Comparison of Climate Policies in the ENTICE-BR Model

*David Popp**

This paper uses the ENTICE-BR model to study the effects of various climate stabilization policies. Because the ENTICE-BR model includes benefits from reduced climate damages, it is possible to calculate the net economic impact of each policy. In general, only the least restrictive concentration limit is welfare enhancing. While the policies are welfare enhancing in simulations using optimistic assumptions about the potential of the backstop energy technology, such assumptions mean that the backstop is also used in the no-policy base case, so that climate change itself is less of a problem. Finally, assumptions about the nature of R&D markets are important. Removing the assumption of partial crowding out from energy R&D nearly doubles the gains from policy-induced energy R&D.

1. INTRODUCTION

ENTICE-BR 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-BR is a dynamic growth model of the global economy that includes links between economic activity, carbon emissions, and the climate. The model 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-BR retains the global framework of the DICE model, rather than dividing the world into separate regions. In this paper, I explore the effect of the various climate stabilization policies used in the Innovation Modeling Comparison Project (IMCP). I begin by discussing the basic structure of the ENTICE-BR model, focusing on how endogenous technological change is incorporated into the model. Section 3 briefly discusses calibration

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* Department of Public Administration, Center for Environmental Policy Administration, Center for Technology and Information Policy, The Maxwell School, Syracuse University, 400 Eggers Hall, Syracuse, NY 13244-1090. ph: 315-443-2482, fax: 315-443-1075, e-mail: dcpopp@maxwell.syr.edu, home page: http://faculty.maxwell.syr.edu/dcpopp/index.html. Faculty Research Fellow, National Bureau of Economic Research.

of the model. Readers interested in more modeling and calibration details are referred to Popp (forthcoming). Section 4 presents the results of simulations of the four carbon concentration stabilization scenarios used in the IMCP: 400, 450, 500, and 550 parts per million (ppm). Section 5 concludes.

2. MODEL STRUCTURE

The ENTICE-BR model maximizes the present value of per capita utility, subject to a set of economic constraints, some of which are presented below [equations (1)-(6)].[1] Output, Q_t, is produced by a combination of labor, L_t, the physical capital stock, K_t, and effective energy units, E_t.[2] Overall technological progress comes through changes in total factor productivity, A_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, $H_{E,t}$. The cost of both fossil fuels and the backstop fuel, $p_{F.t}$ and $p_{B,t}$, are subtracted from total output:[3]

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

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. Defining a_H as a scaling factor determining the level of energy savings resulting from new energy-efficiency knowledge and Φ_t as any remaining exogenous changes in the ratio of carbon emissions per unit of carbon services, energy needs are met by consuming energy inputs or improving knowledge pertaining to energy efficiency, as shown below:

$$E_t = \left[\alpha_H H_{E,t}^{\rho_H} + \left(\left(\frac{F_t}{\alpha_\Phi \Phi_t} \right)^{\rho_B} + B_t^{\rho_B} \right)^{\rho_H/\rho_B} \right]^{1/\rho_H} \tag{2}$$

The first nest in equation (2) relates the use of energy inputs and energy efficiency improvements, while the second allows for substitution between fossil fuels and the backstop technology. This second nest, introduced in van der Zwaan et al (2002), models the backstop and fossil fuels as imperfect substitutes, allowing

1. The equations below represent portions of the model directly incorporating energy-related technological change. Details on other equations, including those linking economic activity and the environment, can be found in Popp (forthcoming).

2. For optimizing with climate policy, output is scaled by the damages caused by carbon concentrations, as shown in Nordhaus and Boyer (2000).

