

THEMATIC ESSAY

Has Economics Caught Up with Climate Science?

Shreekant Gupta *

Oh, East is East, and West is West, and never the twain shall meet,

...

But there is neither East nor West, ...

When two strong men stand face to face, tho' they come from the ends of the earth!

The Ballad of East and West (Rudyard Kipling, 1889)

Abstract: Whereas scientific evidence points towards substantial and urgent reduction in greenhouse gas (GHG) emissions, economic analysis of climate change seems to be out of sync by indicating a more gradual approach. In particular, economic models that use benefit cost analysis, namely, integrated assessment models (IAMs) have been criticised for being conservative in their recommendations on the speed of reducing GHG emissions and the associated levels of carbon taxes. This essay focuses on a prototypical IAM, namely, Nordhaus' DICE model to argue the schism between science and economics is more apparent than real. Analysis of the DICE model suggests extreme climate scenarios can be captured through alternative specifications of the damage function (the impact of temperature on the economy). In particular, damage functions that extend the standard quadratic representation are highly convex (Weitzman 2012). Thus, they are able to capture climate tipping points as well as “fat tail” risks originating from uncertainty with regard to equilibrium climate sensitivity.

1. INTRODUCTION

A fundamental question in climate policy is by how much should greenhouse gases (GHGs) be reduced and how fast?¹ Economists attempt

* Department of Economics, Delhi School of Economics, University of Delhi, Delhi 110007; sgupta@econdse.org.

Copyright © Gupta 2020. Released under Creative Commons Attribution-Non-commercial 4.0 International licence (CC BY-NC 4.0) by the author.

Published by Indian Society for Ecological Economics (INSEE), c/o Institute of Economic Growth, University Enclave, North Campus, Delhi 110007.

ISSN: 2581-6152 (print); 2581-6101 (web).

to answer this question using the framework of benefit-cost analysis (BCA) since the cost of reducing GHG emissions has to be incurred now, whereas the benefit of doing so will accrue in future, though perhaps not so distant future. Put differently, the economic gain from business-as-usual (BAU) is now whereas the pain, that is damages due to climate change, will be down the road. However, the nature, magnitude and timing of these damages is uncertain and sometimes even unknown. Further, some of these damages are irreversible. Thus, economic analysis of climate change is an exercise in intertemporal BCA but with the added dimensions of risk, uncertainty and irreversibility. The centrality of BCA in economic analysis of climate change was epitomised by the award of the Nobel Prize in economics last year to one of its primary exponents, William Nordhaus.² While BCA is the reigning orthodoxy in climate change economics, critics argue it ignores or does not adequately address what climate science is telling us about risk, uncertainty, and irreversibility. According to them this severely limits policy recommendations emanating from BCA, if not making them downright incorrect and misleading (see for instance Weitzman 2009 and Stern 2014).³

Critics contest the mainstream view among economists (based on BCA models) that mitigation of GHGs must start gradually and then be ramped up. The so-called ‘policy ramp’, argues climate policy, should lead to “modest rates of emissions reductions in the near term, followed by sharp reductions in the medium and long term” (Nordhaus 2007).⁴ Critics argue this does not square with what climate science is telling us about tipping points and other abrupt changes in climate. According to them economic analysis based on BCA does not find the need for immediate and deep cuts in GHG emissions and this is problematic.

A more fundamental methodological critique of BCA is by Weitzman (2009), who argues climate science poses an existential question for BCA, namely, in the presence of potentially catastrophic and irreversible damages

¹ In this essay, I cast the analysis at a global aggregate level and thus abstract from issues of burden sharing across nations. Issues of inter-generational burden sharing are of course unavoidable. In fact, intertemporal trade-off is at the heart of the problem being studied.

² In this essay BCA is used in a broad sense as some overall economic analysis focused on maximizing welfare. Thus, it overlaps with an integrated assessment model (IAM) such as the celebrated Dynamic Integrated Climate Economy (DICE) model of Nordhaus and we can treat the two terms as interchangeable.

