Journal of Economic Literature 2013, 51(3), 860–872
http://dx.doi.org/10.1257/jel.51.3.860

Climate Change Policy: What Do the Models Tell Us?†

Robert S. Pindyck*

Very little. A plethora of integrated assessment models (IAMs) have been constructed and used to estimate the social cost of carbon (SCC) and evaluate alternative abatement policies. These models have crucial flaws that make them close to useless as tools for policy analysis: certain inputs (e.g., the discount rate) are arbitrary, but have huge effects on the SCC estimates the models produce; the models' descriptions of the impact of climate change are completely ad hoc, with no theoretical or empirical foundation; and the models can tell us nothing about the most important driver of the SCC, the possibility of a catastrophic climate outcome. IAM-based analyses of climate policy create a perception of knowledge and precision, but that perception is illusory and misleading. (*JEL* C51, Q54, Q58)

1. *Introduction*

There is almost no disagreement among economists that the full cost to society of burning a ton of carbon is greater than its private cost. Burning carbon has an external cost because it produces CO_2 and other greenhouse gases (GHGs) that accumulate in the atmosphere, and will eventually result in unwanted climate change—higher global temperatures, greater climate variability, and possibly increases in sea levels. This external cost is referred to as the social cost of carbon (SCC). It is the basis for taxing or otherwise limiting carbon emissions, and is the focus of policy-oriented research on climate change.

So how large is the SCC? Here there is plenty of disagreement. Some argue that climate change will be moderate, will occur in the distant future, and will have only a small impact on the economies of most countries. This would imply that the SCC is small, perhaps only around \$10 per ton of CO_2. Others argue that without an immediate and stringent GHG abatement policy, there is a reasonable chance of substantial temperature increases that might have a catastrophic economic impact. If so, it would suggest that the SCC is large, perhaps as high as \$200 per ton of CO_2.[1]

* Massachusetts Institute of Technology. My thanks to Millie Huang for her excellent research assistance, and to Janet Currie, Christian Gollier, Chris Knittel, Charles Kolstad, Bob Litterman, and Richard Schmalensee for helpful comments and suggestions.
† Go to http://dx.doi.org/10.1257/jel.51.3.860 to visit the article page and view author disclosure statement(s).

[1] The SCC is sometimes expressed in terms of dollars per ton of carbon. A ton of CO_2 contains 0.2727 tons of carbon, so an SCC of \$10 per ton of CO_2 is equivalent to \$36.67 per ton of carbon. The SCC numbers I present in this paper are always in terms of dollars per ton of CO_2.

Might we narrow this range of disagreement over the size of the SCC by carefully quantifying the relationships between GHG emissions and atmospheric GHG concentrations, between changes in GHG concentrations and changes in temperature (and other measures of climate change), and between higher temperatures and measures of welfare such as output and per capita consumption? In other words, might we obtain better estimates of the SCC by building and simulating *integrated assessment models* (IAMs), i.e., models that "integrate" a description of GHG emissions and their impact on temperature (a climate science model) with projections of abatement costs and a description of how changes in climate affect output, consumption, and other economic variables (an economic model).

Building such models is exactly what some economists interested in climate change policy have done. One of the first such models was developed by William Nordhaus over twenty years ago.[2] That model was an early attempt to integrate the climate science and economic aspects of the impact of GHG emissions, and it helped economists understand the basic mechanisms involved. Even if one felt that parts of the model were overly simple and lacked empirical support, the work achieved a common goal of economic modeling: elucidating the dynamic relationships among key variables, and the implications of those relationships, in a coherent and convincing way. Since then, the development and use of IAMs has become a growth industry. (It even has its own journal, *The Integrated Assessment Journal*.) The models have become larger and more complex, but unfortunately have not done much to better elucidate the pathways by which GHG emissions eventually lead to higher temperatures, which in turn cause (quantifiable) economic damage. Instead, the raison d'etre of these models has been their use as a policy tool. The idea is that by simulating the models, we can obtain reliable estimates of the SCC and evaluate alternative climate policies.

Indeed, a U.S. Government Interagency Working Group has tried to do just that. It ran simulations of three different IAMs, with a range of parameter values, discount rates, and assumptions regarding GHG emissions, to estimate the SCC.[3] Of course, different input assumptions resulted in different SCC estimates, but the Working Group settled on a base case or "average" estimate of $21 per ton, which was recently updated to $33 per ton.[4] Other IAMs have been developed and likewise used to estimate the SCC. As with the Working Group, those estimates vary considerably depending on the input assumptions for any one IAM, and also vary across IAMs.

Given all of the effort that has gone into developing and using IAMs, have they helped us resolve the wide disagreement over the size of the SCC? Is the U.S. government estimate of $21 per ton (or the updated estimate of $33 per ton) a reliable or otherwise useful number? What have these IAMs (and related models) told us? I will argue that the answer is very little. As I discuss below, the models are so deeply flawed as to be close to useless as tools for policy analysis. Worse yet,

[2] See, for example, Nordhaus (1991, 1993a, 1993b).

[3] The three IAMS were DICE (Dynamic Integrated Climate and Economy), PAGE (Policy Analysis of the Greenhouse Effect), and FUND (Climate Framework for Uncertainty, Distribution, and Negotiation). For descriptions of the models, see Nordhaus (2008), Hope (2006), and Tol (2002a, 2002b).