3. 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. The cost of fossil fuels evolves over time, and increases as more fossil fuels are extracted. See Popp (2004a) for more details. The costs of the backstop technology are defined below.

for "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.[4]

Backstop technologies are, by definition, technologies for which scarcity is not a concern. The price of the backstop technology 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:

$$p_{B,t} = \frac{P_{B,0}}{H_{B,t}^{\eta}} \tag{3}$$

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.*

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). R&D is endogenous to the model. The R&D sector is calibrated as discussed in section III, so that growth in energy R&D in the baseline business as usual simulations (BAU) are consistent with historical levels. Moreover, because R&D is endogenous, the level of R&D spending and thus the level of each knowledge stock, increases when climate policies are introduced. Using $R_{i,t}$ to represent R&D spending for either energy efficiency or the backstop technology, the knowledge stocks increase as shown below:

$$H_{i,t+1} = aR_{i,t}^{b_i} H_{i,t}^{\Phi_i} + H_{i,t}, \;\; i = E,B \tag{4}$$

The first term on the right-hand side models the process by which energy R&D, $R_{i,t}$, creates new knowledge. The parameters are chosen so that there are diminishing returns to energy research over time. This assumption is motivated by empirical

4. Note that technology enters equation (2) in one of two ways. $H_{E,t}$ represents technological improvements to energy efficiency that evolve endogenously over time. Technology also enters exogenously through Φ_t, which represents exogenous changes in the ratio of carbon emissions per unit of carbon services. Examples include changes in consumption patterns and switching to less carbon-intensive fossil fuels, such as natural gas. 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. Because the DICE model and its variants are a one-sector macroeconomic growth model, changes in consumption patterns or substitution among types of fossil fuels are not explicitly modeled. Fortunately, Popp (2004a) shows that the percentage of exogenous changes in carbon intensity remaining does not affect the net economic impact of induced technological change, as it is the level of R&D induced between an exogenous and endogenous R&D simulation that is important. Changing the scaling factor only changes the level of emissions in each simulation, but not the *difference* between them.

work in Popp (2002). In this case, diminishing returns to R&D occur 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.[5] 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. I model these positive externalities by constraining the private rate of return for R&D to be four times that of investment in physical capital. 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.

One implication of the high social benefits to R&D is that the model must 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. Note that all output is devoted to either consumption, investment in physical capital, or R&D:

$$Q_t = C_t + I_t + R_{E,t} + R_{B,t} \tag{5}$$

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.[6] 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. This is modeled by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock is:

$$K_t = \{I_t - 4*crowdout*(R_{E,t} + R_{B,t})\}+(1\text{-}\delta)K_{t\text{-}1}, \tag{6}$$

where *crowdout* represents the percentage of other R&D crowded out by energy R&D. As in Popp (forthcoming, 2004a,b), in the base case I assume new energy R&D crowds out 50% of other R&D.

3. CALIBRATION

Popp (forthcoming) describes the basic calibration of the ENTICE-BR model. The model begins in 1995, and is solved in 10-year increments for 350 years. The model has been recalibrated slightly so that output in year 2000 is consistent

5. There is a large body of empirical work that verifies the social returns to R&D are greater than the private returns. For a discussion of this work and its implications for climate models, see Popp (2005).

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

with other papers presented in the IMCP project. As in Popp (forthcoming), parameters are chosen so that the initial elasticity of energy R&D with respect to energy prices across policy simulations is 0.35 (Popp, 2002). This elasticity is primarily controlled by the choice of ρ_H, which for this paper equals 0.38. To calibrate equation (4), the value a is also 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. The value of the scaling factor a_H is chosen so that each new dollar of energy efficiency R&D yields four dollars of energy savings.

To calibrate the backstop energy sector, initial values for backstop R&D and backstop energy consumption are needed. 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.[7] Specifying the initial backstop price is complicated, as a wide range of estimates exists. Moreover, the initial backstop price also defines the elasticity of substitution between backstop and fossil fuel energy sources. Following Popp (forthcoming), I consider three possible starting prices: \$400 ($\rho_B = 0.885$), \$1200 ($\rho_B = 0.542$), and \$2000 ($\rho_B = 0.383$) per carbon ton equivalent (CTE) of backstop energy. Note that lower prices imply a higher elasticity of substitution,[8] and thus yield very high elasticities for backstop energy R&D, resulting in levels of policy-induced R&D inconsistent with empirical evidence. A price of \$2000 CTE provides more reasonable elasticities of backstop energy R&D, as the level of ρ_B implied by this starting price is consistent with the level used for energy efficiency R&D. However, this price is in the upper range of current price estimates.[9]

Finally, I need a value for η, which relates human capital to backstop price decreases. Again, no good empirical estimates exist. The scenarios presented in this paper assume a value of 0.4, which implies a progress ratio of 24 percent. Popp (forthcoming) shows that the model is not very sensitive to the choice of this parameter. This surprising result occurs because changes in the price of the backstop are only significant near the point at which the backstop price approaches the cost of traditional fossil fuels. In other years, changes in this parameter have little impact. Thus, over the 350 year period simulated in ENTICE-BR, there is little impact to changing the value of η.