³ These two citations are representative of several papers and one book by these two economists, who have been the most prominent critics from within the profession of BCA as applied to climate change.

⁴ The climate policy being alluded to is carbon prices which should start low and eventually get ratcheted up to high levels. By corollary, emissions reductions should be modest in the near term and increase gradually.

BCA is not even meaningful. According to him uncertainty permeates climate science especially with regard to equilibrium climate sensitivity (ECS).⁵ Despite decades of research, science has not been able to pin down this key parameter and there is a significant downside risk of it being very high. Thus, “the main purpose of keeping GHG concentrations down is effectively to buy insurance against catastrophic global warming” (Weitzman 2011, 279).

The problem, however, of accepting this argument is that there is “little role for economics or any analysis of trade-offs or assessing costs and benefits because these don’t matter when the science is so clear and the future of mankind is at stake” (McKibbin 2014, 560). Unfortunately, in the messy real world one cannot sidestep economics – the scale and pace at which countries and the world as a whole are reducing GHG emissions reflects trade-offs, if not explicitly then implicitly. While the “deep structural uncertainty” (*a la* Weitzman) surrounding ECS has an important bearing on climate policy, I argue BCA models of climate change can in principle incorporate such uncertainty. It does not make them irrelevant. In particular, I show how BCA can incorporate the possibility of catastrophic climate damages and thus remains a useful framework for climate policy.

The purpose of this essay is not to defend BCA as an end in itself. Indeed, BCA has several ethical and methodological problems embodied in it (Stern 2014). Nonetheless, I argue BCA can lead us to the very conclusion, namely, immediate and large reductions in GHG emissions (henceforth ‘urgent action’) that climate science may suggest. With this limited purpose in mind, the next section describes economic models of climate change that use the BCA framework, the so-called integrated assessment models (IAMs). For expository purposes, I consider a simple and highly aggregated IAM, namely, the Dynamic Integrated Climate Economy (DICE) model of William Nordhaus. I identify the key features of this model that are influenced by climate science. This is followed by a discussion of specific issues in climate science that have a direct bearing on economic analysis, namely, uncertainty regarding equilibrium climate sensitivity (ECS), non-linear climate damages and tipping points. The fourth section shows how these aspects can be captured in IAMs (DICE in particular) and can lead to emissions trajectories consistent with ‘urgent action’. The final section concludes the essay. My basic message is from Kipling’s poem whose first

⁵ “The transient climate response (TCR) is the temperature change at the time of CO₂ doubling” and the “equilibrium climate sensitivity”, T_{2x}, is the temperature change after the system has reached a new equilibrium for doubled CO₂, i.e., after the “additional warming commitment” has been realised” (Comín, Francisco and MA Rodríguez-Arias 2003, 21). As I show later, there is a non-negligible probability of ECS being very high.

line is widely cited but whose third and fourth lines, though less well known, are more applicable in the context of this essay.

2. ECONOMIC MODELING OF CLIMATE CHANGE

The standard economic approach to modeling climate change is through integrated assessment models. As the phrase suggests, these are scientific models that combine knowledge from several domains into one framework in order to better understand a problem that has multiple dimensions.⁶ This is particularly true for climate change, which is closely connected with geophysical sciences and economic activities. Thus, IAMs of climate change integrate geophysical stocks and flows, especially of GHGs, with economic stocks and flows so that all key endogenous variables can be analysed simultaneously. “IAMs generally do not pretend to have the most detailed and complete representation of each included system. Rather, they aspire to have, at a first level of approximation, a representation that includes all the modules simultaneously and with reasonable accuracy” (Gillingham *et al.* 2018). The first climate-economy IAMs were essentially energy models that included a carbon emissions module and later a small climate model. There are five key links that map anthropogenic climate change in an IAM:

- a) from ‘people’ (producers/consumers) to emissions of GHGs
- b) from emissions to stocks of GHGs
- c) from GHG stocks to changes in temperature
- d) from rising temperature to climate change more broadly
- e) from climate change to human (economic) impact

