hastens the rate at which traditional fossil fuels become obsolete. As a result, consuming more fossil fuels in the short-run makes sense.

Not surprisingly, the small effect on emissions results in small changes in the mean global temperature as well. This is illustrated in Figure 5, which shows deviation from 1900 global mean temperature levels over time for both the optimal policy scenarios and the restrictive emissions policy. The top group of lines shows temperature in the BAU scenarios. The middle group shows temperature under an optimal climate policy, and the bottom line shows temperature under the restrictive emissions policy. In either the BAU or the optimal policy,

[22] The elasticities presented here are calculated for each year based on the difference in both energy R&D and carbon prices in simulations with and without policy.

[23] To account for the effect of economic growth, all elasticities are calculated using the ratio of energy R&D to output.

adding a backstop technology has almost no impact on atmospheric temperature. This suggests an important policy lesson: simply relying on alternative technologies is not sufficient to limit the increases in global temperature – restrictive policy measures will also be needed.

C. Restricting Emissions to 1995 Levels

Compared to the optimal policy scenario, adding a backstop to the ENTICE model is more important under more restrictive policy scenarios, such as restricting emissions to 1995 levels. Table 5 and Figure 6 present the welfare gains (or losses) for the three backstop price assumptions from the restrictive emissions policies. As found in Popp (2003), without a backstop technology, the restrictive policy reduces welfare by $8.2 trillion. Adding a backstop reduces this loss. The change is small for the high price assumption, as welfare increases by just 9.1%. However, for the low price assumption, the more restrictive policy increases welfare by over 100%, so that the net economic impact is now positive, although less than $1 trillion.

Adding backstop R&D is also important, although not as significant as adding the backstop technology itself. Compared to a constant backstop price scenario, adding backstop R&D enhances welfare by an additional 10.7% to 27.3%. Policy-induced R&D increases welfare from 4.7% to 22.6%. These results are of particular interest, as they are opposite those found in the ENTICE model without a backstop technology. There, the potential of induced innovation was smaller under a restrictive emissions policy, as the opportunity costs of the increased R&D were significant. Here, the potential welfare gains from using the backstop technology more quickly appear to offset that somewhat, so that induced R&D is more important under the restrictive policy for both the low and medium price case.

The increased importance of both the backstop technology itself, as well as backstop R&D, occurs under a restrictive emissions reduction policy because the level of carbon taxes necessary to implement such a policy make the backstop competitive with fossil fuels sooner. Even in the high backstop price scenario, the backstop is competitive with fossil fuels by 2045. By allowing an option for emissions reduction that can maintain energy use, adding an alternative energy technology lowers the costs of complying with restrictive emissions reductions. Thus, incorporating a backstop technology into climate change models is important, as most proposals considered by policy makers are considerably more restrictive than the optimal policy presented in the previous section.

Furthermore, the potential of ITC increases in the restrictive policy case because of changes to the level of energy efficiency R&D. Whereas most backstop energy R&D is new R&D in the optimal policy simulation, here some backstop energy R&D substitutes for energy efficiency R&D. Thus, the opportunity costs of this additional energy efficiency research are avoided. For example, compared to the restricted policy scenario with no backstop technology, energy efficiency R&D is 6% lower by 2055, and 8% lower by 2105. By comparison, energy efficiency R&D for each of these years falls by just 1% when backstop R&D is added to the optimal policy scenario.

Table 6 shows how other variables change when backstop energy R&D is considered.[24] By lowering the cost of alternative technologies, backstop R&D lowers the cost of compliance, and thus reduces carbon taxes. This is more significant in the short run, where carbon taxes fall by nearly 10%. Unlike the optimal policy, emissions do not change after induced innovation is included in the model, since this is a command and control policy. Thus, the changes in the carbon tax provide a guideline as to how much tax rates could potentially fall in the optimal scenario if the level of emissions did not change.

[24] Once again, only results from the high backstop price case are shown.

IV. Sensitivity Analysis

In developing a model such as the ENTICE model, several key assumptions must be made. Popp (2003) explores the implications of several of these on the base ENTICE model. Here, I examine two assumptions unique to the ENTICE-BR model: the elasticity of substitution between fuels and the progress ratio. Also, since Popp (2003) demonstrates the importance of market imperfections on the effects of R&D, I look at two key assumptions about R&D markets: deviation between private and social rates of return and potential crowding out of other R&D. Readers interested in a discussion of other parameters are referred to Popp (2003).

A. Elasticity of Substitution Between Fuels

As illustrated in section III, the initial backstop price has a large impact on the model results. One reason, of course, is that lower prices mean that the backstop becomes competitive with fossil fuels more rapidly. However, changing the initial backstop price has another important effect. To be consistent with initial conditions, changes in the initial backstop price imply different rates for the elasticity of substitution between fuels. This elasticity of substitution ranges from 1.6 in the high price scenario, to 2.2 in the medium scenario, to 8.7 in the low price scenario.

This has important implications for the model. In particular, higher elasticities of substitution induce more backstop R&D. This is illustrated in Figure 7, which plots the elasticity of backstop R&D across time under each scenario. Popp (2002) estimates an elasticity of energy R&D and energy prices of 0.35. In each case, the elasticity begins above that level. More importantly, it stays well above that level when the elasticity of substitution is high, suggesting that such a case does not accurately reflect R&D markets.

Another interesting variation under a high elasticity of substitution is that global temperature change is moderated significantly. Figure 8 plots the global mean temperature for each optimal scenario, as well as for the BAU run in the low price scenario. The figure also illustrates temperature under a restrictive emissions policy. Note that, with a high elasticity of substitution, the temperature in *both the BAU and optimal policy runs* is lower than the restrictive policy. Optimistic assumptions about backstop technologies not only imply that the costs of dealing with climate change are lower, but that climate change itself is less of a problem!

B. Progress Ratio

The other new parameter introduced in the ENTICE-BR model is the progress ratio between new knowledge and backstop prices. In the base case, this is nearly 24%. Such a level produces realistic behavior for R&D, but is lower than suggested by historical data, and could result in the backstop technology having less impact than assumed in other studies. However, changing the progress ratio does not have much impact on the model. The welfare gains from backstop R&D are only two to six percent higher with a progress ratio of 50%. A higher progress ratio does result in a greater share of backstop energy in the long run. However, because of the cumulative nature of R&D, the short-run increase in backstop usage resulting from a higher progress ratio are minimal. Because this benefit does not come until far into the future, and because backstop energy itself is a small part of the overall economy, increasing the progress ratio leads to little change in other variables. The nature of energy R&D markets appears more important than the effect of new technology on backstop prices.

C. The Opportunity Cost of R&D

By crowding out other types of R&D investments, policy-induced energy research may have negative impacts elsewhere in the economy. As demonstrated in Popp (2003), assumptions about the opportunity cost of R&D affect the magnitude of the role induced technological change can play. Differences in this assumption help explain variation in results across models. Models that ignore crowding out, such as Buonanno *et al*. (2003) are much more optimistic about the potential for ITC than models including crowding out.

Moreover, models implementing technological change via learning-by-doing also ignore potential crowding out effects. At the same time, most models using learning-by-doing are bottom-up models that feature several different technologies, such as Gerlagh and van der Zwaan (2002) and Manne and Richels (2003). These models consistently find that technological change plays an important role. For example, Gerlagh and van der Zwaan report that welfare improves by a factor of three when learning-by-doing is included, and Manne and Richels find that cost fall from 42-72 percent when learning-by-doing is considered. While ignoring opportunity costs offers one explanation for such results, the presence of an alternative technology must also help. Thus, here I explore the effect of opportunity costs of R&D in a model with a backstop technology.

Recall that the base model assumes 50% of energy R&D comes at the expense of other research opportunities. To examine the importance of this assumption, I consider a low opportunity cost case with no crowding out, and a high opportunity cost case with complete crowding out. In doing so, it is important to note that changing the opportunity cost of R&D changes the level of energy R&D. However, the model is designed to be calibrated to actual values of energy R&D. Thus, I present lower bound and upper bound values for the sensitivity to potential crowding out effects. The *upper bound* scenario allows R&D to adjust as a result of changes in the opportunity cost. This, for example, could be thought of as the maximum gains possible from government policy that was able to alleviate potential crowding out effects.[25] As a *lower bound*, I run the model changing the opportunity cost of R&D, but constrain energy R&D in each case to equal energy R&D in the corresponding base case scenario. Here, for example, welfare gains in the low opportunity cost case should be interpreted as the gains from removing the *assumption* of partial crowding out. They are not the gains that would result if the government intervened to remedy the problem of partial crowding out.

As in the base ENTICE model, assumptions about potential crowding out have important effects. Table 7 shows how the gains from ITC change as assumptions about the opportunity cost of R&D change. With partial crowding out, ITC improves welfare by 6.0% under an optimal policy, compared to a model with exogenous technological change. When crowding out is ignored, this increases to a range of 12.2 to 30.5%. Similarly, assuming a high opportunity cost of R&D results in policy-induced R&D having almost no additional effect. Nearly identical effects are found for the restrictive emissions policy. These results are similar to those found in Popp (2003). Even with alternative technologies available as emission reduction options, the opportunity cost of R&D remains an important limitation to the potential of ITC. Models ignoring these potential costs, including those modeling technological change via learning-by-doing, likely provide overly optimistic estimates of the potential of innovation to lower the costs of reducing carbon emissions.

[25] In these simulations, energy R&D levels change in both the base case and in the policy scenarios. The effect of policy that addressed opportunity costs only in conjunction with a climate policy will fall in between the upper and lower bounds.

D. R&D Subsidies

The base model constrains the social rate of return on R&D to be four times greater than that of the return on other investment. This assumption is consistent with the empirical finding that firms underinvest in research, as they are unable to capture the entire social returns. However, the problem of underinvestment could be addressed by subsidies to energy R&D, if government investments in R&D are set so that all social returns are captured. Models that do not include market failures, such as Buonanno *et al*. (2003) implicitly assume that government R&D subsidies are sufficient to correct all market failures.

Popp (2003) finds that R&D subsidies can have an important impact. Table 8 summarizes the results found there, as well as new results using ENTICE-BR. Results are presented for the high backstop price case only.[26] In the model without a backstop, energy efficiency R&D subsidies improve welfare by 6.7%. With a constant price backstop, energy R&D subsidies increase welfare by 4.4%. Finally, in the model with both energy efficiency and backstop energy R&D, backstop energy R&D subsidies have little effect, increasing welfare by only 0.9%. Adding energy efficiency subsidies as well increases welfare by an additional 4.0%. Similar results are found in the restrictive policy case. While R&D subsidies remain important, they are slightly less important than in the original ENTICE model. A backstop technology provides an additional option for reducing carbon emissions, and thus provides more flexibility with or without R&D subsidies.

Finally, to illustrate the importance of having a policy in place, the last row of Table 8 presents results from a simulation including optimal R&D subsidies for both energy efficiency and backstop energy R&D, but without a carbon tax in place. Note that the welfare gains here are trivial. As shown in section III, even in a model with induced technological change, factor substitution still plays an important role in reducing emissions. R&D subsidies alone will not address the climate problem, as they do not offer incentives for factor substitution.