7. Although van der Zwaan et al do not specify the fuels represented by their backstop technology, this figure would be consistent with including hydroelectric and solar-based renewables (e.g. solar, wind, and geothermal), but not including nuclear energy. Given the political difficulties in siting new nuclear power plants, as well as the environmental costs of dealing with nuclear waste, this assumption seems practical.

8. This is because the both the elasticity of substitution and initial backstop price must be consistent with backstop usage in the base year. As the initial price falls, either the elasticity of substitution must increase, or the level of backstop usage in the base year would have to increase.

9. See footnote 18 in Popp (forthcoming) for a discussion.

4. SIMULATION RESULTS

This section simulates the effects of limiting atmospheric carbon concentrations to 400, 450, 500, or 550 ppm. I begin with results using the medium elasticity of substitution between the backstop and fossil fuels, which is the base case in Popp (forthcoming). I present sensitivity analysis on this choice, as well as examining the effect of R&D opportunity costs and R&D market imperfections. Readers interested in sensitivity analysis of other parameters are referred to Popp (forthcoming, 2004a).

Table 1 presents the net economic impact of each policy under the various scenarios. 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.[10] Note that measures of output in the DICE family of models include damages from climate change. Thus, output measures include both the costs of reducing emissions and any potential benefits from these reductions. As such, unlike models that do not explicitly include damages, changes in GDP cannot be used as a measure of the cost of a policy.

Note that, with the exception of the case where the elasticity of substitution between the backstop and fossil fuels is high (and thus the starting price of the backstop is low), only the least restrictive of the climate policies enhances welfare. In the base case, the present value of consumption falls by over 25 trillion dollars for the most restrictive policy limiting concentrations to 400 parts per million (ppm). This finding is robust, as even with a low opportunity cost of research or a model that removes the imperfections in R&D markets, the net economic impact of this policy is still a loss of nearly 25 trillion dollars.

In addition to the base results, Table 1 also shows the benefits from policy-induced technological change (ITC) in the energy sector. Column 2 shows the net economic impact of each policy when technology is exogenous – that is, energy R&D levels remain at baseline levels even after climate policy is enforced. Column 3 shows the difference between columns 1 and 2, and column 4 expresses this difference as a percentage increase from the net economic impact without ITC. Because more restrictive polices induce more R&D, the gains from ITC are greater for the more restrictive policies. However, because the welfare losses are so large with the restrictive policies, the percentage gain is smaller.

While it may seem surprising that the effects of ITC are small, it is important to note that R&D occurs even in the business as usual (BAU) simulation that does not include climate policy. Thus, these welfare gains are not for the effect of technology per se, but only of the gains from the additional energy R&D that is induced by a climate policy. Table 2 shows the level of energy R&D (both backstop and energy efficiency R&D) under each policy.[11] Looking at the base

10. For the business as usual case in which emissions are uncontrolled, the model is first optimized ignoring climate damages, and output is then adjusted to account for the damages that occur from such suboptimal behavior.