In this section, I focus on Nordhaus’ DICE model as a prototypical IAM. Without going into too much technical detail, I describe heuristically its main features especially how it models climate damages.⁷ While there are several widely used IAMs (see Gillingham *et al.* 2018 for a recent comparison), the DICE model is a simple yet elegant construct that goes to the heart of the policy question stated at the beginning of this essay. The genesis of DICE model can be traced back to Nordhaus’ papers in 1977 and was first articulated in its current form by Nordhaus in 1992.⁸ DICE belongs to a class of IAMs known as benefit-cost (BC) IAMs as contrasted to detailed process (DP) IAMs (see Weyant 2017) for details). While both

⁶ In effect the term “integrated assessment”, of course, is generic and can apply to a range of contexts. Here it is used explicitly in the context of climate-economy models.

⁷ The complete DICE model can be found in Nordhaus (2008) and also at http://webdice.rdccep.org/static/docs/Equations_141227.pdf

⁸ See, Nordhaus (1977 a, b) and Nordhaus (1992 a, b). For a history of the evolution of the DICE model see Newbold (2010).

classes of models analyse climate-economy interactions, the former are simpler and present a highly aggregate representation of costs of GHG mitigation and of climate damages.⁹ The primary motivation for BC IAMs is to “compute the optimal trajectory of global GHG emissions, and the corresponding prices to charge for those emissions” (Weyant 2014, 381). Together these constitute what is often termed as ‘optimal’ climate policy. An ‘optimal’ emissions trajectory is one that equates the marginal (discounted) benefits of avoided climate damage with the marginal (discounted) costs of GHG mitigation. Put differently, this time path of GHG emissions maximises the discounted present value of global welfare.¹⁰ A benefit-cost IAM such as DICE calculates this time path and also the shadow prices of emissions, namely, the social cost of carbon (SCC).¹¹

2.1. Overview of the DICE model

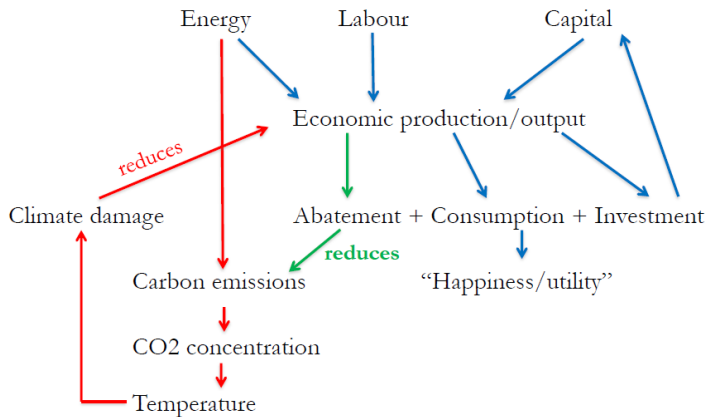
The DICE model views climate change within the framework of neoclassical economic growth theory. In the Ramsey–Cass–Koopmans (RCK) optimal growth model (Ramsey 1928; Cass 1965; Koopmans 1965) society invests in capital goods by reducing consumption today in order to increase consumption in future. The main decision in each time period is how much to consume and save. The DICE model “extends this approach by including the ‘natural capital’ of the climate system as an additional kind of capital stock. In other words, it views concentrations of greenhouse gases as negative natural capital, and emissions reductions as investments that raise the quantity of natural capital (or reduce the negative capital). By devoting output to emissions reductions, economies reduce consumption today but prevent economically harmful climate change and thereby increase consumption possibilities in the future” (Nordhaus 2013, 1080). An increase in concentration of GHGs has a negative impact on future economic output because of its influence on the global mean surface temperature (GMST or T_{AT} or simply T).¹² The fraction of output (Y)

⁹ For example, in the DICE model the world is taken as one region. DICE also has a regionally disaggregated companion model, namely, the Regional Integrated Climate Economy (RICE) model (Nordhaus and Yang 1996). In its most recent version, the RICE model divides the world into 12 regions of which India is one (Nordhaus 2010).