[4] See Interagency Working Group on Social Cost of Carbon (2010). For an illuminating and very readable discussion of the Working Group's methodology, the models it used, and the assumptions regarding parameters, GHG emissions, and other inputs, see Greenstone, Kopits, and Wolverton (2011). The updated study used new versions of the DICE, PAGE, and FUND models, and arrived at a new "average" estimate of $33 per ton for the SCC. See Interagency Working Group on Social Cost of Carbon (2013).

their use suggests a level of knowledge and precision that is simply illusory, and can be highly misleading.

The next section provides a brief overview of the IAM approach, with a focus on the arbitrary nature of the choice of social welfare function and the values of its parameters. Using the three models that the Interagency Working Group chose for its assessment of the SCC as examples, I then discuss two important parts of IAMS where the uncertainties are greatest and our knowledge is weakest—the response of temperature to an increase in atmospheric CO_2, and the economic impact of higher temperatures. I then explain why an evaluation of the SCC must include the possibility of a catastrophic outcome, why IAMs can tell us nothing about such outcomes, and how an alternative and simpler approach is likely to be more illuminating. As mentioned above, the number of IAMs in existence is large and growing. My objective is not to survey the range of IAMs or the IAM-related literature, but rather to explain why climate change policy can be better analyzed without the use of IAMs.

2. *Integrated Assessment Models*

Most economic analyses of climate change policy have six elements, each of which can be global in nature or disaggregated on a regional basis. In an IAM-based analysis, each of these elements is either part of the model (determined endogenously), or else is an exogenous input to the model. These six elements can be summarized as follows:

1. Projections of future emissions of a CO_2 equivalent (CO_2e) composite (or individual GHGs) under "business as usual" (BAU) and one or more abatement scenarios. Projections of emissions in turn require projections of both GDP growth and "carbon intensity," i.e., the amount of CO_2e released per dollar of GDP, again under BAU and alternative abatement scenarios, and on an aggregate or regionally disaggregated basis.

2. Projections of future atmospheric CO_2e concentrations resulting from past, current, and future CO_2e emissions. (This is part of the climate science side of an IAM.)

3. Projections of average global (or regional) temperature changes—and possibly other measures of climate change such as temperature and rainfall variability, hurricane frequency, and sea level increases—likely to result over time from higher CO_2e concentrations. (This is also part of the climate science side of an IAM.)

4. Projections of the economic impact, usually expressed in terms of lost GDP and consumption, resulting from higher temperatures. (This is the most speculative element of the analysis, in part because of uncertainty over adaptation to climate change.) "Economic impact" includes both direct economic impacts as well as any other adverse effects of climate change, such as social, political, and medical impacts, which under various assumptions are monetized and included as part of lost GDP.

5. Estimates of the cost of abating GHG emissions by various amounts, both now and throughout the future. This in turn requires projections of technological change that might reduce future abatement costs.

6. Assumptions about social utility and the rate of time preference, so that lost consumption from expenditures on abatement can be valued and weighed against future gains in consumption from the

reductions in warming that abatement would bring about.

These elements are incorporated in the work of Nordhaus (2008), Stern (2007), and others who evaluate abatement policies though the use of IAMs that project emissions, CO_2e concentrations, temperature change, economic impact, and costs of abatement. Interestingly, however, Nordhaus (2008), Stern (2007), and others come to strikingly different conclusions regarding optimal abatement policy and the implied SCC. Nordhaus (2008) finds that optimal abatement should initially be very limited, consistent with an SCC around $20 or less, while Stern (2007) concludes that an immediate and drastic cut in emissions is called for, consistent with an SCC above $200.[5] Why the huge difference? Because the inputs that go into the models are so different. Had Stern used the Nordhaus assumptions regarding discount rates, abatement costs, parameters affecting temperature change, and the function determining economic impact, he would have also found the SCC to be low. Likewise, if Nordhaus had used the Stern assumptions, he would have obtained a much higher SCC.[6]

2.1 *What Goes In and What Comes Out*

And here we see a major problem with IAM-based climate policy analysis: the modeler has a great deal of freedom in choosing functional forms, parameter values, and other inputs, and different choices can give wildly different estimates of the SCC and the optimal amount of abatement. You might think that some input choices are more reasonable or defensible than others, but no, "reasonable" is very much in the eye of the modeler. Thus these models can be used to obtain almost any result one desires.[7]

There are two types of inputs that lend themselves to arbitrary choices. The first is the social welfare (utility) function and related parameters needed to value and compare current and future gains and losses from abatement. The second is the set of functional forms and related parameters that determine the response of temperature to changing CO_2e concentrations and (especially) the economic impact of rising temperatures. I discuss the social welfare function here, and leave the functional forms and related parameters to later when I discuss the "guts" of these models.

2.2 *The Social Welfare Function*

Most models use a simple framework for valuing lost consumption at different points in time: time-additive, constant relative risk aversion (CRRA) utility, so that social welfare is

$$(1) \qquad W = \frac{1}{1-\eta}\,\mathcal{E}_0 \int_0^{\infty} C_t^{1-\eta} e^{-\delta t}\, dt,$$

where η is the index of relative risk aversion (IRRA) and δ is the rate of time preference. Future consumption is unknown, so I included the expectation operator $\mathcal{E}$, although most IAMs are deterministic in nature. Uncertainty, if incorporated at all, is usually analyzed by running Monte Carlo simulations in which probability distributions

[5] In an updated study, Nordhaus (2011) estimates the SCC to be $12 per ton of CO_2.