V. Discussion

These results suggest that estimates of the costs of complying with climate policies do fall when alternative technologies are considered. This is particularly significant for policies placing a cap on emissions. Thus, adding a backstop technology to climate models is important. Policy-induced innovation on this backstop technology is also important, but its potential is limited by the effects of crowding out of other productive R&D. The welfare gains from simply adding a backstop technology to ENTICE are nearly double the gains from then endogenizing R&D on that technology.

One important modeling lesson that can be derived from these results is the importance of getting the baseline right. Although there are dramatic improvements to welfare when a backstop is added to the model, the appropriate comparison is between business as usual and policy in a model making the same assumptions about technology. In models with optimistic assumptions about potential technological progress, climate change will be less of a problem even under business as usual.

In addition, the results support the notion that the opportunity costs of R&D are important, even when alternative energy technologies are considered. As in the base ENTICE model, removing the assumption of partial crowding out of energy R&D dramatically increases

[26] Results for other assumptions are similar, with one exception. Backstop energy R&D subsidies improve welfare by nearly 16% in the low backstop price scenario. Since the technology is already competitive, the additional R&D

the potential of ITC. Thus, models ignoring these opportunity costs, including models in which technology proceeds by learning-by-doing, overestimate the potential gains from technological innovation. Given this important limitation, more research on both the magnitude of any crowding out that may occur, as well as policies that could help alleviate crowding out, would both be helpful.

Finally, limitations of the ENTICE-BR model must be discussed. First, by modeling the world as a single region, the ENTICE model simplifies policy dramatically. Expanding these results to a regional model, based on Nordhaus' RICE model, would be beneficial. However, to do so would require research on how innovative effects vary by region, and how technology diffuses across regions. In general, new innovations are developed in the industrialized world and diffuse slowly to developing countries. For example, of the $500 billion spent on R&D in the 28 OECD countries in 1997, 85% occurred in just 7 countries (National Science Board, 2000).

Second, the ENTICE-BR model does not include uncertainty. As markets for renewable energy are not yet well-developed, the potential role that renewable energy may play is still unclear. As shown in both this and other papers, the range of possibilities is large. Adding endogenous technological change to a model allowing for uncertain climate effects, such as Nordhaus and Popp (1997), would help provide guidance as to how policy should proceed in the face of this uncertainty.

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has a larger impact on the share of backstop energy consumed.

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Figure 1 – Backstop Price in BAU

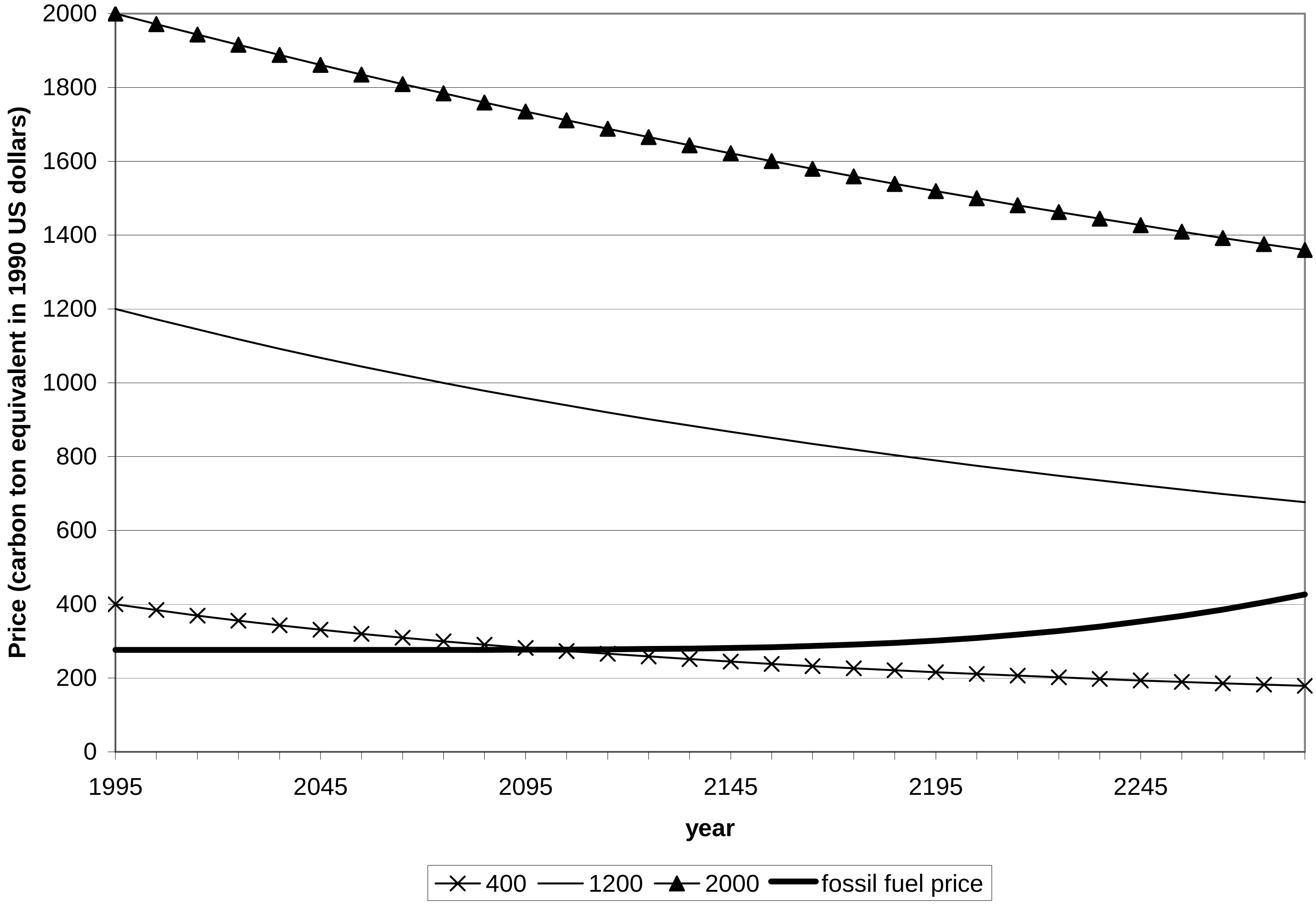


Figure shows changes in the price of the backstop technology over time in the BAU simulation for each of three initial price assumptions. Also shown is the price of fossil fuels. Note that only with a low initial price does the backstop ever become cheaper than fossil fuels.

Figure 2 – Percentage Contribution of Backstop Technology

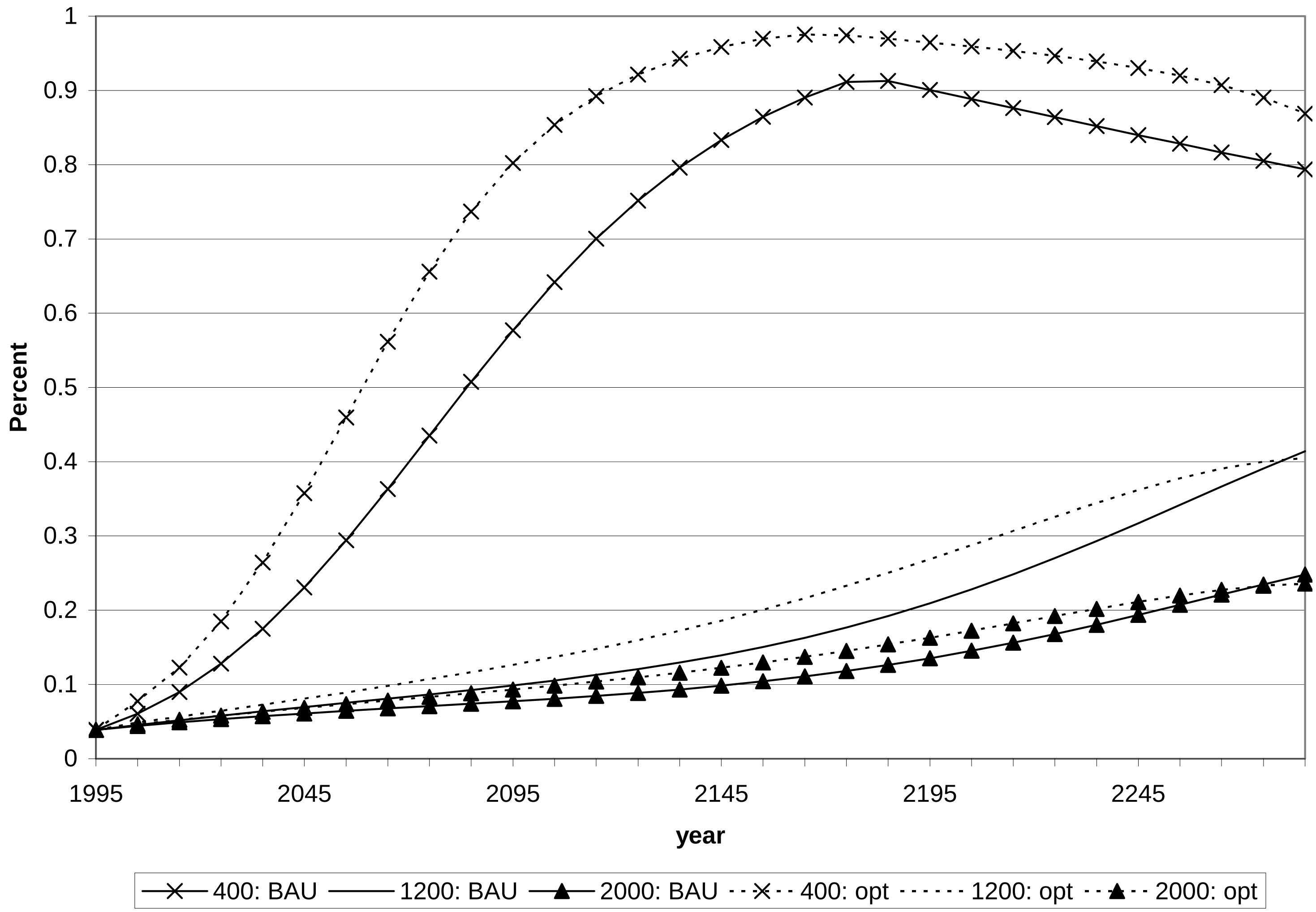
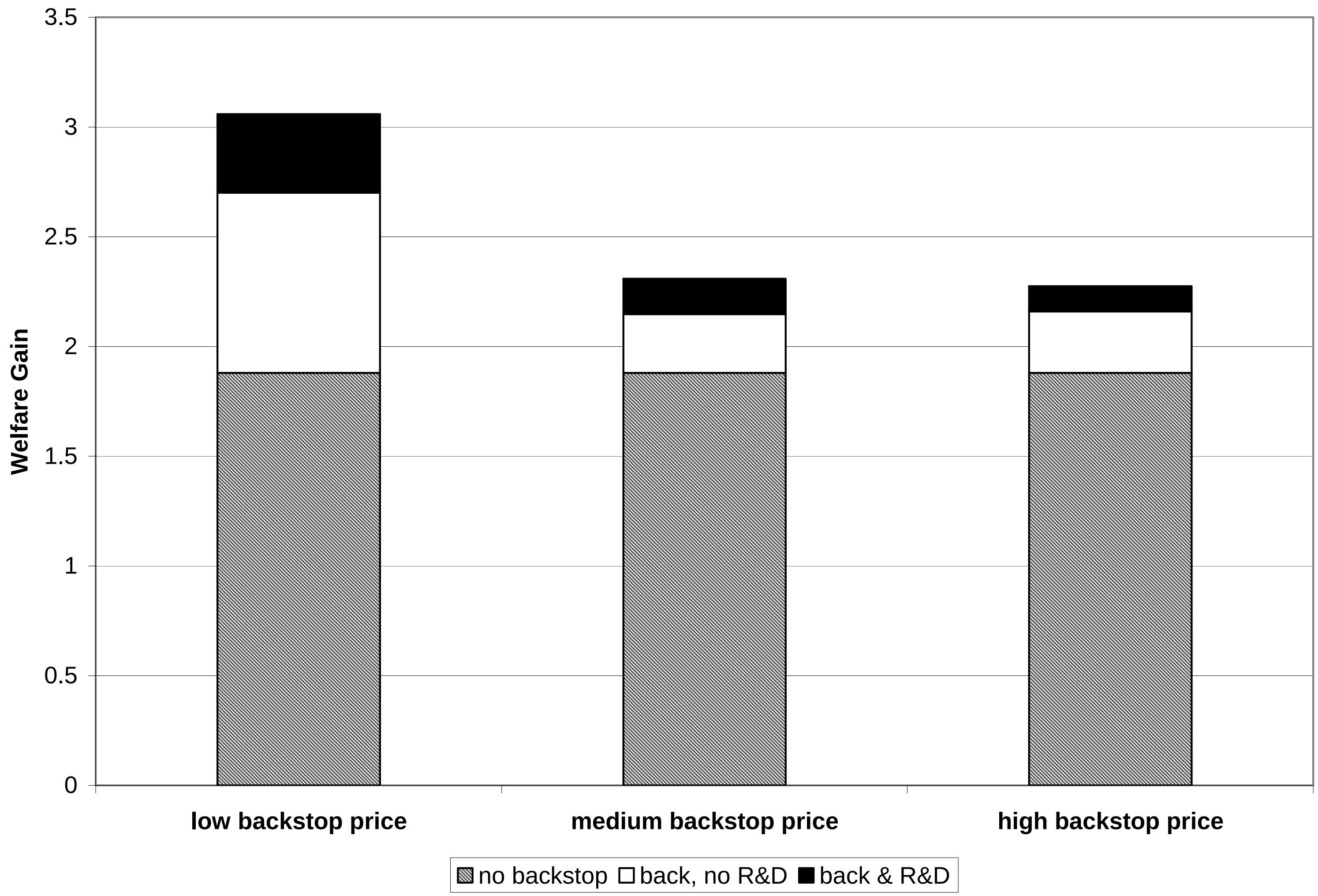