¹⁰ Some readers may find this framing problematic. Indeed, there are a number of critiques of IAMs some methodological and others more broad ranging (e.g., Ackerman *et al.* 2009; Pindyck 2013, 2017; Stern 2013). Again, my objective is not to defend IAMs as an epistemology. It is to demonstrate that IAMs like DICE with suitable modification can result in a big bang reduction in GHG emissions.

¹¹ The only GHG that is controlled in DICE is emissions of CO₂ from industries. CO₂ from land-use change (e.g., deforestation) and other GHGs are treated as exogenous trends.

¹² Captured through equilibrium climate sensitivity (ECS) parameter. Also note T_{AT} actually refers to a change in temperature from pre-industrial baseline.

Figure 1: Schematic illustration of the DICE model

Note: . The dark blue arrows represent the economic component of the model. Red arrows show how the economy impacts climate and vice versa. Green arrows illustrate the effect of climate policy.

Source: Adapted from Wieners (2018)

lost in each time period is captured through a Hicks-neutral damage function (Ω). By devoting some portion of economic output to GHG abatement (Λ) (investment in natural capital), future temperature increases and associated climate damages (Ω) can be avoided. The net output in each period (Q) then is divided between consumption and investment in physical capital (figure 1).

Following Nordhaus (2008), net output at time t , $Q(t)$ is gross output $Y(t)$ scaled by climate damages $\Omega(t)$ and minus abatement expenditures $\Lambda(t)$ (percentage of output spent on reducing GHG emissions). $Q(t)$ is further allocated between consumption $C(t)$ (broadly defined) and investment $I(t)$.¹³

¹³ It should be emphasized that consumption is broadly defined to include marketed goods and services and also non-market goods and services especially environmental amenities. Similarly, damages reflect “damages in various economic sectors, notably agriculture, farming, forestry, tourism, water, energy and real estate (human settlements), as well as impacts on human health and ecosystems. These are due to a number of mechanisms involving an increase in average temperature, sea level rise, and (extreme) weather patterns and events like rainfall, storms, heat waves and hurricanes” (Botzen and van den Bergh 2012, 373).

$$Q(t) = \Omega(t)[1 - \Lambda(t)]Y(t) \quad (1)$$

$$Y(t) = \Lambda(t)K(t)^\gamma L(t)^{1-\gamma} \quad (2)$$

$$\Omega(t) = 1/[1 + \pi_1 T_{AT}(t) + \pi_2 T_{AT}(t)^2] \quad (3)$$

$$Q(t) = C(t) + I(t) \quad (4)$$

Here, the damage function $\Omega(t)$ represents one minus the fraction of aggregate output lost due to climate change, i.e., net output. For $T = 0$, $\Omega(t) = 1$ (no climate damage) whereas for large temperature changes $\Omega(t)$ approaches zero (maximum damage).¹⁴ It is evident then the damage function plays a central role in the DICE model and in BCA more generally. It maps the impact of increase in temperature due to an increase in GHG concentration into lost output. As I show below, alternative functional forms of the damage function can lead to very different results.

The climate module in DICE tracks stocks and flows of carbon in 3 reservoirs: lower atmosphere, shallow ocean, and deep ocean. “The climate equations are a simplified representation that includes an equation for radiative forcing and two equations for the climate system. The radiative forcing equation calculates the impact of the accumulation of GHGs on the radiation balance of the globe. The climate equations calculate global mean surface temperature (T_{AT}) and the average temperature of the deep oceans for each time-step. These equations draw upon and are calibrated to large-scale general circulation models of the atmosphere and ocean systems” (Nordhaus 2008, 36).

DICE generates an optimised path of savings and reduction in GHGs over a planning horizon of several centuries. The objective function that is maximized is the discounted sum of future utility from consumption.¹⁵ The utility function is of the constant relative risk aversion (CRRA) form where

¹⁴The DICE damage function is calibrated to damages in the range of 2 to 4°C which as we shall see later is problematic.