[6] Nordhaus (2007), Weitzman (2007), Mendelsohn (2008), and others argue (and I would agree) that the Stern study (which used a version of the PAGE model) makes assumptions about temperature change, economic impact, abatement costs, and discount rates that are generally outside the consensus range. But see Stern (2008) for a detailed (and very readable) explanation and defense of these assumptions.

[7] A colleague of mine once said "I can make a model tie my shoe laces."

are attached to one or more parameters.[8] Equation (1) might be applied to the United States (as in the Interagency Working Group study), to the entire world, or to different regions of the world.

I will put aside the question of how meaningful equation (1) is as a welfare measure, and focus instead on the two critical parameters, δ and η. We can begin by asking what is the "correct" value for the rate of time preference, δ? This parameter is crucial because the effects of climate change occur over very long time horizons (50 to 200 years), so a value of δ above 2 percent would make it hard to justify even a very moderate abatement policy. Financial data reflecting investor behavior and macroeconomic data reflecting consumer and firm behavior suggest that δ is in the range of 2 to 5 percent. While a rate in this range might reflect the preferences of investors and consumers, should it also reflect intergenerational preferences and thus apply to time horizons greater than fifty years? Some economists (e.g., Stern 2008 and Heal 2009) have argued that on *ethical grounds* δ should be zero for such horizons, i.e., that it is unethical to discount the welfare of future generations relative to our own welfare. But why is it unethical? Putting aside their personal views, economists have little to say about that question.[9] I would argue that the rate of time preference is a *policy parameter*, i.e., it reflects the choices of policy makers, who might or might not believe (or care) that their policy decisions reflect the values of voters. As a policy parameter, the rate of time preference might be positive, zero, or even negative.[10] The problem is that if we can't pin down δ, an IAM can't tell us much; any given IAM will give a wide range of values for the SCC, depending on the chosen value of δ.

What about η, the IRRA? The SCC that comes out of almost any IAM is also very sensitive to this parameter. Generally, a higher value of η will imply a lower value of the SCC.[11] So what value for η should be used for climate policy? Here, too, economists disagree. The macroeconomics and finance literatures suggest that a reasonable range is from about 1.5 to at least 4. As a policy parameter, however, we might consider the fact that η also reflects aversion to consumption inequality (in this case across generations), suggesting a reasonable range of about 1 to 3.[12] Either way, we are left with a wide range of reasonable values, so that any given IAM can give a wide range of values for the SCC.

Disagreement over δ and η boils down to disagreement over the discount rate used to

[8] A recent exception is Cai, Judd, and Lontzek (2013), who developed a stochastic dynamic programming version of the Nordhaus DICE model. Also, Kelly and Kolstad (1999) show how Bayesian learning can affect policy in a model with uncertainty.

[9] Suppose John and Jane both have the same incomes. John saves 10 percent of his income every year in order to help finance the college educations of his (yet-to-be-born) grandchildren, while Jane prefers to spend all of her disposable income on sports cars, boats, and expensive wines. Does John's concern for his grandchildren make him more ethical than Jane? Many people might say yes, but that answer would be based on their personal values rather than economic principles.

[10] Why negative? One could argue, perhaps based on altruism or a belief that human character is improving over time, that the welfare of our great-grandchildren should be valued more highly than our own.

[11] The larger is η, the faster the marginal utility of consumption declines as consumption grows. Since consumption is expected to grow, the value of additional future consumption is smaller the larger is η. But η also measures risk aversion; if future consumption is uncertain, a larger η makes future welfare smaller, raising the value of additional future consumption. Most models show that unless risk aversion is extreme (e.g., η is above 4), the first effect dominates, so an increase in η (say from 1 to 4) will reduce the benefits from an abatement policy. See Pindyck (2012) for examples.

[12] If a future generation is expected to have twice the consumption as the current generation, the marginal utility of consumption for the future generation is $1/2^{\eta}$ as large as for the current generation, and would be weighted accordingly in any welfare calculation. Values of η above 3 or 4 imply a relatively very small weight for the future generation, so one could argue that a smaller value is more appropriate.

put gains and losses of future consumption (as opposed to utility) in present value terms. In the simplest (deterministic) Ramsey framework, that discount rate is $R = \delta + \eta g$, where g is the real per capita growth rate of consumption, which historically has been around 1.5 to 2 percent per annum, at least for the United States. Stern (2007), citing ethical arguments, sets $\delta \approx 0$ and $\eta = 1$, so that R is small and the estimated SCC is very large. By comparison, Nordhaus (2008) tries to match market data, and sets $\delta = 1.5$ percent and $\eta = 2$, so that $R \approx 5.5$ percent and the estimated SCC is far smaller.[13] Should the discount rate be based on "ethical" arguments or market data? And what ethical arguments and what market data? The members of the Interagency Working Group got out of this morass by focusing on a middle-of-the-road discount rate of 3 percent, without taking a stand on whether this is the "correct" rate.

3. *The Guts of the Models*

Let's assume for the moment that economists could agree on the "correct" value for the discount rate R. Let's also assume that they (along with climate scientists) could also agree on the rate of emissions under BAU and one or more abatement scenarios, as well as the resulting time path for the atmospheric CO_2e concentration. Could we then use one or more IAMs to produce a reliable estimate of the SCC? The answer is no, but to see why, we must look at the insides of the models. For some of the larger models, the "guts" contain many equations and can seem intimidating. But in fact, there are only two key organs that we need to dissect. The first translates increases in the CO_2e concentration to increases in temperature, a mechanism that is referred to as *climate sensitivity*. The second translates higher temperatures to reductions in GDP and consumption, i.e., the *damage function*.