Figure shows the share of energy consumption provided by the backstop technology over time in both the BAU and optimal policy simulations for each of three initial price assumptions.

Figure 3 – Backstop Technology Contribution to Welfare – Optimal Policy



The figure shows the welfare gains from an optimal climate policy with and without a backstop technology. Note that the largest gains come from factor substitution. Also, simply adding a backstop to the model increases welfare more than considering backstop R&D.

Figure 4 – Emissions Control Rates Under an Optimal Carbon Policy

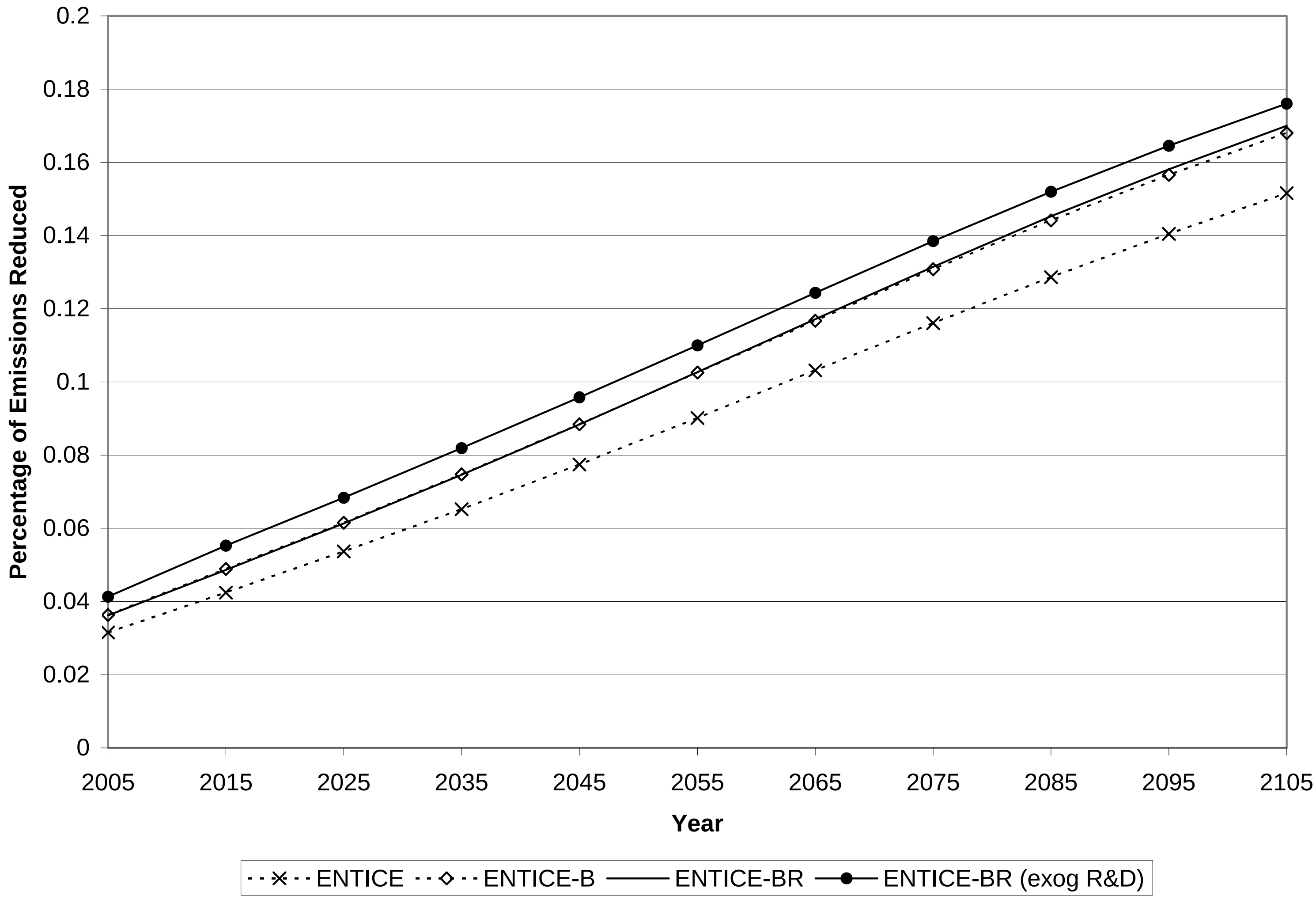
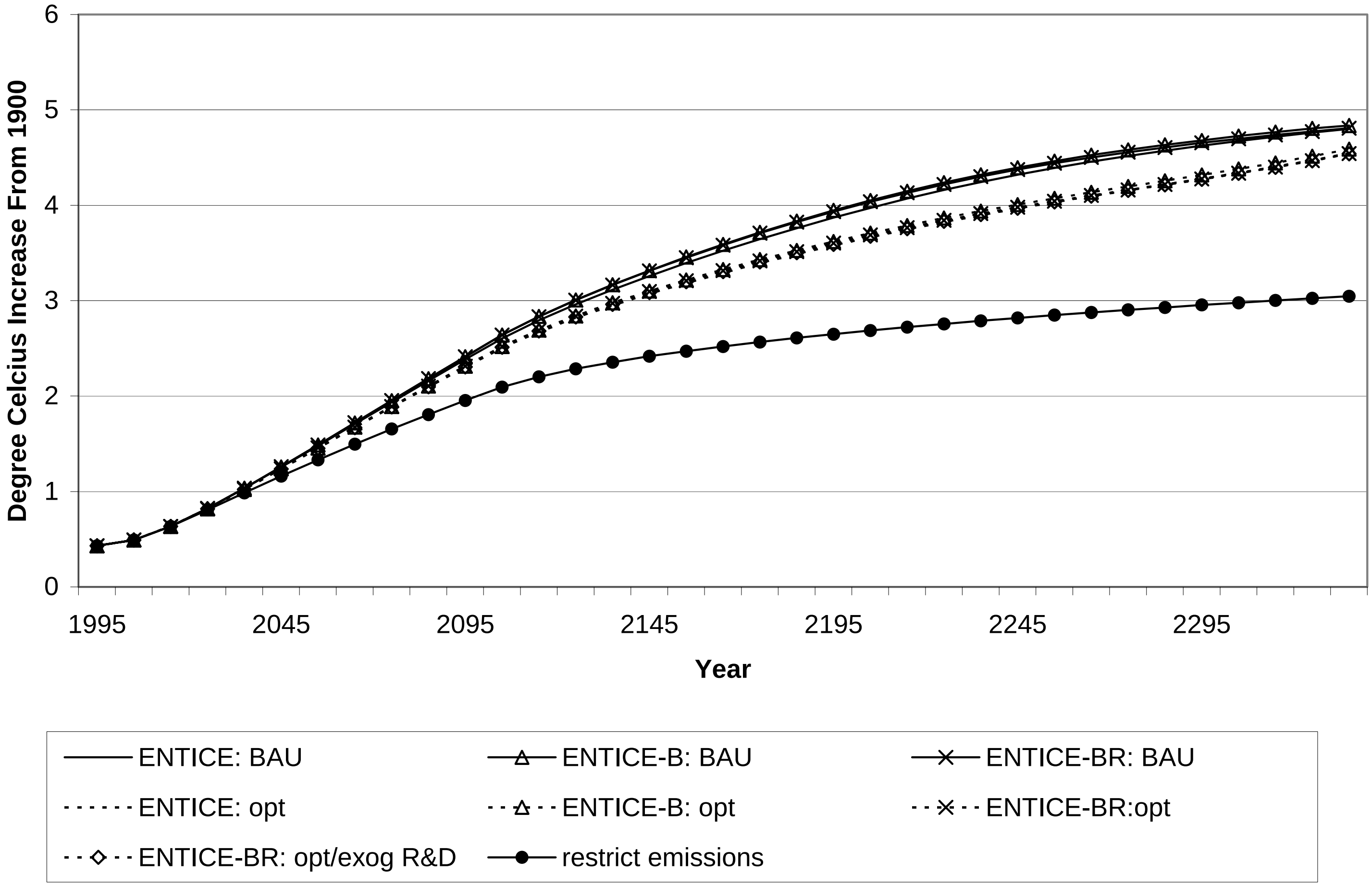