¹⁵ More formally, the objective function is $W = \sum_{t=1}^{T_{max}} U[c(t), L(t)]R(t)$ where U is utility, $c(t)$ is

consumption in period t and $L(t)$ is the population in period t . $R(t) = \frac{1}{(1+\rho)^t}$ is the discount

factor determined by the pure rate of time preference ρ (also known as the utility discount rate). Optimal policy is the path of emissions reductions that maximizes the objective function and the carbon tax that achieves those reductions.

future utility is discounted at a constant pure rate of time preference ρ .¹⁶ DICE can also be thought of as an optimal control model where GHG emissions are control variables,¹⁷ whereas change in global mean surface temperature (T) is a state variable. T is a key variable that describes the climate system and a change in T depicts (one dimension) climate change. Through policy instruments, such as carbon taxes, policymakers can influence GHG emissions.

Three key features of the DICE model drive the ‘policy ramp’ recommendation that was mentioned earlier: (i) the discount rate (not to be confused with the pure rate of time preference or the utility discount rate),¹⁸ (ii) ECS and (iii) damage function $\Omega(t)$. While the choice of discount has profound implications for ‘urgent action’ (or the lack of it), the latter two are the ones most relevant for this essay. We focus on them in the next section.

3. WHAT DOES CLIMATE SCIENCE TELL US?

Recall five key links that map anthropogenic climate change in an IAM:

- a) from ‘people’ (producers/consumers) to emissions of GHGs
- b) from emissions to stocks of GHGs
- c) from GHG stocks to changes in temperature
- d) from rising temperature to climate change more broadly
- e) from climate change to human (economic) impact

Climate science is deeply embedded in links (b), (c) and (d). While there is not much debate about quantification of (b), considerable uncertainty surrounds (c) or ECS. I discuss this in detail below and the interlinked issue of “fat tails”. The DICE model suffers from two major problems vis-à-vis climate science. First, it does not handle well the uncertainty vis-à-vis ECS and its implications for catastrophic outcomes. Second, DICE skips link (d) and goes directly from (c) to (e) via the damage function $\Omega(t)$ described

¹⁶ Also known as the constant intertemporal elasticity of substitution (CIES) utility function

$U(c) = \frac{c^{1-\eta}}{1-\eta}$ which can be represented by logarithmic utility $U(c) = \log c$ when $\eta = 1$.

¹⁷ In DICE this is the *emissions control rate*, i.e., the fraction of emissions reduced by a climate policy, for example, carbon taxes. Under business as usual scenario emissions control rate is set to zero.

¹⁸ The discount rate $r = \rho + \eta g$ (Ramsey Rule) where ρ is the pure rate of time preference (utility discount rate), η is the parameter of the CRRA/CIES utility function and g is the growth rate of consumption.

earlier in equation (4). This is a potential problem since it is (d) that links rising temperatures to climate impacts such as sea level rise and a greater frequency of extreme weather events. It is also here that tipping points and nonlinearities can be captured.¹⁹ In the absence of this link, increases in temperature directly enter (e) and the climate damage function in the DICE model gets seriously flawed. But all is not lost. In the next section I show how DICE can be modified to address these shortcomings. Before doing that, it is important to discuss the key uncertainty in climate science, namely, climate sensitivity and its corollary, “fat tails”.

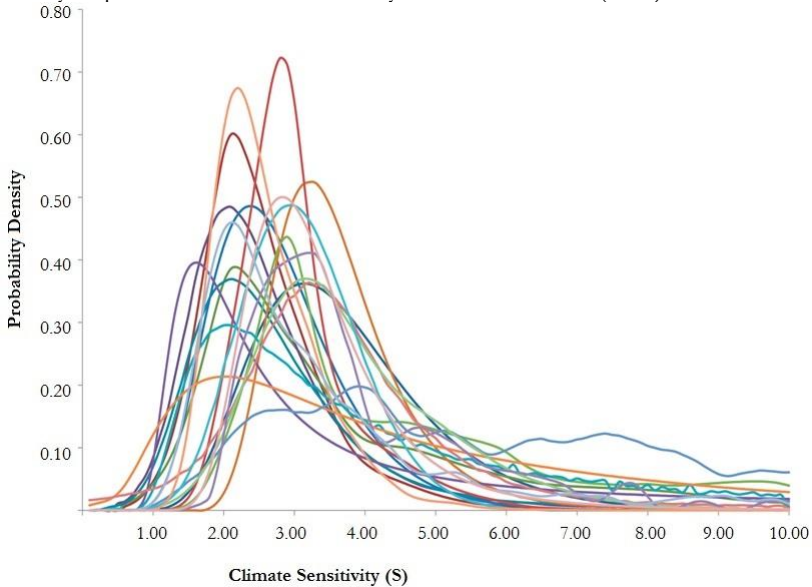
3.1. Equilibrium climate sensitivity (ECS) and the problem of “fat tails”