3.1 *Climate Sensitivity*

Climate sensitivity is defined as the temperature increase that would eventually result from an anthropomorphic doubling of the atmospheric CO_2e concentration. The word "eventually" means after the world's climate system reaches a new equilibrium following the doubling of the CO_2e concentration, a period of time in the vicinity of fifty years. For some of the simpler IAMs, climate sensitivity takes the form of a single parameter; for larger and more complicated models, it might involve several equations that describe the dynamic response of temperature to changes in the CO_2e concentration. Either way, it can be boiled down to a number that says how much the temperature will eventually rise if the CO_2e concentration were to double. And either way, we can ask how much we know or don't know about that number. This is an important question because climate sensitivity is an exogenous input into each of the three IAMs used by the Interagency Working Group to estimate the SCC.

Here is the problem: the physical mechanisms that determine climate sensitivity involve crucial feedback loops, and the parameter values that determine the strength (and even the sign) of those feedback loops are largely unknown, and for the foreseeable future may even be unknowable. This is not a shortcoming of climate science; on the contrary, climate scientists have made enormous progress in understanding the physical mechanisms involved in climate change. But part of that progress is a clearer realization that there are limits (at least currently) to our ability to pin down the strength of the key feedback loops.

[13] Uncertainty over consumption growth or over the discount rate itself can reduce R, and depending on the type of uncertainty, lead to a time-varying R. See Gollier (2013) for an excellent treatment of the effects of uncertainty on the discount rate. Weitzman (2013) shows how the discount rate could decline over time.

The Intergovernmental Panel on Climate Change (2007) (IPCC) surveyed twenty-two peer-reviewed published studies of climate sensitivity and estimated that they implied an expected value of 2.5°C to 3.0°C for climate sensitivity.[14] Each of the individual studies included a probability distribution for climate sensitivity, and by putting the distributions in a standardized form, the IPCC created a graph that showed all of the distributions in a summary form. A number of studies—including the Interagency Working Group study—used the IPCC's results to infer and calibrate a single distribution for climate sensitivity, which in turn could be used to run alternative simulations of one or more IAMs.[15]

Averaging across the standardized distributions summarized by the IPCC suggests that the 95th percentile is about 7°C, i.e., there is roughly a 5 percent probability that the true climate sensitivity is above 7°C. But this implies more knowledge than we probably have. This is easiest to see in the relatively simple climate model developed by Roe and Baker (2007). Using their notation, let λ_0 be climate sensitivity in the absence of any feedback effects, i.e., absent feedback effects, a doubling of the atmospheric CO_2e concentration would lead to an increase in radiative forcing that would in turn cause a temperature increase of $\Delta T_0 = \lambda_0$°C. But as Roe and Baker explain, the initial temperature increase ΔT_0 "induces changes in the underlying processes . . . which modify the effective forcing, which, in turn, modifies ΔT." Thus the actual climate sensitivity is given by

$$\lambda = \frac{\lambda_0}{1-f}, \quad (2)$$

where $f (0 \leq f \leq 1)$ is the total feedback factor (which in a more complete and complex model would incorporate several feedback effects).

Unfortunately, we don't know the value of f. Roe and Baker point out that if we knew the mean and standard deviation of f, denoted by $\bar{f}$ and σ_f respectively, and if σ_f is small, then the standard deviation of λ would be proportional to $\sigma_f/(1-\bar{f})^2$. Thus uncertainty over λ is greatly magnified by uncertainty over f, and becomes very large if f is close to 1. Likewise, if the true value of f is close to 1, climate sensitivity would be huge.

As an illustrative exercise, Roe and Baker assume that f is normally distributed (with mean $\bar{f}$ and standard deviation σ_f), and derive the resulting distribution for λ, climate sensitivity. Given their choice of $\bar{f}$ and σ_f, the resulting median and 95th percentile are close to the corresponding numbers that come from averaging across the standardized distributions summarized by the IPCC.[16]

The Interagency Working Group calibrated the Roe–Baker distribution to fit the composite IPCC numbers more closely, and then applied that distribution to each of the three IAMs as a way of analyzing the

[14] The IPCC also provides a detailed and readable overview of the physical mechanisms involved in climate change, and the state of our knowledge regarding those mechanisms.

[15] Newbold and Daigneault (2009) and Pindyck (2012) (who fit a gamma distribution to the IPCC's summary graph) used the distribution to infer the implications of uncertainty over climate sensitivity for abatement policy. But as discussed below, they probably underestimated the extent of the uncertainty.

[16] The Roe–Baker distribution is given by:

$$g(\lambda; \bar{f}, \sigma_f, \theta) = \frac{1}{\sigma_f \sqrt{2\pi} z^2} \exp\left[-\frac{1}{2}\left(\frac{1-\bar{f}-1/z}{\sigma_f}\right)^2\right],$$

where $z = \lambda + \theta$. The parameter values are $\bar{f} = 0.797$, $\sigma_f = 0.0441$, $\theta = 2.13$. This distribution is fat-tailed, i.e., declines to zero more slowly than exponentially. Weitzman (2009) has shown that parameter uncertainty can lead to a fat-tailed distribution for climate sensitivity, and that this implies a relatively high probability of a catastrophic outcome, which in turn suggests that the value of abatement is high. Pindyck (2011a) shows that a fat-tailed distribution by itself need not imply a high value of abatement.

sensitivity of their SCC estimates to uncertainty over climate sensitivity.