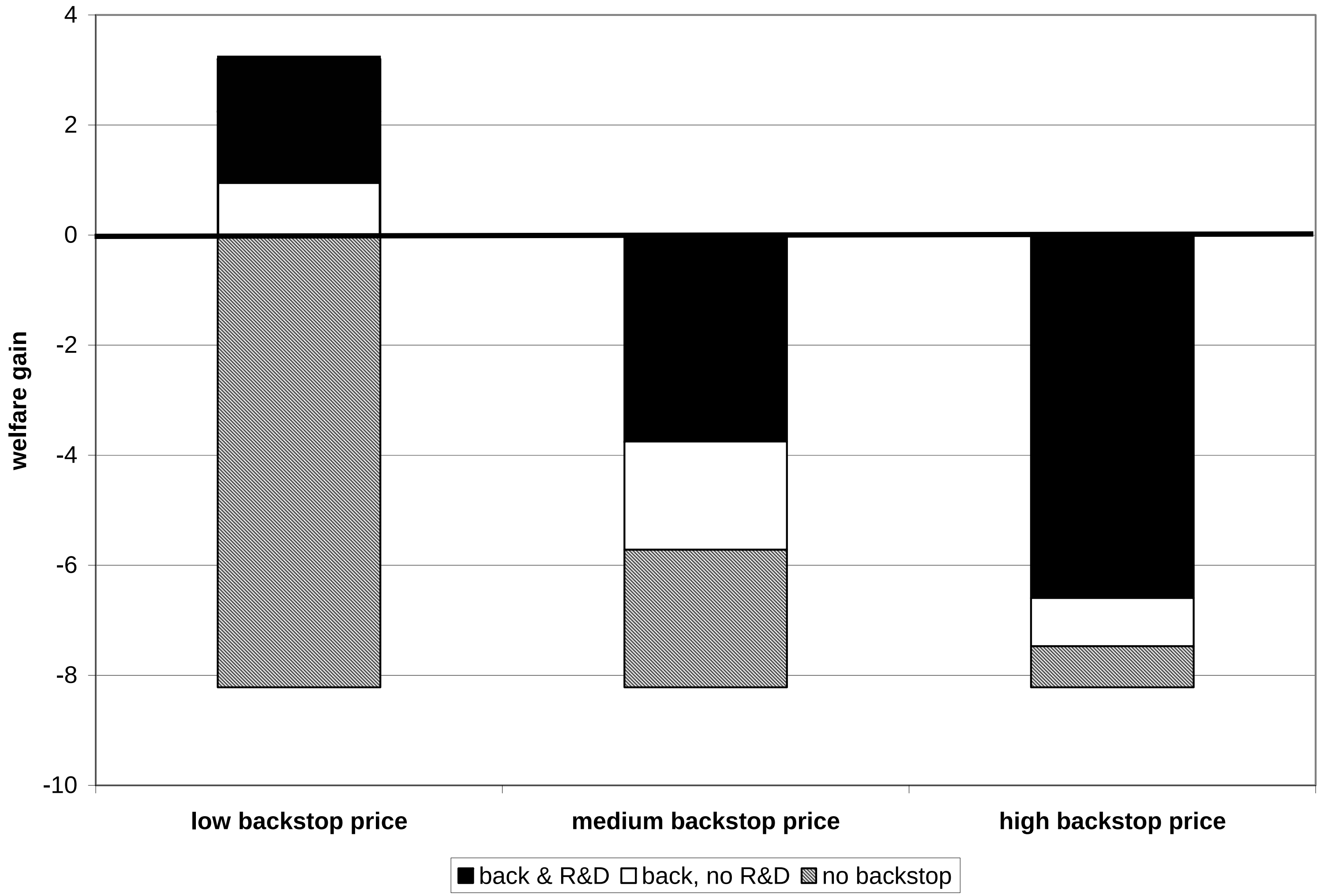
Figure shows the carbon emission control rates for each technology assumption. Control rates are highest with exogenous backstop R&D. When backstop R&D is endogenous, a small increase in emissions makes sense in the short run, as increased technological progress will make fossil fuels obsolete more quickly.

Figure 5 – Mean Global Temperature



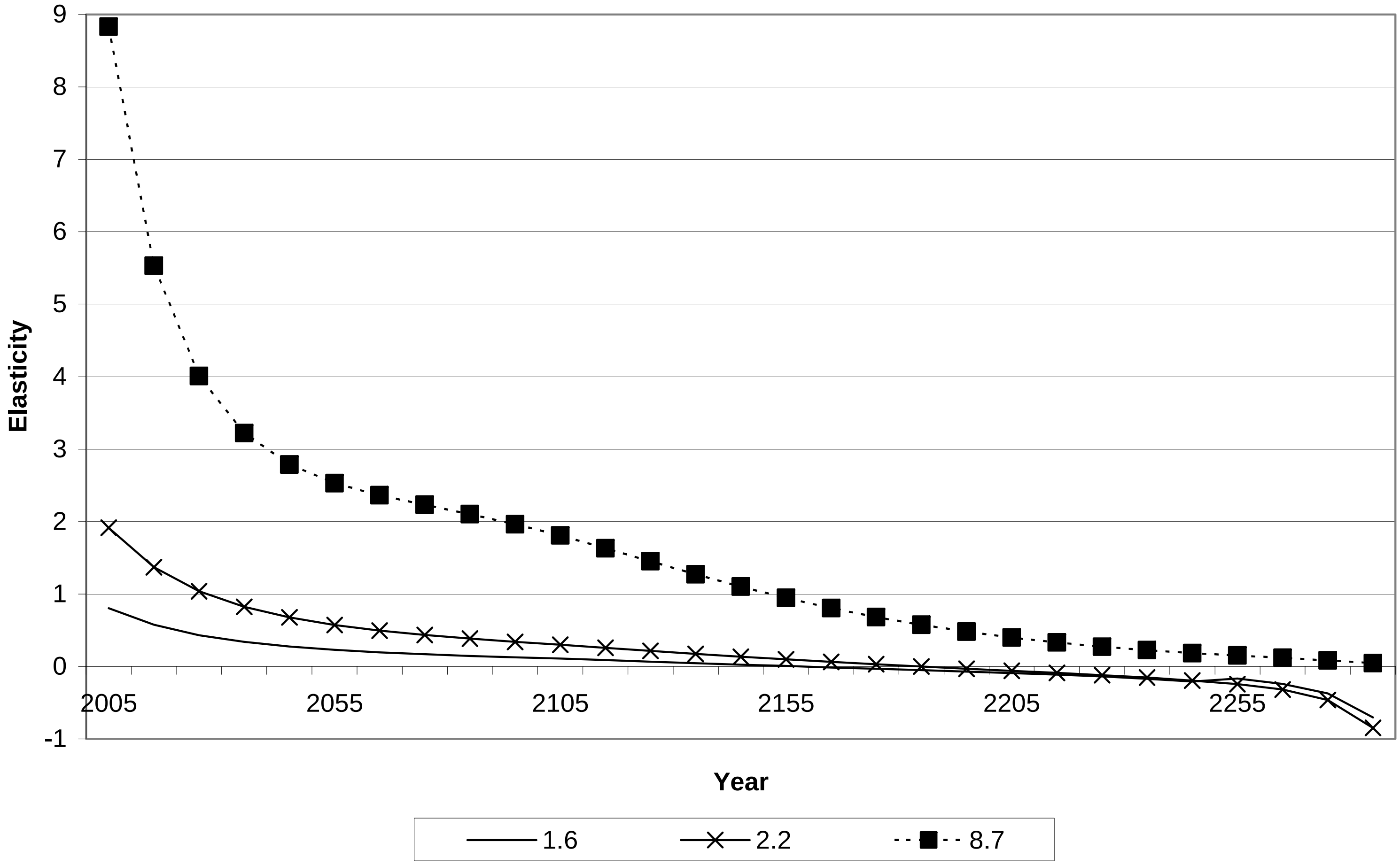
The figure shows the departure of mean global temperature from 1990 levels, reported in degrees Celsius. Note that neither induced R&D nor adding a backstop technology have little effect on temperature.

Figure 6 – Backstop Technology Contribution to Welfare – Restricted Emissions Policy



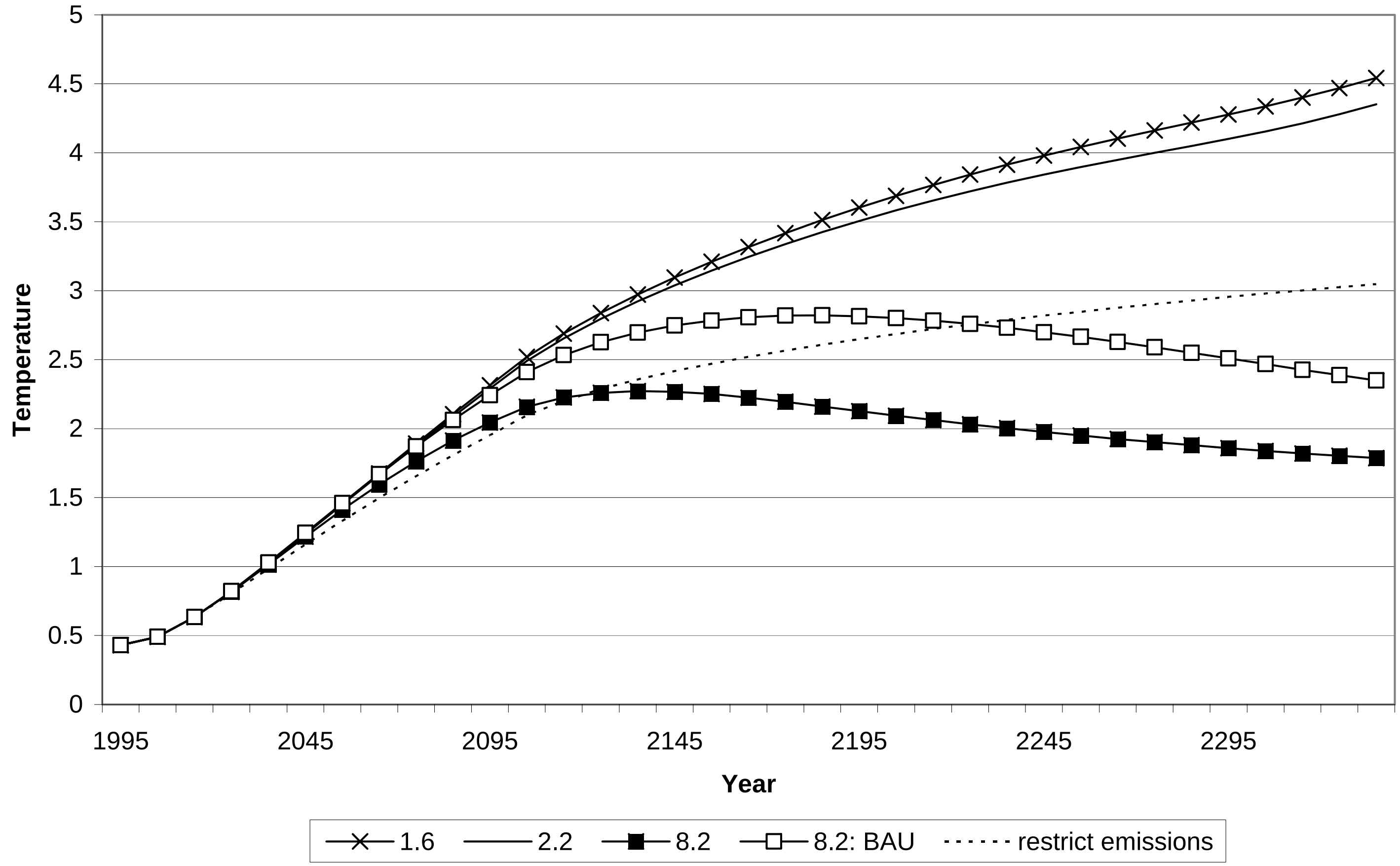
The figure shows the welfare gains from a policy restricting emissions to 1995 levels with and without a backstop technology. Note that adding a backstop technology reduces the welfare costs of complying with such a policy, and that the welfare improvements from the backstop technology are more substantial than under an optimal climate policy.