ECS and TCR (see, footnote 5) are useful metrics summarising the temperature response of the climate system to an externally imposed radiative forcing (RF).²⁰ While TCR is a short-run concept, ECS is the *eventual* temperature response to increases in GHG concentrations. More precisely, ECS is the equilibrium change in GMST following a doubling of the atmospheric carbon dioxide concentration (for details see Stocker *et al.* 2013, TFE.6). It measures how sensitive global average temperature is to changes in CO₂ concentration in the long run. “It is perhaps the most studied and most frequently quoted summary statistic in all of climate science” (Heal and Millner 2014, 121). The problem, however, as mentioned at the beginning of this essay, is that despite decades of research, science has not been able to pin down this key parameter and there is a significant downside risk of it being very high. Figure 2 depicts various estimates of the probability distribution for climate sensitivity (Millner, Dietz and Heal, 2013). Rather than going into technical detail on why they differ, note instead that all of them indicate “it is very *unlikely* that climate sensitivity is less than 1°C. In addition, a lot of the weight in most of the

¹⁹ A tipping point is an irreversible change such as the collapse of the Western Antarctic or Greenland ice sheets or the melting of the permafrost. See, Lemoine and Traeger (2016) for a discussion especially in the context of DICE. Nonlinearities imply climate damage functions do not follow neat quadratic, exponential, or other smooth functional forms. A very recent paper in *Nature* shows tipping points are much more imminent than previously believed (Lenton *et al.* 2019).

²⁰ Radiative forcing or climate forcing is the difference between insolation (sunlight) absorbed by the Earth and energy radiated back to space. Changes to Earth's radiative equilibrium, that cause temperatures to rise or fall over decadal periods, are called climate forcings. Positive radiative forcing means Earth receives more incoming energy from sunlight than it radiates to space. This net gain of energy will cause warming. Conversely, negative radiative forcing means that Earth loses more energy to space than it receives from the sun, which produces cooling. A system in thermal equilibrium has zero radiative forcing. (Wikipedia contributors 2020)

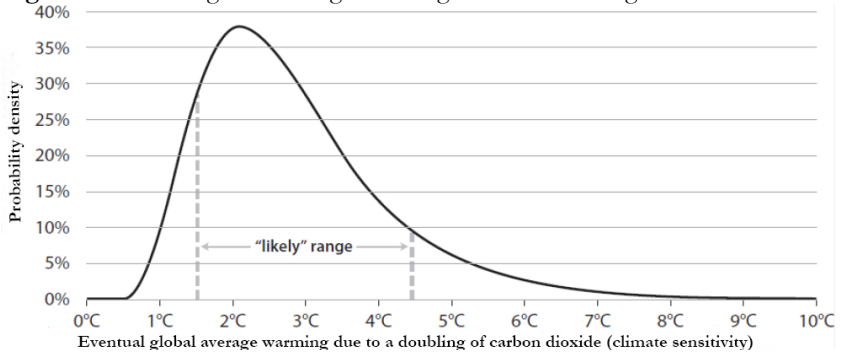
Figure 2: Estimated probability density functions for climate sensitivity from a variety of published studies collated by Meinshausen *et al.* (2009)



Source: Millner, Dietz and Heal (2013).

distributions is in the 2 to 4.5°C range, which is the IPCC’s official “likely” range for climate sensitivity. The disagreement between the estimates occurs in the upper tails of the distributions, that is, the data do not limit the estimates of the high end of climate change well at all (Allen *et al.* 2006; Roe and Baker 2007) which means that we understand little about the likelihood of worst case outcomes” (Heal and Millner 2014, 123). In graphical terms, most of the climate sensitivity distributions are right skewed – implying realisations of higher temperatures are more likely than low ones. In other words, the long right tails of these distributions have non-negligible probability. Weitzman picturesquely phrases this as “extreme disaster lurking in the distant tails of distributions” (Weitzman 2007, 17).