Given the limited available information, the Interagency Working Group did the best it could. But it is likely that they—like others who have used IAMs to analyze climate change policy—have understated our uncertainty over climate sensitivity. We don't know whether the feedback factor f is in fact normally distributed (nor do we know its mean and standard deviation). Roe and Baker simply assumed a normal distribution. In fact, in an accompanying article in the journal *Science*, Allen and Frame (2007) argued that climate sensitivity is in the realm of the "unknowable."

3.2 *The Damage Function*

When assessing climate sensitivity, we at least have scientific results to rely on, and can argue coherently about the probability distribution that is most consistent with those results. When it comes to the damage function, however, we know almost nothing, so developers of IAMs can do little more than make up functional forms and corresponding parameter values. And that is pretty much what they have done.

Most IAMs (including the three that were used by the Interagency Working Group to estimate the SCC) relate the temperature increase T to GDP through a "loss function" $L(T)$, with $L(0) = 1$ and $L'(T) < 0$. Thus GDP at time t is $\mathrm{GDP}_t = L(T_t)\mathrm{GDP}'_t$, where GDP'_t is what GDP would be if there were no warming. For example, the Nordhaus (2008) DICE model uses the following inverse-quadratic loss function:

$$L = 1/[1 + \pi_1 T + \pi_2 (T)^2]. \tag{3}$$

Weitzman (2009) suggested the exponential-quadratic loss function:

$$L(T) = \exp[-\beta(T)^2], \tag{4}$$

which allows for greater losses when T is large. But remember that neither of these loss functions is based on any economic (or other) theory. Nor are the loss functions that appear in other IAMs. They are just *arbitrary functions*, made up to describe how GDP goes down when T goes up.

The loss functions in PAGE and FUND, the other two models used by the Interagency Working Group, are more complex but equally arbitrary. In those models, losses are calculated for individual regions and (in the case of FUND) individual sectors, such as agriculture and forestry. But there is no pretense that the equations are based on any theory. When describing the sectoral impacts in FUND, Tol (2002b) introduces equations with the words "The *assumed* model is:" (e.g., pages 137–39, emphasis mine), and at times acknowledges that "The model used here is therefore ad hoc" (142).

The problem is not that IAM developers were negligent and ignored economic theory; there is no economic theory that can tell us what $L(T)$ should look like. If anything, we would expect T to affect the *growth rate* of GDP, and not the level. Why? First, some effects of warming will be permanent; e.g., destruction of ecosystems and deaths from weather extremes. A growth rate effect allows warming to have a permanent impact. Second, the resources needed to counter the impact of warming will reduce those available for R&D and capital investment, reducing growth.[17] Third, there is some empirical support for a growth rate effect. Using data

[17] Adaptation to rising temperatures is equivalent to the cost of increasingly strict emission standards, which, as Stokey (1998) has shown with an endogenous growth model, reduces the rate of return on capital and lowers the growth rate. To see this, suppose total capital $K = K_p + K_a(T)$, with $K_a'(T) > 0$, where K_p is directly productive capital and $K_a(T)$ is capital needed for adaptation to the temperature increase T (e.g., stronger retaining walls and pumps to counter flooding, more air conditioning and insulation, etc.). If all capital depreciates at rate δ_K, $\dot{K}_p = \dot{K} - \dot{K}_a = I - \delta_K K - K_a'(T)\dot{T}$, so the rate of growth of K_p is reduced. See Brock and Taylor (2010) and Fankhauser and Tol (2005) for related analyses.

on temperatures and precipitation over fifty years for a panel of 136 countries, Dell, Jones, and Olken (2012) have shown that higher temperatures reduce GDP growth rates but not levels. Likewise, using data for 147 countries during 1950 to 2007, Bansal and Ochoa (2011, 2012) show that increases in temperature have a negative impact on economic growth.[18]

Let's put the issue of growth rate versus level aside and assume that the loss function of eqn. (3) is a credible description of the economic impact of higher temperatures. Then the question is how to determine the values of the parameters π_1 and π_2. Theory can't help us, nor is data available that could be used to estimate or even roughly calibrate the parameters. As a result, the choice of values for these parameters is essentially guesswork. The usual approach is to select values such that $L(T)$ for T in the range of 2°C to 4°C is consistent with common wisdom regarding the damages that are likely to occur for small to moderate increases in temperature. Most modelers choose parameters so that $L(1)$ is close to 1 (i.e., no loss), $L(2)$ is around 0.99 or 0.98, and $L(3)$ or $L(4)$ is around 0.98 to 0.96. Sometimes these numbers are justified by referring to the IPCC or related summary studies. For example, Nordhaus (2008) points out that the 2007 IPCC report states that "global mean losses could be 1–5 percent GDP for 4°C of warming" (51). But where did the IPCC get those numbers? From its own survey of several IAMs. Yes, it's a bit circular.