Figure 7 – Backstop Energy R&D Elasticity Over Time – Sensitivity to the Elasticity of Substitution



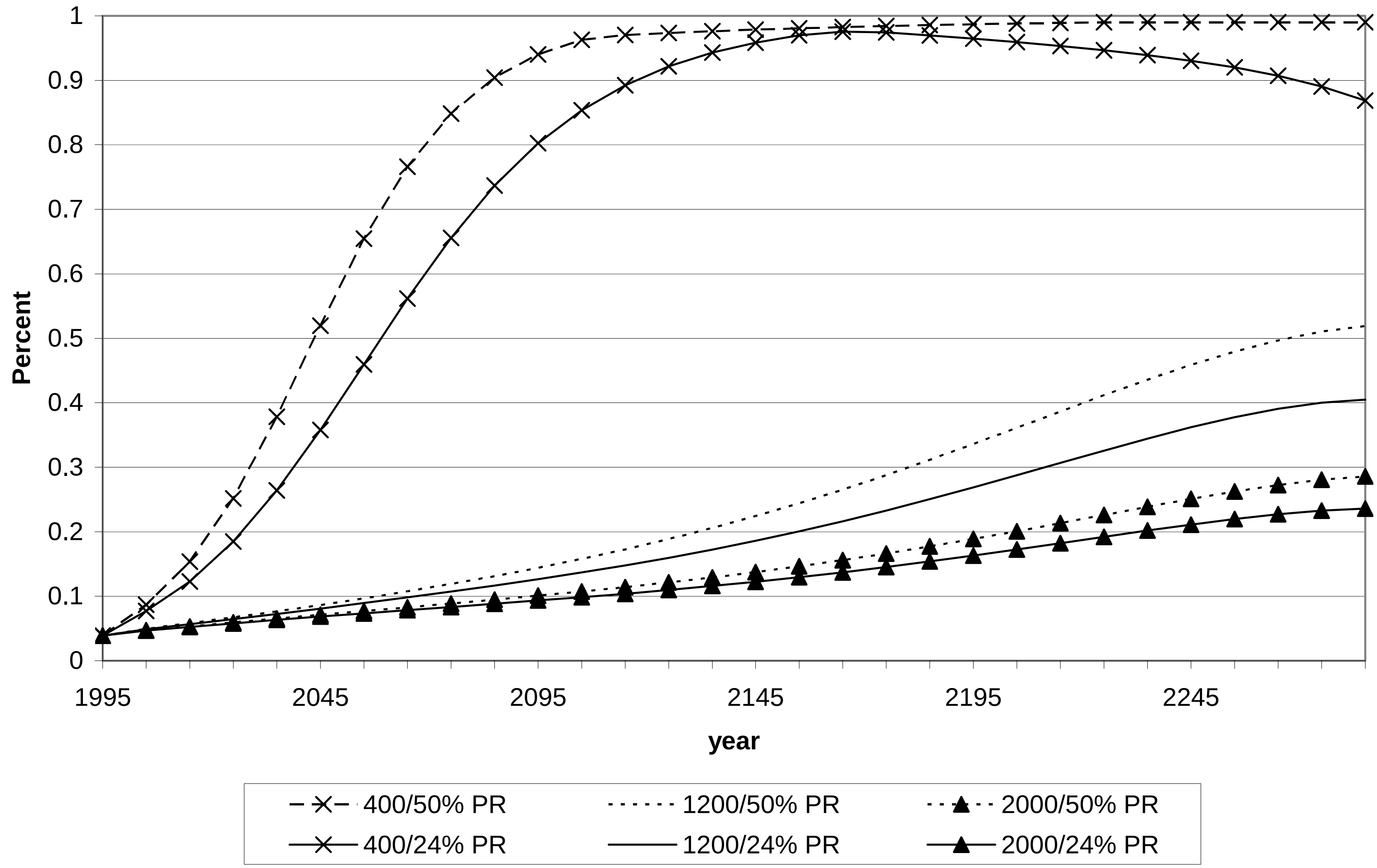
The figure shows how the elasticity of backstop R&D to energy prices changes over time for each of the three assumptions about the elasticity of substitution between fossil fuels and the backstop technology. In each case, diminishing returns causes the elasticity to fall over time. Nonetheless, the elasticity is unrealistically high when assuming a high elasticity of substitution

Figure 8 – Temperature Over Time – Sensitivity to the Elasticity of Substitution



The figure shows the departure of mean global temperature from 1990 levels, reported in degrees Celsius, under the optimal policy scenario for each elasticity of substitution between fossil fuels and the backstop technology. It also shows the temperature for the BAU scenario with a high elasticity of substitution, as well as temperature under a policy restricting emission to 1995 levels. Note that temperature is lowest with a high elasticity of substitution.

Figure 9 – Share of Backstop Energy Over Time – Sensitivity to the Progress Ratio



The figure illustrates sensitivity to the progress ratio of the share of total energy for the backstop fuel. For each initial backstop price assumption, a dashed line represents the share with a higher progress ratio. Because of the cumulative nature of R&D, doubling the progress ratio has almost no effect on the share in the first 100 years. As a result, there is also little change in other variables.

Table 1 – Summary of Parameter Values

backstop parameters					*calculated parameters*			*Revised energy efficiency IPF parameters*		
initial price	effect of technology on backstop price: η	IPF: *a*	IPF: *b*	IPF: ϕ	sub between backstop/fossil fuels	sub elas backstop/fossil fuels	Share of energy in production: β	IPF: *a*	IPF: *b*	IPF: ϕ
400	0.4	0.0155	0.0525	0.55	0.885	8.672	0.074	0.0286	0.2	0.55
1200	0.4	0.0122	0.1	0.54	0.542	2.185	0.082	0.0264	0.2	0.54
2000	0.4	0.0075	0.105	0.53	0.383	1.621	0.089	0.0255	0.22	0.53
400	1	0.0073	0.032	0.55	0.885	8.672	0.074	0.0286	0.2	0.55
1200	1	0.00505	0.073	0.54	0.542	2.185	0.082	0.0264	0.2	0.54
2000	1	0.0033	0.075	0.53	0.383	1.621	0.089	0.0255	0.22	0.53

The table presents parameter values for the ENTICE-BR model. The center columns are calculated based on the initial backstop price and level.

Table 2 – Welfare Gains from Optimal Climate Policy

	Welfare gains compared to BAU case without backstop:		*Gain from optimal policy*		
low backstop price	BAU	Optimal	Gain from optimal policy	% gain to optimal policy from adding backstop	% gain from induced R&D
No Backstop	N/A	1.880	1.880		
Backstop w/constant price	2.605	5.305	2.701	43.7%	
Backstop w/R&D	17.645	20.701	3.057	62.6%	
Backstop w/exogenous R&D	N/A	20.346	2.702		13.1%
medium backstop price	BAU	Optimal	Gain from optimal policy	% gain to optimal policy from adding backstop	% gain from induced R&D
No Backstop	N/A	1.880	1.880		
Backstop w/constant price	4.871	7.019	2.148	14.2%	
Backstop w/R&D	9.356	11.665	2.309	22.8%	
Backstop w/exogenous R&D	N/A	11.518	2.162		6.8%
high backstop price	BAU	Optimal	Gain from optimal policy	% gain to optimal policy from adding backstop	% gain from induced R&D
No Backstop	N/A	1.880	1.880		
Backstop w/constant price	5.788	7.947	2.159	14.8%	
Backstop w/R&D	9.680	11.955	2.275	21.0%	
Backstop w/exogenous R&D	N/A	11.825	2.145		6.0%

Note: all figures in trillions of 1990 US dollars.

The table shows the net economic impact, measured by the difference in the present value of consumption between an optimal climate policy and a no policy (BAU) simulation, for each assumption about the initial backstop price. The figures on the left show the gain from a BAU scenario without a backstop technology. Thus, reading down for each price assumption, one obtains the gains from adding a backstop to the model in both the BAU and optimal policy cases. The right set of figures show the gains from an optimal policy, holding assumptions about technology constant. This is obtained by reading across each row. While R&D on the backstop technology is important, simply adding a backstop to the model has a larger effect.

Table 3 – Returns to Marginal R&D

24% Progress Ratio	energy efficiency R&D	backstop R&D
low backstop price	4.96	26.00
medium backstop price	4.93	6.76
high backstop price	4.74	4.85
50% Progress Ratio		
low backstop price	4.22	37.85
medium backstop price	5.02	8.08
high backstop price	4.77	6.06

Note: all figures in billions of 1990 US dollars.

The table shows the welfare gains from an additional $1 billion of R&D for each R&D type. Figures are in billions of 1990 U.S. dollars.