11. The table also presents optimal energy R&D subsidies. These are discussed below.

Table 1. Net Impact of Stabilization Policies

Stabilization goal	(1) Net economic impact with ITC	(2) Net economic impact without ITC	(3) Gain from ITC (trillions 1995 US $)	(4) % gain from ITC	(5) Net economic impact with low R&D opportunity cost	(6) Gain from low opp cost (trillions 1995 US $)	(7) % gain from low opp cost	(8) Net economic impact with R&D subsidies	(9) Gain from R&D subsidies (trillions 1995 US $)	(10) Gain from R&D subsidies
Base -- medium elasticity of substitution										
400 ppm	-25.64	-26.62	0.98	3.7%	-24.90	0.74	2.9%	-25.41	0.23	0.9%
450 ppm	-8.19	-8.83	0.64	7.2%	-7.70	0.49	6.0%	-7.97	0.22	2.7%
500 ppm	-1.42	-1.87	0.45	24.0%	-1.05	0.36	25.7%	-1.23	0.19	13.3%
550 ppm	1.32	0.99	0.33	33.6%	1.62	0.29	22.1%	1.49	0.16	12.5%
low elasticity of substitution										
400 ppm	-35.25	-35.99	0.74	2.0%	-34.61	0.65	1.8%	-35.05	0.20	0.6%
450 ppm	-13.39	-13.87	0.48	3.5%	-12.96	0.43	3.2%	-13.19	0.19	1.4%
500 ppm	-4.39	-4.74	0.35	7.3%	-4.06	0.33	7.6%	-4.23	0.16	3.7%
550 ppm	-0.37	-0.64	0.27	41.6%	-0.09	0.28	76.0%	-0.23	0.14	37.0%
high elasticity of substitution										
400 ppm	2.83	1.92	0.91	47.4%	3.16	0.33	11.8%	2.99	0.16	5.6%
450 ppm	3.50	3.04	0.47	15.4%	3.62	0.11	3.2%	3.91	0.41	11.6%
500 ppm	3.58	3.04	0.54	17.8%	3.72	0.14	3.9%	3.91	0.33	9.2%
550 ppm	3.71	3.04	0.68	22.3%	3.93	0.21	5.7%	3.91	0.20	5.3%

The table shows the *net economic impact*, measured as the change from business as usual in the present value of consumption, for various climate stabilization scenarios. In all cases, gains are expressed in trillions of 1995 US dollars. Column (1) shows the gain with a model including policy-induced technological change, while column (2) is the gain from a model with exogenous technological change, in which energy R&D with policy is constrained to be the same as in the no policy case. Column (3) is the difference between columns (1) and (2). It is the welfare gain from including ITC in the model, measured in trillions of 1995 US dollars. Column (4) expresses this gain as a percentage increase from column (2). Column (5) presents the net economic impact from a model with no crowding out from energy R&D. Columns (6) and (7) present the marginal gain from removing crowding out, compared to the results in column (1). Finally, column (8) is the net economic impact when R&D is subsidized at its optimal level. Columns (9) and (10) present the marginal gain from these subsidies, compared to column (1).

case, note that energy R&D increases from 14.6 billion to 15.8 billion dollars in 2000 and from 48.5 to 62.8 billion in 2100 under the most restrictive policy. In contrast, energy R&D increases to just 14.9 billion in 2000 and 53.0 billion with the least restrictive policy. Thus, even with the most restrictive policy, the majority of the R&D that occurs takes place *with or without* climate policy in place.[12] Also, note the inverse relationship between the elasticity of substitution between energy sources and induced R&D. There is less energy R&D induced when the elasticity of substitution is high. However, recall that the high elasticity of substitution corresponds with an initial low backstop price. As such, the backstop price falls to a threshold below fossil fuel prices more rapidly, so that the share of energy coming from the backstop grows more quickly.

To better understand the impact of these policies, Table 3 summarizes results for four key outputs of the model: output (in trillions of 1995 US dollars), the carbon tax necessary to achieve the policy goal,[13] the percentage of energy coming from the backstop technology, and atmospheric carbon concentrations.[14] Results for each policy option, as well as a business as usual scenario that has no climate policy, are presented for each of the three initial backstop prices. The results presented include induced technological change in the energy sector.[15] Consistent with the net economic impact shown in Table 1, in most cases output is lower with policy in place. These effects are most notable in the long run, as the carbon tax necessary to limit concentrations grows over time. For the most restrictive policy, the carbon tax grows from \$72.75 per ton in 2000 to \$1,102.51 in 2100. In contrast, for the least restrictive policy, the carbon tax is \$10.97 per ton in 2000, and just \$170.23 in 2100. Still, the near-term effects of even this policy appear negative, as output in the base case remains lower, even in 2100. It is only the case of a high elasticity of substitution that output increases with a climate policy in place.