The bottom line here is that the damage functions used in most IAMs are completely made up, with no theoretical or empirical foundation. That might not matter much if we are looking at temperature increases of 2 or 3°C, because there is a rough consensus (perhaps completely wrong) that damages will be small at those levels of warming. The problem is that these damage functions tell us nothing about what to expect if temperature increases are larger, e.g., 5°C or more.[19] Putting $T = 5$ or $T = 7$ into equation (3) or (4) is a completely meaningless exercise. And yet that is exactly what is being done when IAMs are used to analyze climate policy.

I do not want to give the impression that economists know nothing about the impact of climate change. On the contrary, considerable work has been done on specific aspects of that impact, especially with respect to agriculture. One of the earliest studies of agricultural impacts, including adaptation, is Mendelsohn, Nordhaus, and Shaw (1994); more recent ones include Deschenes and Greenstone (2007) and Schlenker and Roberts (2009). A recent study that focuses on the impact of climate change on mortality, and our ability to adapt, is Deschenes and Greenstone (2011). And recent studies that use or discuss the use of detailed weather data include Dell, Jones, and Olken (2012) and Auffhammer et al. (2013). These are just a few examples; the literature is large and growing.

Statistical studies of this sort will surely improve our knowledge of how climate change might affect the economy, or at least some sectors of the economy. But the data used in these studies are limited to relatively short time periods and small fluctuations in temperature and other weather variables—the data do not, for example, describe what

[18] See Pindyck (2011b, 2012) for further discussion and an analysis of the policy implications of a growth rate versus level effect. Note that a climate-induced catastrophe, on the other hand, could reduce both the growth rate and level of GDP.

[19] Some modelers are aware of this problem. Nordhaus (2008) states: "The damage functions continue to be a major source of modeling uncertainty in the DICE model" (51). To get a sense of the wide range of damage numbers that come from different models, even for $T = 2$ or 3°C, see table 1 of Tol (2012). Stern (2013) argues that IAM damage functions ignore a variety of potential climate impacts, including possibly catastrophic ones.

has happened over twenty or fifty years following a 5°C increase in mean temperature. Thus these studies cannot enable us to specify and calibrate damage functions of the sort used in IAMs. In fact, those damage functions have little or nothing to do with the detailed econometric studies related to agricultural and other specific impacts.

4. *Catastrophic Outcomes*

Another major problem with using IAMs to assess climate change policy is that the models ignore the possibility of a catastrophic climate outcome. The kind of outcome I am referring to is not simply a very large increase in temperature, but rather a very large economic effect, in terms of a decline in human welfare, from whatever climate change occurs. That such outcomes are ignored is not surprising; IAMs have nothing to tell us about them. As I explained, IAM damage functions, which anyway are ad hoc, are calibrated to give small damages for small temperature increases, and can say nothing meaningful about the kinds of damages we should expect for temperature increases of 5°C or more.

4.1 *Analysis of Catastrophic Outcomes*

For climate scientists, a "catastrophe" usually takes the form of a high temperature outcome, e.g., a 7°C or 8°C increase by 2100. Putting aside the difficulty of estimating the probability of that outcome, what matters in the end is not the temperature increase itself, but rather its impact. Would that impact be "catastrophic," and might a smaller (and more likely) temperature increase be sufficient to have a catastrophic impact?

Why do we need to worry about large temperature increases and their impact? Because even if a large temperature outcome has low probability, if the economic impact of that change is very large, it can push up the SCC considerably. As discussed in Pindyck (2013a), the problem is that the possibility of a catastrophic outcome is an essential driver of the SCC. Thus we are left in the dark; IAMs cannot tell us anything about catastrophic outcomes, and thus cannot provide meaningful estimates of the SCC.

It is difficult to see how our knowledge of the economic impact of rising temperatures is likely to improve in the coming years. More than temperature change itself, economic impact may be in the realm of the "unknowable." If so, it would make little sense to try to use an IAM-based analysis to evaluate a stringent abatement policy. The case for stringent abatement would have to be based on the (small) likelihood of a catastrophic outcome in which climate change is sufficiently extreme to cause a very substantial drop in welfare.

4.2 *What to Do?*

So how can we bring economic analysis to bear on the policy implications of possible catastrophic outcomes? Given how little we know, a detailed and complex modeling exercise is unlikely to be helpful. (Even if we believed the model accurately represented the relevant physical and economic relationships, we would have to come to agreement on the discount rate and other key parameters.) Probably something simpler is needed. Perhaps the best we can do is come up with rough, subjective estimates of the probability of a climate change sufficiently large to have a catastrophic impact, and then some distribution for the size of that impact (in terms, say, of a reduction in GDP or the effective capital stock).

The problem is analogous to assessing the world's greatest catastrophic risk during the Cold War—the possibility of a U.S.–Soviet thermonuclear exchange. How likely was such an event? There were no data or models that could yield reliable estimates, so analyses had to be based on the plausible, i.e., on events that could reasonably be expected to play out, even with low probability. Assessing the range of potential impacts of a thermonuclear exchange had to be done in much the same way. Such analyses were useful because they helped evaluate the potential benefits of arms control agreements.

The same approach might be used to assess climate change catastrophes. First, consider a plausible range of catastrophic outcomes (under, for example, BAU), as measured by percentage declines in the stock of productive capital (thereby reducing future GDP). Next, what are plausible probabilities? Here, "plausible" would mean acceptable to a range of economists and climate scientists. Given these plausible outcomes and probabilities, one can calculate the present value of the benefits from averting those outcomes, or reducing the probabilities of their occurrence. The benefits will depend on preference parameters, but if they are sufficiently large and robust to reasonable ranges for those parameters, it would support a stringent abatement policy. Of course this approach does not carry the perceived precision that comes from an IAM-based analysis, but that perceived precision is illusory. To the extent that we are dealing with unknowable quantities, it may be that the best we can do is rely on the "plausible."