Table 4 – Key Variables – Optimal Policy

	1995	2005	2015	2025	2055	2105
Carbon Tax ($/ton)						
Endogenous R&D: no backstop	N/A	$10.19	$14.61	$19.54	$36.89	$70.21
& Backstop	N/A	$10.40	$15.00	$20.13	$38.25	$73.17
& Backstop R&D	N/A	$10.42	$15.03	$20.19	$38.41	$73.65
Exogenous R&D: no backstop	N/A	$10.20	$14.62	$19.55	$36.89	$70.19
& Backstop R&D	N/A	$10.40	$14.99	$20.13	$38.29	$73.44
% Δ Endog vs. Exog.: no backstop	N/A	-0.10%	-0.07%	-0.05%	0.00%	0.03%
& Backstop R&D	N/A	0.19%	0.27%	0.30%	0.31%	0.29%
Energy R&D -- billions 1990 US dollars						
Endogenous R&D: no backstop	10.00	13.33	17.07	20.03	27.26	39.85
& Backstop	10.00	13.37	17.18	20.17	27.34	39.94
& Backstop R&D	10.00	13.30	17.07	20.03	27.08	39.36
Exogenous R&D: no backstop	10.00	13.13	16.83	19.71	26.59	38.55
& Backstop R&D	10.00	13.08	16.91	19.82	26.62	38.52
Elasticity: no backstop	N/A	0.35	0.24	0.22	0.22	0.23
& Backstop R&D	N/A	0.39	0.15	0.13	0.15	0.18
Backstop Energy R&D -- billions 1990 US dollars						
Endogenous R&D	1.00	1.35	1.59	1.82	2.47	3.70
Exogenous R&D	1.00	1.31	1.54	1.76	2.40	3.67
Elasticity	N/A	0.81	0.57	0.43	0.23	0.11
Emissions -- billion tons						
No Policy or Backstop	6.187	7.173	8.015	8.774	10.904	14.156
& Backstop	6.187	7.186	8.099	8.925	11.261	14.829
& Backstop R&D	6.187	7.212	8.129	8.951	11.255	14.734
Endogenous R&D: no backstop	6.187	6.947	7.675	8.303	9.921	12.01
& Backstop	6.187	6.925	7.703	8.376	10.106	12.337
& Backstop R&D	6.187	6.951	7.734	8.402	10.099	12.229
Exogenous R&D: no backstop	6.187	6.947	7.677	8.308	9.931	12.026
& Backstop R&D	6.187	6.914	7.68	8.339	10.017	12.14
% Δ Endog vs. Exog.: no backstop		0.00%	-0.03%	-0.06%	-0.10%	-0.13%
& Backstop R&D		0.54%	0.70%	0.76%	0.82%	0.73%
Output -- trillions $1990 US dollars						
No Policy or Backstop	22.61	30.00	36.94	43.72	63.55	95.19
& Backstop	22.61	29.93	37.05	44.00	64.34	96.96
& Backstop R&D	22.61	29.93	37.08	44.06	64.52	97.46
Endogenous R&D: no backstop	22.61	30.01	36.92	43.68	63.42	94.95
& Backstop	22.61	29.93	37.03	43.95	64.20	96.71
& Backstop R&D	22.61	29.94	37.06	44.01	64.39	97.23
Exogenous R&D: no backstop	22.61	30.01	36.91	43.65	63.35	94.77
& Backstop R&D	22.61	29.94	37.05	43.98	64.30	97.04
% Δ Endog vs. Exog.: no backstop		0.00%	0.03%	0.06%	0.12%	0.19%
& Backstop R&D		0.00%	0.05%	0.08%	0.15%	0.19%

Table 5 – Welfare Gains from Restricted Emissions Policy

	Welfare gains compared to BAU case without backstop:		*Gain from climate policy*		
low backstop price	BAU	Optimal	Gain from climate policy	% gain to welfare policy from adding backstop	% gain from induced R&D
No Backstop	N/A	-8.219	-8.219		
Backstop w/constant price	2.605	3.556	0.952	111.6%	
Backstop w/R&D	17.645	20.845	3.200	138.9%	
Backstop w/exogenous R&D	N/A	20.256	2.611		22.6%
medium backstop price	BAU	Optimal	Gain from climate policy	% gain to welfare policy from adding backstop	% gain from induced R&D
No Backstop	N/A	-8.219	-8.219		
Backstop w/constant price	4.871	-0.846	-5.717	30.4%	
Backstop w/R&D	9.356	5.606	-3.750	54.4%	
Backstop w/exogenous R&D	N/A	5.197	-4.159		9.8%
high backstop price	BAU	Optimal	Gain from climate policy	% gain to welfare policy from adding backstop	% gain from induced R&D
No Backstop	N/A	-8.219	-8.219		
Backstop w/constant price	5.788	-1.684	-7.473	9.1%	
Backstop w/R&D	9.680	3.085	-6.595	19.8%	
Backstop w/exogenous R&D	N/A	2.758	-6.923		4.7%

Note: all figures in trillions of 1990 US dollars.

The table shows the net economic impact, measured by the difference in the present value of consumption between a climate policy restricting emissions to 1995 levels and a no policy (BAU) simulation, for each assumption about the initial backstop price. The figures on the left show the gain from a BAU scenario without a backstop technology. Thus, reading down for each price assumption, one obtains the gains from adding a backstop to the model in both the BAU and optimal policy cases. The right set of figures show the change in welfare from climate policy, holding assumptions about technology constant. This is obtained by reading across each row. Adding a backstop technology reduces the costs of achieving these emissions reductions.

Table 6 – Key Variables – Restricted Emissions Policy

	1995	2005	2015	2025	2055	2105
Carbon Tax ($/ton)						
Endogenous R&D: no backstop	N/A	$375.08	$775.20	$1,168.54	$2,342.75	$4,194.19
& Backstop	N/A	$324.59	$697.33	$1,062.46	$2,149.59	$3,873.84
& Backstop R&D	N/A	$362.51	$740.49	$1,099.84	$2,146.80	$3,769.18
Exogenous R&D: no backstop	N/A	$377.69	$779.35	$1,175.33	$2,360.07	$4,234.74
& Backstop R&D	N/A	$320.25	$686.63	$1,043.85	$2,096.94	$3,733.24
% Δ Endog vs. Exog.: no backstop	N/A	-0.69%	-0.53%	-0.58%	-0.73%	-0.96%
& Backstop R&D	N/A	13.20%	7.84%	5.36%	2.38%	0.96%
Energy R&D -- billions 1990 US dollars						
Endogenous R&D: no backstop	10.00	14.08	18.35	21.82	30.58	45.91
& Backstop	10.00	13.90	18.02	21.28	29.23	43.22
& Backstop R&D	10.00	13.82	17.90	21.12	28.89	42.36
Exogenous R&D: no backstop	10.00	13.13	16.83	19.71	26.59	38.55
& Backstop R&D	10.00	13.08	16.91	19.82	26.62	38.52
Elasticity: no backstop	N/A	0.09	0.08	0.08	0.10	0.12
& Backstop R&D	N/A	0.07	0.05	0.05	0.06	0.08
Backstop Energy R&D -- billions 1990 US dollars						
Endogenous R&D	1.00	1.47	1.71	1.96	2.82	4.58
Exogenous R&D	1.00	1.31	1.54	1.76	2.40	3.67
Elasticity	N/A	0.15	0.09	0.09	0.11	0.15
Emissions -- billion tons						
No Policy or Backstop	6.187	7.173	8.015	8.774	10.904	14.156
& Backstop	6.187	7.186	8.099	8.925	11.261	14.829
& Backstop R&D	6.187	7.212	8.129	8.951	11.255	14.734
Endogenous R&D: no backstop	6.187	6.187	6.187	6.187	6.187	6.187
& Backstop	6.187	6.187	6.187	6.187	6.187	6.187
& Backstop R&D	6.187	6.187	6.187	6.187	6.187	6.187
Exogenous R&D: no backstop	6.187	6.187	6.187	6.187	6.187	6.187
& Backstop R&D	6.187	6.187	6.187	6.187	6.187	6.187
% Δ Endog vs. Exog.: no backstop		0.000%	0.000%	0.000%	0.000%	0.000%
& Backstop R&D		0.000%	0.000%	0.000%	0.000%	0.000%
Output -- trillions $1990 US dollars						
No Policy or Backstop	22.61	30.00	36.94	43.72	63.55	95.19
& Backstop	22.61	29.93	37.05	44.00	64.34	96.96
& Backstop R&D	22.61	29.93	37.08	44.06	64.52	97.46
Endogenous R&D: no backstop	22.61	29.98	36.71	43.26	62.25	92.66
& Backstop	22.61	29.92	36.84	43.55	63.07	94.52
& Backstop R&D	22.61	29.92	36.87	43.62	63.29	95.16
Exogenous R&D: no backstop	22.61	29.98	36.69	43.21	62.12	92.35
& Backstop R&D	22.61	29.92	36.85	43.58	63.17	94.90
% Δ Endog vs. Exog.: no backstop		0.00%	0.06%	0.11%	0.21%	0.34%
& Backstop R&D		0.00%	0.06%	0.11%	0.19%	0.27%

Table 7 – Effect of Crowding Out

A. Optimal Policy

	Gain from optimal policy	Compare to exog R&D	Gains from ITC
Backstop w/R&D	2.275	2.145	6.0%
low opportunity cost -- lower bound	2.414	2.152	12.2%
low opportunity cost -- upper bound	2.445	1.874	30.5%
high opportunity cost -- lower bound	2.123	2.155	-1.5%
high opportunity cost -- upper bound	2.227	2.200	1.2%

B. Restrict Emissions to 1995 Levels

	Gain from policy	Compare to exog R&D	Gains from ITC
Backstop w/R&D	-6.595	-6.922	4.7%
low opportunity cost -- lower bound	-6.467	-6.918	6.5%
low opportunity cost -- upper bound	-6.263	-7.152	12.4%
high opportunity cost -- lower bound	-6.868	-6.910	0.6%
high opportunity cost -- upper bound	-6.843	-7.048	2.9%

Note: all figures in trillions of 1990 US dollars.

The table shows how the welfare gains from induced technological change vary as assumptions about the opportunity cost of R&D vary. To illustrate the gains from ITC, the first column presents the net economic impact of policy with ITC, and the second column presents the net economic impact of policy with exogenous energy R&D.

Table 8 – Effect of R&D Subsidies

A. Optimal Policy

	Gain from BAU	% gain from optimal policy/no backstop
No Backstop	1.880	
with R&D subsidies	2.006	6.7%
Backstop w/constant price	2.159	14.8%
with R&D subsidies	2.241	19.2%
Backstop w/R&D	2.275	21.0%
with backstop R&D subsidies only	2.292	21.9%
with R&D subsidies	2.367	25.9%
R&D subsidies only -- no tax	0.177	

B. Restrict Emissions to 1995 Levels

	Gain from BAU	% gain from optimal policy/no backstop
No Backstop	-8.219	
with R&D subsidies	-7.964	3.1%
Backstop w/constant price	-7.473	9.1%
with R&D subsidies	-7.319	11.0%
Backstop w/R&D	-6.595	19.8%
with backstop R&D subsidies only	-6.597	19.7%
with R&D subsidies	-6.459	21.4%

Note: all figures in trillions of 1990 US dollars.

The table shows how the welfare gains change when R&D subsidies are used along with climate policy.

Appendix A – Equations of the ENTICE Model

This appendix presents the complete equations of the ENTICE model.