The welfare gains that occur with a high elasticity of substitution (as well as the lower carbon taxes to achieve each policy goal), occur because the high elasticity of substitution case corresponds with a lower initial backstop price. In this scenario, the backstop price falls below the price of carbon-based fuel in 2090, making it easier to achieve carbon reductions. Indeed, note that BAU carbon concentrations barely exceed 500, even in the no policy case.

12. It is important to note that the BAU scenario is calibrated beginning with 1995 energy R&D levels, and assuming that this R&D evolves over time in a way consistent with historical trends. Of course, past energy R&D has also been influenced by policy, such as country-level attempts at carbon taxes, requirements that a certain percentage of energy be produced with renewable sources, and through public funding of R&D. Thus, the BAU scenario should not be interpreted as a case with no policy, but rather a case in which current policies continue but are not augmented by more restrictive emissions limits.

13. As ENTICE-BR is a global model, permit trading is not a direct policy option. However, the carbon tax can also be seen as the permit price that would result in a global trading market.

14. Note that, except in the case of 400 ppm, the concentration constraint does not become binding until after 2100.

15. For each variable, there is little change when technology is exogenous.

Table 2. Energy R&D

Energy R&D (billions of 1995 US dollars)				
2000	2020	2050	2100	
Base -- medium elasticity of substitution				
BAU	14.61	24.89	34.51	48.51
400 ppm	15.81	29.19	44.89	62.83
with subsidies	16.51	35.19	56.48	83.85
450 ppm	15.17	26.77	38.87	60.48
with subsidies	15.59	31.11	52.03	80.57
500 ppm	14.94	25.92	36.82	57.40
with subsidies	15.18	29.12	47.75	77.80
550 ppm	14.85	25.57	35.98	52.96
with subsidies	15.00	28.20	45.35	73.44
low elasticity of substitution				
BAU	14.67	25.88	35.45	49.60
400 ppm	16.00	29.21	44.34	62.16
with subsidies	16.42	34.88	56.26	83.42
450 ppm	15.44	27.18	38.74	59.80
with subsidies	15.57	31.14	51.84	80.05
500 ppm	15.16	26.58	37.11	56.85
with subsidies	15.19	29.31	47.85	77.40
550 ppm	14.99	26.37	36.53	52.96
with subsidies	15.02	28.44	45.54	73.36
high elasticity of substitution				
BAU	14.58	24.77	34.42	48.10
400 ppm	15.51	28.15	39.97	52.81
with subsidies	15.60	31.20	47.82	69.69
450 ppm	15.01	26.41	37.98	52.83
with subsidies	15.10	28.98	46.55	69.71
500 ppm	14.88	25.73	36.32	52.34
with subsidies	15.10	28.98	46.55	69.71
550 ppm	14.84	25.55	35.85	50.76
with subsidies	15.10	28.98	46.55	69.71

The table presents total energy R&D in billions of 1995 US dollars. Lines labeled "with subsidies" present the level of energy R&D when R&D market imperfections are removed from the model.

Thus, carbon concentrations are not much higher than mandated by the two weaker policy options analyzed. This is important, as it indicates that *optimistic assumptions about the potential benefits of technology should be included not only in simulations that include a policy, but in analysis of the no-policy base case as well* (Popp, forthcoming). Thus, even without a carbon policy in place, the majority of energy comes from backstop sources by 2100. Indeed, Table 3 shows a large increase in the BAU percentage of energy coming from backstop sources for the high elasticity of substitution case between 2050, when the backstop is still more expensive, and 2100, when it is cheaper. In contrast, since the two other elasticities of substitution correspond with higher initial backstop prices, the price of the backstop does not become competitive without high carbon taxes. Thus, BAU usage of the backstop remains at 10 percent or less. As such, carbon concentrations in the BAU case range between 568 and 574 ppm by 2010, necessitating that restrictive climate policies be put in place if the stabilization goals are to be met.