5. *Conclusions*

I have argued that IAMs are of little or no value for evaluating alternative climate change policies and estimating the SCC. On the contrary, an IAM-based analysis suggests a level of knowledge and precision that is nonexistent, and allows the modeler to obtain almost any desired result because key inputs can be chosen arbitrarily.

As I have explained, the physical mechanisms that determine climate sensitivity involve crucial feedback loops, and the parameter values that determine the strength of those feedback loops are largely unknown. When it comes to the impact of climate change, we know even less. IAM damage functions are completely made up, with no theoretical or empirical foundation. They simply reflect common beliefs (which might be wrong) regarding the impact of 2°C or 3°C of warming, and can tell us nothing about what might happen if the temperature increases by 5°C or more. And yet those damage functions are taken seriously when IAMs are used to analyze climate policy. Finally, IAMs tell us nothing about the likelihood and nature of catastrophic outcomes, but it is just such outcomes that matter most for climate change policy. Probably the best we can do at this point is come up with plausible estimates for probabilities and possible impacts of catastrophic outcomes. Doing otherwise is to delude ourselves.

My criticism of IAMs should *not* be taken to imply that, because we know so little, nothing should be done about climate change right now, and instead we should wait until we learn more. Quite the contrary. One can think of a GHG abatement policy as a form of insurance: society would be paying for a guarantee that a low-probability catastrophe will not occur (or is less likely). As I have argued elsewhere, even though we don't have a good estimate of the SCC, it would make sense to take the Interagency Working Group's $21 (or updated $33) number as a rough and politically acceptable starting point and impose a carbon tax (or equivalent policy) of that amount.[20] This would help to establish that there is a social cost of carbon, and that social cost must be internalized in the prices that consumers and firms pay. (Yes, most economists already understand this, but politicians and the public are a different matter.) Later, as we learn more about the true size of the SCC, the carbon tax could be increased or decreased accordingly.

[20] See Pindyck (2013b). Litterman (2013) and National Research Council (2011) come to a similar conclusion.

References

Allen, Myles R., and David J. Frame. 2007. "Call Off the Quest." *Science* 318 (5850): 582–83.

Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel. 2013. "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." National Bureau of Economic Research Working Paper 19087.

Bansal, Ravi, and Marcelo Ochoa. 2011. "Welfare Costs of Long-Term Temperature Shifts." National Bureau of Economic Research Working Paper 17574.

Bansal, Ravi, and Marcelo Ochoa. 2012. "Temperature, Aggregate Risk, and Expected Returns." National Bureau of Economic Research Working Paper 17575.

Brock, William A., and M. Scott Taylor. 2010. "The Green Solow Model." *Journal of Economic Growth* 15 (2): 127–53.

Cai, Yongyang, Kenneth L. Judd, and Thomas S. Lontzek. 2013. "The Social Cost of Stochastic and Irreversible Climate Change." National Bureau of Economic Research Working Paper 18704.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review* 97 (1): 354–85.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3 (4): 152–85.

Fankhauser, Samuel, and Richard S. J. Tol. 2005. "On Climate Change and Economic Growth." *Resource and Energy Economics* 27 (1): 1–17.

Gollier, Christian. 2013. *Pricing the Planet's Future: The Economics of Discounting in an Uncertain World*. Princeton and Oxford: Princeton University Press.

Greenstone, Michael, Elizabeth Kopits, and Ann Wolverton. 2011. "Estimating the Social Cost of Carbon for Use in U.S. Federal Rulemakings: A Summary and Interpretation." National Bureau of Economic Research Working Paper 16913.

Heal, Geoffrey. 2009. "Climate Economics: A Meta-review and Some Suggestions for Future Research." *Review of Environmental Economics and Policy* 3 (1): 4–21.

Hope, Chris. 2006. "The Marginal Impact of CO_2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern." *Integrated Assessment* 6 (1): 19–56.

Intergovernmental Panel on Climate Change. 2007. *Climate Change 2007: Synthesis Report*. Geneva: Intergovernmental Panel on Climate Change.

Kelly, David L., and Charles Kolstad. 1999. "Bayesian Learning, Growth, and Pollution." *Journal of Economic Dynamics and Control* 23 (4): 491–518.

Litterman, Bob. 2013. "What Is the Right Price for Carbon Emissions?" *Regulation* 36 (2): 38–43.

Mendelsohn, Robert. 2008. "Is the *Stern Review* an Economic Analysis?" *Review of Environmental Economics and Policy* 2 (1): 45–60.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review* 84 (4): 753–71.

National Research Council. 2011. *America's Climate Choices*. Washington, D.C.: National Academies Press.

Newbold, Stephen C., and Adam Daigneault. 2009. "Climate Response Uncertainty and the Benefits of Greenhouse Gas Emissions Reductions." *Environmental and Resource Economics* 44 (3): 351–77.

Nordhaus, William D. 1991. "To Slow or Not to Slow: The Economics of the Greenhouse Effect." *Economic Journal* 101 (407): 920–37.

Nordhaus, William D. 1993a. "Optimal Greenhouse-Gas Reductions and Tax Policy in the 'DICE' Model." *American Economic Review* 83 (2): 313–17.