Exogenous variables and parameters

t = time
L_t = population at time t, also equal to labor inputs
L_0 = initial population level
$g_{L,t}$ = growth rate of population
$g_{L,0}$ = initial value of the growth rate of population
d_L = rate of decline of $g_{L,t}$
R_t = pure time preference discount factor
r_0 = initial value of the pure rate of social time preference
g_r = growth rate of the social time preference
A_t = total factor productivity
A_0 = initial value of total factor productivity
$g_{L,t}$ = growth rate of total factor productivity
$g_{L,0}$ = initial value of the growth rate of total factor productivity
d_L = rate of decline of $g_{A,t}$
γ = elasticity of output with respect to capital
β = elasticity of output with respect to energy/carbon inputs
Φ_t = ratio of carbon emissions per unit of carbon services
$g^z{}_t$ = growth rate of Φ_t per decade
δ^z = rate of decline of $g^z{}_t$
ζ_1, ζ_2, ζ_3 = parameters of the long-run carbon supply curve
markup= energy services price markup
*CumC** = Total carbon resources available
δ = rate of depreciation of the physical capital stock
δ_H = rate of depreciation of energy knowledge stock
crowdout = percentage of overall R&D crowded out by energy R&D
a, b, ϕ = parameters of the innovation possibilities curve
η = effect of backstop energy knowledge on backstop price
α_H = scaling factor for the stock of energy knowledge
α_Φ = percentage of exogenous carbon intensity reduction
ρ_H = substitution parameter for energy and knowledge
ρ_B = substitution parameter between fossil fuels and backstop energy
LU_t = Land-use carbon emissions
LU_0 = Initial land-use carbon emissions
δ_{LU} = Rate of decline of land-use carbon emissions
ϕ_{11}, ϕ_{12}, ϕ_{21}, ϕ_{22}, ϕ_{23}, ϕ_{32}, ϕ_{33} = Parameters of the carbon transition matrix
O_t = Increase in radioactive forcing over preindustrial levels due to exogenous anthropogenic causes
σ_1, σ_2, σ_3 = Temperature dynamics parameters
θ_1, θ_2 = Parameters of the damage function

$4.1/\lambda$ = Climate sensitivity – equilibrium increase in temperature from a doubling of CO_2 concentrations)

Endogenous Variables

U_t = utility in period t
c_t = per capita consumption
Q_t = output (trillions of 1990 US dollars)
Ω_t = damages from climate change
μ_t = emissions control rate in DICE model
K_t = physical capital stock (trillions of 1990 US dollars)
E_t = energy inputs
$p_{F,t}$ = price of fossil fuels
$p_{B,t}$ = price of backstop energy
F_t = fossil fuel/carbon inputs, also equal to CO_2 emissions
B_t = backstop energy, in carbon ton equivalents (CTE)
q_F = marginal cost of fossil fuel extraction
$CumC_t$ = cumulative carbon extractions by year t
I_t = investment in physical capital
C_t = total consumption
H_{E_t} = stock of energy efficiency knowledge
H_{B_t} = stock of backstop energy knowledge
R_{E_t} = energy R&D
EM_t = Carbon emissions
$M_{A,t}$ = Atmospheric CO_2 concentration
$M_{U,t}$ = Upper oceans/biosphere CO_2 concentration
$M_{L,t}$ = Lower oceans CO_2 concentration
$FORCE_t$ = Radioactive forcing, increase over preindustrial level
T_t = Atmospheric temperature, increase over 1900 level
TL_t = Lower ocean temperature, increase over 1900 level

The ENTICE model maximizes per capita utility, defined in equation (A 1) below, subject to a set of environmental and economic constraints. Economic constraints are represented by equations (A 2) – (A 17). Equations (A 18) – (A 27) are the environmental constraints.

(A 1) $$\max V = \sum_{t=0}^{T} U[c_t, L_t] R_t$$

Economic Constraints

(A 2) $$U_t = L_t \log(C_t / L_t)$$

(A 3) $$R_t = \prod_{v=0}^{t}\left[1 + r_0 e^{-g_r t}\right]^{10}$$

(A 4) $$Q_t = \Omega_t (A_t K_t^{\gamma} L_t^{1-\gamma-\beta} E_t^{\beta}) - p_{F,t} F_t - p_{B,t} B_t$$

(A 5) $K_t = \{I_t - 4*crowdout*(R_{E,t} + R_{B,t})\} + (1\text{-}\delta)K_{t\text{-}1}$.

(A 6) $L_t = L_0\exp(g_{L,t})$

(A 7) $g_{L,t} = (g_{L,0}/d_L)*(1\text{-}\exp(\text{-}d_L*t))$

(A 8) $A_t = A_0\exp(g_{A,t})$

(A 9) $g_{A,t} = (g_{A,0}/d_A)*(1\text{-}\exp(\text{-}d_A*t))$

(A 10) $$E_t = \left[\alpha_H H_{E,t}^{\rho_H} + \left(\left(\frac{F_t}{\alpha_\Phi \Phi_t}\right)^{\rho_B} + B_t^{\rho_B}\right)^{\rho_H / \rho_B}\right]^{1/\rho_H}, \qquad \rho \le 1$$

$$\Phi_t = \exp\left[\left(\frac{g_t^z}{\delta^z}\right)\left(1 - \exp\left(-\delta^z t\right)\right)\right]$$

(A 11) $P_F = q_F + markup$

(A 12) $q_F = \zeta_1 + \zeta_2[CumC_t / CumC^*]^{\zeta_3}$

(A 13) $CumC_t = CumC_{t\text{-}1} + 10*F_t$

(A 14) $F_t < 0.1 * (CarbMax - CumC_t)/10$

(A 15) $H_{i,t} = h(R_{i,t}) + (1-\delta_H)H_{i,t-1},$ $\qquad i = E,B$

(A 16) $h(R_{i,t}) = aR^b{}_{i,t}H^{\phi}{}_{i,t},$ $\qquad i = E,B$

(A 17) $Q_t = C_t + I_t + R_{E_t} + R_{B_t}$

Environmental Constraints

(A 18) $LU_t = LU_0(1\text{-}\delta_{LU})^t$

(A 19) $EM_t = F_t + LU_t$

(A 20) $M_{A,t} = 10*EM_t + \phi_{33}M_{L,t\text{-}1} + \phi_{23}M_{U,t\text{-}1}$

(A 21) $M_{L,t} = \phi_{11}M_{A,t\text{-}1} + \phi_{21}M_{U,t\text{-}1}$

(A 22) $M_{U,t} = \phi_{12}M_{A,t\text{-}1} + \phi_{22}M_{U,t\text{-}1} + \phi_{32}M_{L,t\text{-}1}$

(A 23) $FORCE_t = 4.1*\{\log(M_{A,t}/596.4)/\log(2)\} + O_t$

(A 24) $O_t = \text{-}0.1965 + 0.13465t,$ $\qquad t < 11$

$O_t = 1.15,$ $t \geq 11$

(A 25) $T_t = T_{t-1} + \sigma_1\{FORCE_t - \lambda T_{t-1} - \sigma_2(T_{t-1} - TL_{t-1})\}$

(A 26) $TL_t = TL_{t-1} + \sigma_3(T_{t-1} - TL_{t-1})$

(A 27) $\Omega_t = 1/(1 + \mathrm{a}_1 + T_t + \mathrm{a}_2 * T_t^2)$

Appendix B – Calibration of the ENTICE-BR Model

This appendix describes the steps taken to calibrate the ENTICE-BR model. I begin by summarizing calibration of the ENTICE model without a backstop technology, followed by a discussion of changes necessary to incorporate the backstop technology.

As a global macroeconomic model, ENTICE uses Nordhaus' DICE model (1994, Nordhaus and Boyer 2000) as its basic building block. Since the current version of Nordhaus' DICE model does not include carbon emissions as an input, but rather simply models emissions as a byproduct of output requiring control, the first step to constructing the model is to add a fossil fuel sector that mimics the behavior of the original DICE model. I do this using the same modeling structure as Nordhaus' RICE model, except that I apply the equations at a global, rather than regional, level. Key equations of the economic sector of the DICE model, along with the modifications necessary to include carbon emissions as an input, are included in the modeling appendix. I calibrate this basic model, with no energy R&D, so that the results are comparable to Nordhaus' DICE model. To begin, I take the initial value of F from the latest version of the DICE model. I then solve for initial values of A and K that reproduce the initial output found in the DICE model. Next, I calculate the elasticity of output to with respect to energy, β, as the percentage of output spent on fossil fuels in the initial period, using the 1995 price of carbon based on equations (6) and (7).[27] Finally, the growth rate of Φ, g^z (-15.49), and the rate of decline of this growth rate, $\gamma^{\bar{z}}$ (23.96), are chosen to produce an emissions path as close as possible to the DICE model. These values represent the rate of exogenous decline in carbon intensity without any energy R&D in the model. Figures B1 and B2 compares the emissions and output that result from this calibration.

[27] References to equation numbers refer to equations in the text of the main paper.

Having added carbon fuels as an input to production in the DICE model, the next step is to add induced technological change to the ENTICE model. The modeling for this stage is described the main text of the paper. Calibration requires choosing values for the following parameters:

- the initial value of energy research, R_{E0}.
- ρ, the substitution parameter in equation (10),
- parameters in the invention possibilities frontier (9): a, b, and ϕ, and
- the initial level of energy human capital, H_{E0},[28]
- α_H, the scaling factor for the effect of this human capital, and
- α_Φ, the percentage of exogenous technological change remaining.

To calibrate the energy R&D sector, three goals must be met. First, R&D levels should be consistent with historical levels. A starting value of $10 billion is chosen for the base year of 1995. To get this value, I begin with an estimated level of total global spending on R&D of $500 billion. This figure is based largely on data from OECD countries. Energy R&D data is not available on a global basis. However, it is available for the United States. In the U.S., two percent of R&D spending in 1995 went to energy-related R&D. The $10 billion figure used in this paper is simply two percent of the global level of R&D. This figure is also close to the initial value of R&D used by Nordhaus (2002).

Second, the behavior of energy R&D should be consistent with empirical studies both *across time* and *across policy dimensions*. Based on Popp (2002), I use an elasticity of energy R&D with respect to energy prices of 0.35 for the base model. As the price of carbon rises over time, the time path of energy R&D should follow the path predicted by this value as closely as possible.[29] In addition, elasticities of energy R&D calculated on differences in the carbon price with and without a carbon tax in the optimal policy simulation should also equal 0.35. Since the goal of this paper is to explore the consequences of omitting endogenous technological change from earlier climate change models, when these two goals are incompatible, the second takes precedence. Furthermore, since Popp (2002) also notes that energy R&D experiences diminishing returns over time, the calibrated elasticity should fall over time. Figure B3 shows the calibrated levels of energy R&D and what would be predicted by a constant elasticity over time of 0.35.

Finally, Popp (2001) estimates a 4:1 ratio on the returns to energy R&D. Thus, each dollar of energy R&D should lead to a four dollar reduction in energy savings. The model is calibrated so that a weighted average of energy savings each period (weighted by the discount factors used in the model) produce a 4:1 ratio of energy savings to energy R&D.

Using these goals as guidelines for choosing the parameters, I first choose the value of HE_0 to approximate baseline emissions in early years of the simulation. Next, I choose ρ to approximate the elasticity of energy R&D between the no-policy and optimal policy simulations. Third, the value of the scaling factor α_H is chosen to yield the appropriate rate of return on energy R&D. To calibrate the inventions possibility frontier, the value a is chosen so that the change in energy R&D between 1995 and 2005 in the optimal policy simulation is consistent with the elasticity of 0.35. Values of b and ϕ are chosen so that future elasticities fit the desired time path – falling slowly in the near future due to diminishing returns to R&D. Once the desired time path of R&D is calibrated, the scaling factor α_Φ can be adjusted to change the level

[28] Note that, since human capital enters the invention possibilities frontier multiplicatively, the initial value cannot be zero.