Turning to sensitivity analysis of assumptions about R&D markets, columns (5)-(7) of Table 1 show the net economic impact of simulations assuming that all energy R&D is new R&D, so that no other beneficial R&D is crowded out. As shown in column (6), lowering this opportunity cost nearly doubles the benefits of ITC. For example, with the most restrictive policy in the base case, ITC increases welfare by 0.98 trillion dollars. Removing the assumption of partial crowding out leads to an additional 0.74 trillion dollars of welfare gain. As before, these effects are most important for the more restrictive policies, as they induce higher levels of R&D.

Finally, the last three columns of Table 1 show the effect of removing R&D market imperfections.[16] This can be seen as a case where the government subsidizes energy R&D at an optimal level. While this also enhances welfare, the gains are not as large as removing the assumption of crowding out.[17] Moreover, there is less variation in the gain from R&D subsidies as there are in the gains from ITC. Table 2 includes the total level of energy R&D when subsidies are included. As with policy-induced ITC, subsidies are higher under more restrictive climate policies.

5. CONCLUSION

This paper uses the ENTICE-BR model (Popp, forthcoming) to study the effects of various climate stabilization policies used in the IMCP. Because the ENTICE-BR model includes benefits from reduced climate damages, it is possible to calculate the net economic impact of each policy. Except in the case of a low initial backstop price, only the least restrictive concentration limit (550 ppm) is welfare enhancing. With a low initial backstop price, each of the climate stabilization policies is welfare enhancing. With a low backstop price, the stabilization policies imply little cost. When the backstop price is low, it becomes competitive with fossil fuels more quickly, and thus is also used in the no-policy base case.[18] As a result, carbon concentrations in the BAU scenario are lower, so that climate change itself is less of a problem. Thus, the emission reductions

16. That is, the return on energy R&D is no longer constrained to be four times that of other investments.

17. The R&D simulations include the assumption of partial crowding out. Popp (2004a) shows that this is important. There, I show that the rate of return on energy R&D is still higher than the rate of return on private investment after the restriction on returns to R&D is removed, because the optimal level of energy R&D must be low enough to account for crowing out of other investments.

18. See Popp (forthcoming) for a more detailed discussion.

Table 3. Effect of Stabilization Policies on Key Variables

	Output (trillions)				Carbon Tax			
2000	**2020**	**2050**	**2100**	**2000**	**2020**	**2050**	**2100**	
Base -- medium elasticity of substitution								
BAU	32.03	49.85	75.57	116.45	N/A	N/A	N/A	N/A
400 ppm	32.00	49.28	72.87	111.54	$72.75	$187.14	$657.81	$1102.51
450 ppm	32.03	49.69	74.79	112.89	$25.64	$63.15	$189.30	$722.10
500 ppm	32.03	49.78	75.26	114.57	$14.32	$33.53	$85.82	$394.26
550 ppm	32.03	49.81	75.40	115.79	$10.97	$24.72	$55.58	$170.23
low elasticity of substitution								
BAU	32.01	49.94	75.94	117.31	N/A	N/A	N/A	N/A
400 ppm	31.98	49.27	72.81	110.71	$83.20	$214.40	$761.89	$1459.71
450 ppm	32.01	49.75	74.98	112.69	$29.18	$72.64	$221.62	$910.49
500 ppm	32.02	49.86	75.55	114.84	$15.87	$37.71	$99.99	$487.03
550 ppm	32.02	49.89	75.73	116.37	$11.74	$26.84	$62.55	$211.53
high elasticity of substitution								
BAU	32.04	49.78	75.34	116.66	N/A	N/A	N/A	N/A
400 ppm	32.04	49.62	74.84	117.27	$21.59	$56.47	$118.04	$79.03
450 ppm	32.04	49.74	75.22	116.87	$8.56	$18.57	$36.62	$70.17
500 ppm	32.04	49.76	75.26	116.84	$8.62	$18.69	$36.84	$70.56
550 ppm	32.04	49.76	75.28	116.85	$8.63	$18.75	$36.93	$70.74