Nordhaus, William D. 1993b. "Rolling the 'DICE': An Optimal Transition Path for Controlling Greenhouse Gases." *Resource and Energy Economics* 15 (1): 27–50.

Nordhaus, William D. 2007. "A Review of the *Stern Review on the Economics of Climate Change*." *Journal of Economic Literature* 45 (3): 686–702.

Nordhaus, William D. 2008. *A Question of Balance: Weighing the Options on Global Warming Policies*. New Haven and London: Yale University Press.

Nordhaus, William D. 2011. "Estimates of the Social Cost of Carbon: Background and Results from the RICE-2011 Model." National Bureau of Economic Research Working Paper 17540.

Pindyck, Robert S. 2011a. "Fat Tails, Thin Tails, and Climate Change Policy." *Review of Environmental Economics and Policy* 5 (2): 258–74.

Pindyck, Robert S. 2011b. "Modeling the Impact of Warming in Climate Change Economics." In *The Economics of Climate Change: Adaptations Past and Present*, edited by Gary D. Libecap and Richard H. Steckel, 47–72. Chicago and London: University of Chicago Press.

Pindyck, Robert S. 2012. "Uncertain Outcomes and Climate Change Policy." *Journal of Environmental Economics and Management* 63 (3): 289–303.

Pindyck, Robert S. 2013a. "The Climate Policy Dilemma." *Review of Environmental Economics and Policy* 7 (2): 219–37.

Pindyck, Robert S. 2013b. "Pricing Carbon When We Don't Know the Right Price." *Regulation* 36 (2): 43–46.

Roe, Gerard H., and Marcia B. Baker. 2007. "Why Is Climate Sensitivity So Unpredictable?" *Science* 318 (5850): 629–32.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe

Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37): 15594–98.
Stern, Nicholas. 2007. *The Economics of Climate Change: The Stern Review*. Cambridge and New York: Cambridge University Press.
Stern, Nicholas. 2008. "The Economics of Climate Change." *American Economic Review* 98 (2): 1–37.
Stern, Nicholas. 2013. "The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models." *Journal of Economic Literature* 51 (3): 838–59.
Stokey, Nancy L. 1998. "Are There Limits to Growth?" *International Economic Review* 39 (1): 1–31.
Tol, Richard S. J. 2002a. "Estimates of the Damage Costs of Climate Change, Part I: Benchmark Estimates." *Environmental and Resource Economics* 21 (1): 47–73.
Tol, Richard S. J. 2002b. "Estimates of the Damage Costs of Climate Change, Part II: Dynamic Estimates." *Environmental and Resource Economics* 21 (2): 135–60.
Tol, Richard S. J. 2012. "Targets for Global Climate Policy: An Overview." Unpublished.
U.S. Interagency Working Group on Social Cost of Carbon. 2010. "Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis." Washington, D.C.: U.S. Government
U.S. Interagency Working Group on Social Costs of Carbon. 2013. "Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis." Washington, D.C.: U.S. Government.
Weitzman, Martin L. 2007. "A Review of the *Stern Review on the Economics of Climate Change*." *Journal of Economic Literature* 45 (3): 703–24.
Weitzman, Martin L. 2009. "On Modeling and Interpreting the Economics of Catastrophic Climate Change." *Review of Economics and Statistics* 91 (1): 1–19.
Weitzman, Martin L. 2013. "Tail-Hedge Discounting and the Social Cost of Carbon." *Journal of Economic Literature* 51 (3): 873–82.

This article has been cited by:

1. Geoffrey Heal. 2017. The Economics of the Climate. *Journal of Economic Literature* **55**:3, 1046-1063. [Abstract] [View PDF article] [PDF with links]
2. Mark D. Partridge, Bo Feng, Mark Rembert. 2017. Improving Climate-Change Modeling of US Migration. *American Economic Review* **107**:5, 451-455. [Abstract] [View PDF article] [PDF with links]
3. Eric Danan, Thibault Gajdos, Brian Hill, Jean-Marc Tallon. 2016. Robust Social Decisions. *American Economic Review* **106**:9, 2407-2425. [Abstract] [View PDF article] [PDF with links]
4. Ian W. R. Martin, Robert S. Pindyck. 2015. Averting Catastrophes: The Strange Economics of Scylla and Charybdis. *American Economic Review* **105**:10, 2947-2985. [Abstract] [View PDF article] [PDF with links]
5. Melissa Dell, Benjamin F. Jones, Benjamin A. Olken. 2014. What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature* **52**:3, 740-798. [Abstract] [View PDF article] [PDF with links]
6. Gary D. Libecap. 2014. Addressing Global Environmental Externalities: Transaction Costs Considerations. *Journal of Economic Literature* **52**:2, 424-479. [Abstract] [View PDF article] [PDF with links]
7. Cass R. Sunstein. 2014. On Not Revisiting Official Discount Rates: Institutional Inertia and the Social Cost of Carbon. *American Economic Review* **104**:5, 547-551. [Abstract] [View PDF article] [PDF with links]
8. Martin L. Weitzman. 2014. Fat Tails and the Social Cost of Carbon. *American Economic Review* **104**:5, 544-546. [Abstract] [View PDF article] [PDF with links]
9. Nicholas Stern. 2013. The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models. *Journal of Economic Literature* **51**:3, 838-859. [Abstract] [View PDF article] [PDF with links]