[29] Note that, to account for growth in the level of economic activity, all elasticities are calculated based on a ratio of energy R&D to global output.

of baseline emissions as appropriate. A value of 0.8 is used in the base model, meaning that 80 percent of exogenous technological change remains in the ENTICE model. As a result, purposeful R&D efforts to improve energy efficiency are only a small portion of the changes that take place over time to reduce energy intensity. Table 1 in Popp (2003) presents a complete list of the parameter values chosen for both the base model and various sensitivity analysis scenarios.

When adding a backstop, the first critical piece of information is the initial conditions. Based on Nakicenovic *et al*. (1998), the backstop technology is assumed to contribute four percent of total energy in 1995. This yields an initial backstop level of 0.25 carbon ton equivalents (CTE). The parameter β from the production function, which equals the share of energy expenses taken from output, is adjusted accordingly, as the share of production costs going to energy is now greater. To be consistent with R&D data (Anderson 1997), the initial level of backstop energy R&D is ten percent of energy efficiency R&D, or $1 billion. The initial stock of backstop knowledge, $H_{B,0}$ is normalized to 1.

As with energy efficiency R&D, the value of ρ_B has a significant impact on the elasticity of backstop energy R&D. However, its value is not set independently. Based on the first-order conditions for energy demand, ρ_B is determined by initial energy consumption and the relative prices of fossil fuels and the backstop technology. Unfortunately, a wide range of possibilities for the starting price exists. For example, in appropriate conditions, the price of electricity from wind is nearing competitive levels. Burtraw *et al* (1995) report the cost of wind energy to be 44% higher than that of energy from fossil fuels. This yields an initial price of $400 per carbon ton equivalent (CTE) of backstop energy. Gerlagh and Lise (2003) report prices for alternative energy sources ranging from 2 to 5 times that of fossil fuels. Using the upper range of this as an alternative, I consider an initial price of $1200 as a second option. Unfortunately, the resulting elasticity of substitution yields very high elasticities of R&D in each case. Thus, I also consider a starting price of $2000 CTE. This provides more reasonable elasticities of backstop energy R&D, as the resulting elasticity of substitution is similar to that for energy efficiency R&D.

Next, a value for η, which relates human capital to backstop price decreases, is chosen. Again, no good empirical estimates exist. Results for two values, 0.5 and 1.0, are presented. These yield progress ratios of 24 and 50 percent respectively. A 50 percent progress means that a doubling of the knowledge stock reduces the backstop price by 50 percent. More importantly, under realistic base case R&D scenarios, the share of energy consumption resulting time paths for backstop energy R&D are comparable to other studies. Such rapid progress is comparable to changes in patenting and prices during the past 20 years. The 24 percent progress ratio yields slightly lower shares of backstop energy than comparable scenarios. However, as shown in the results section, the marginal returns to R&D are more realistic. Thus, a 24 percent progress ratio is used for the base case.

Finally, the parameters of the inventions possibilities frontier are chosen as before. At the same time, the parameters a and b for energy efficiency R&D are changed slightly so that base case R&D is comparable in simulations with and without a backstop technology. Table 1 in the paper provides a list of the new parameters needed for the ENTICE-BR model.

Figure B1 – Industrial Emissions in the ENTICE & RICE Models

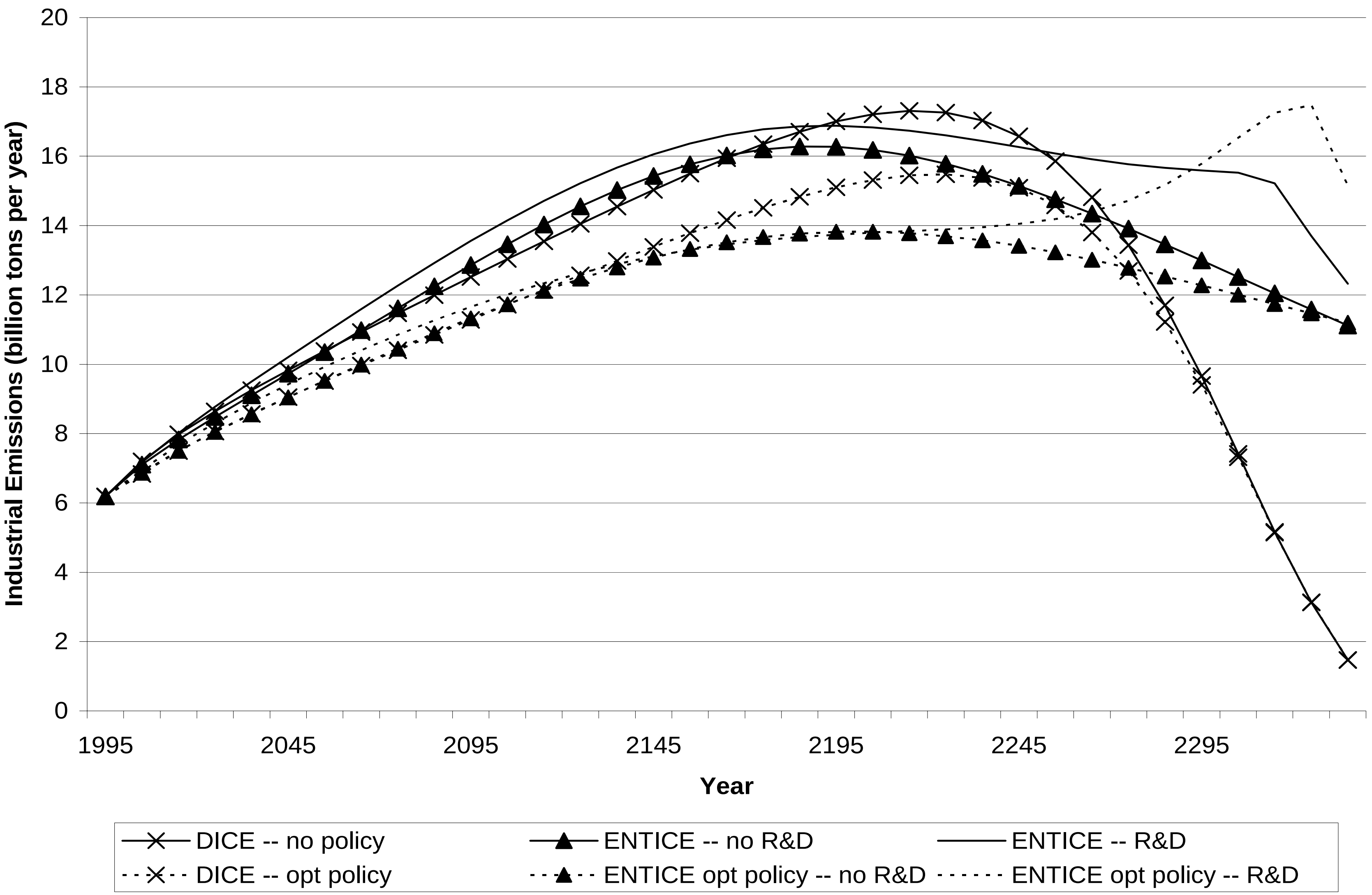


Figure B2 – Output in the ENTICE & RICE Models

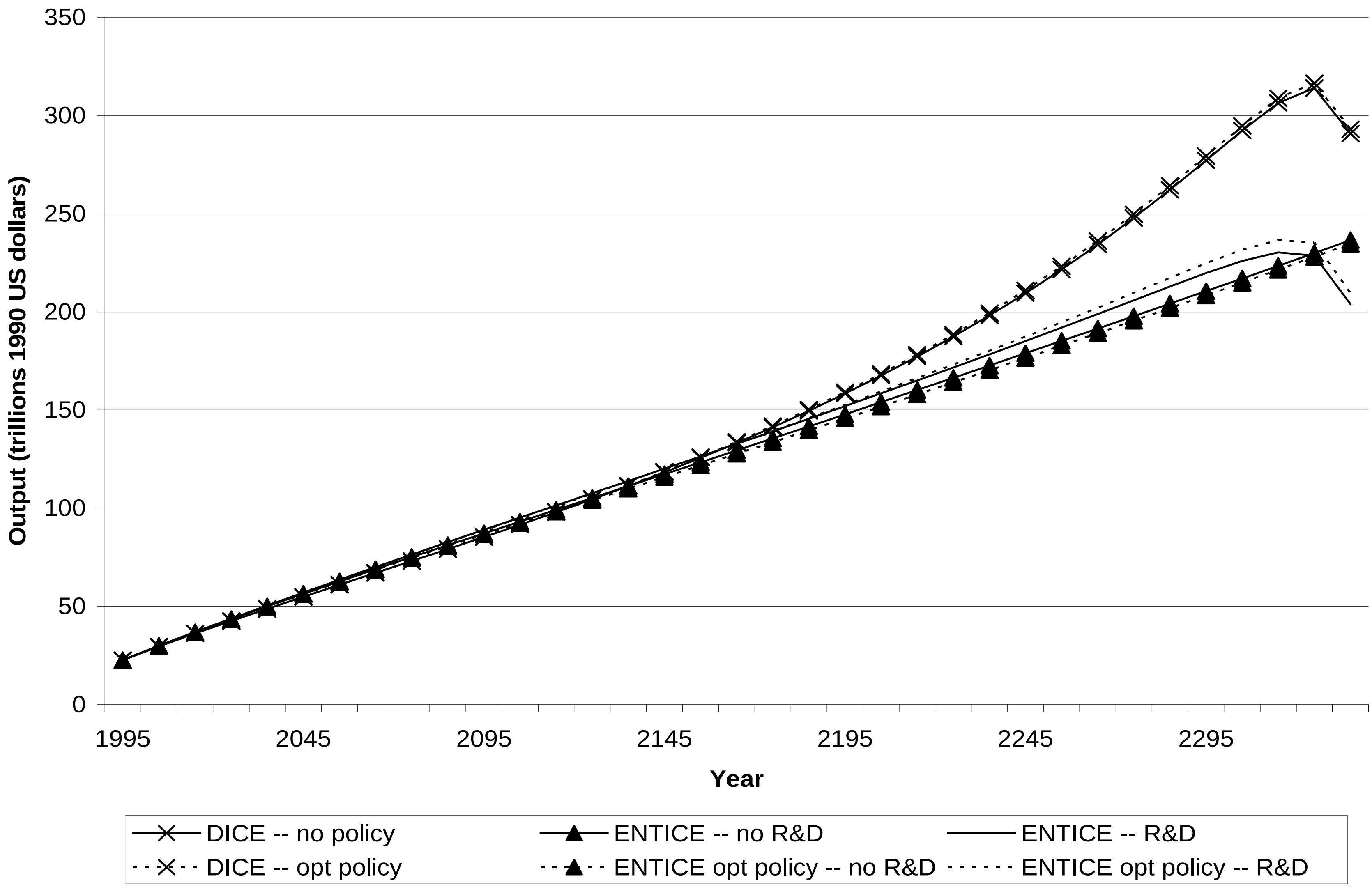


Figure B3 – Predicted and Actual Energy R&D