	Percentage of Energy from Backstop				Concentration (ppm)			
2000	**2020**	**2050**	**2100**	**2000**	**2020**	**2050**	**2100**	
Base -- medium elasticity of substitution								
BAU	4.2%	5.6%	7.5%	10.7%	355.11	395.24	457.98	568.03
400 ppm	5.4%	12.2%	36.8%	60.8%	355.11	381.69	399.73	400.00
450 ppm	4.6%	7.6%	14.9%	45.8%	355.11	389.64	431.59	450.00
500 ppm	4.4%	6.6%	10.6%	29.6%	355.11	392.09	443.51	498.17
550 ppm	4.4%	6.3%	9.4%	18.1%	355.11	392.87	447.61	524.15
low elasticity of substitution								
BAU	4.1%	5.1%	6.3%	8.0%	355.11	395.42	459.47	574.30
400 ppm	5.1%	9.9%	25.1%	43.9%	355.11	381.03	399.34	400.00
450 ppm	4.5%	6.7%	11.4%	31.3%	355.11	389.37	430.89	450.00
500 ppm	4.3%	5.9%	8.5%	20.3%	355.11	392.07	443.78	498.19
550 ppm	4.3%	5.7%	7.6%	12.9%	355.11	392.98	448.54	526.19
high elasticity of substitution								
BAU	4.9%	11.7%	30.1%	67.9%	355.11	394.57	448.65	504.40
400 ppm	6.7%	30.3%	77.8%	89.9%	355.11	386.52	400.00	400.00
450 ppm	5.6%	16.7%	46.9%	88.1%	355.11	391.29	432.48	446.23
500 ppm	5.6%	16.7%	46.5%	87.8%	355.11	391.80	433.86	448.48
550 ppm	5.6%	16.7%	46.4%	87.6%	355.11	391.95	434.35	449.46

The table presents the levels of key variables under different climate stabilization policies. Dollar values are presented using 1995 US dollars.

required by each concentration scenario are smaller and easier to achieve. Finally, when evaluating the potential of induced technological change to lower the costs of climate policy, assumptions about the nature of R&D markets are important. Removing the assumption of partial crowding out from energy R&D nearly doubles the gains from policy-induced energy R&D. This is important, as it suggests that models ignoring the costs of R&D necessary to develop new technologies, such as those relying solely on learning-by-doing, overstate the gains from policy-induced technological change.

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REFERENCES

Ibenholt, K. (2002). “Explaining Learning Curves for Wind Power”. *Energy Policy* 30: 1181-89.

Nakicenovic, N.A., A. Grübler, and A. McDonald. (1998). *Global Energy Perspectives,* IIASA-WEC, Cambridge, UK: Cambridge University Press.

Nordhaus, W.D. (1994). *Managing the Global Commons: The Economics of the Greenhouse Effect.* Cambridge, MA: MIT Press.

Nordhaus, W.D. and J. Boyer (2000). *Warming the World: Economic Models of Global Warming.* Cambridge, MA: MIT Press.

Nordhaus, W.D. and Z. Yang (1996). “A Regional Dynamic General-Equilibrium Model of Alternative Climate Change Strategies.” *American Economic Review,* 886: 741-765.

Popp, D. (forthcoming). “ENTICE-BR: The Effects of Backstop Technology R&D on Climate Policy Models.” NBER Working Paper #10285, revised version forthcoming in Energy Economics.

Popp, D. (2005). “Lessons From Patents: Using Patents To Measure Technological Change in Environmental Models.” *Ecological Economics,* 54(2-3): 209-226.

Popp, D. (2004a). “ENTICE: Endogenous Technological Change in the DICE Model of Global Warming.” *Journal of Environmental Economics and Management* 48(1): 742-768.

Popp, D. (2004b). “R&D Subsidies and Climate Policy: Is there a ‘Free Lunch’?” NBER Working Paper #10880.

Popp, D. (2002). “Induced Innovation and Energy Prices.” *American Economic Review*, 92(1): 160-180.

van der Zwaan, B.C.C., R. Gerlagh, G. Klaassen, and L. Schrattenholzer (2002). ”Endogenous Technological Change in Climate Change Modeling.” *Energy Economics,* 24: 1-19.