A revised estimate of ECS, based on different and newer datasets and expert judgement, is found in the IPCC Fifth Assessment Report (FAR) of 2013. Using IPCC terminology for uncertainty, it is *likely* (66% or greater probability) that ECS will be in the 1.5°C to 4.5°C range. It is *extremely unlikely* (up to 5% probability) to be less than 1°C and *very unlikely* (up to 10% probability) that it will be greater than 6°C. This is shown in figure 3 where a log-normal distribution is fitted around the “likely” range for

Figure 3. Eventual global average warming due to a doubling of carbon dioxide

Source: Adapted from Wagner and Weitzman (2015)

climate sensitivity in IPCC FAR. To show why these probabilities are disconcerting we must turn our attention to so-called “fat tails”.

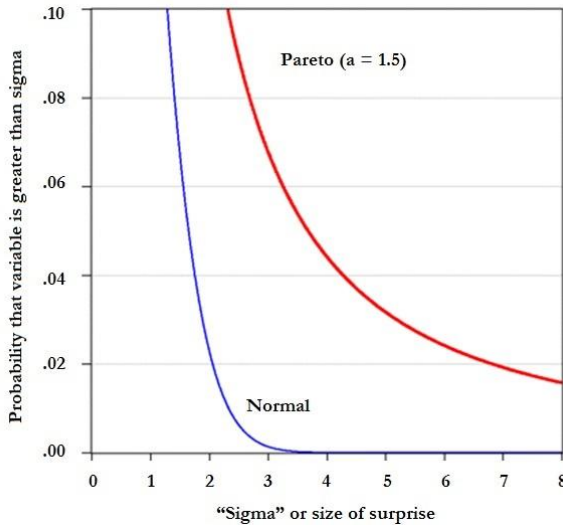
3.2. “Fat tails” and their consequences for climate policy

As mentioned earlier, climate sensitivity is a key indicator of the eventual temperature response to greenhouse gas (GHG) changes. It is likely to be in the range 1.5°C to 4.5°C with a best estimate of 3°C but values substantially higher than 4.5°C cannot be excluded. This leads us to the issue of fat tailed probability distributions. Whereas in a thin tailed distribution, such as the normal distribution, the probability of reaching the extremes of the tails converges to zero relatively quickly, for a fat tailed distribution the probability in the extreme ends converges to zero very slowly. As stated earlier, Weitzman was the most vocal proponent of “fat tails” as applied to climate policy. Figure 4 shows the difference in probability for each standard deviation (“sigma”) from the mean between a thin tailed normal and a fat tailed Pareto distribution (Nordhaus 2011). It is evident that assuming a thin tail distribution when it is fat tailed can lead to a serious underestimate of probabilities in the tails.

As an illustration of fat tails in the context of climate change, consider the following point from Wagner and Weitzman (2015). Though global average warming of 5 or even 6°C is horrifying and unimaginable, when we combine ECS from IPCC with a likely 700 ppm scenario (IEA 2013) this doomsday scenario has a greater than 10 percent of occurring (figure 5).²¹ The show the consequences of this scenario with just one fact — the last time global average temperatures were about 2 to 3.5°C above the

²¹Like figure 3, this one fits a log normal distribution around the IPCC’s (2013) “likely” range for climate sensitivity. But in the specific context of GHG concentrations of 700 ppm CO₂e.

Figure 4: Illustration of tails for a normal distribution and a Pareto distribution with scale parameter $a = 1.5$.



Note 1: Sigma = standard deviation from mean

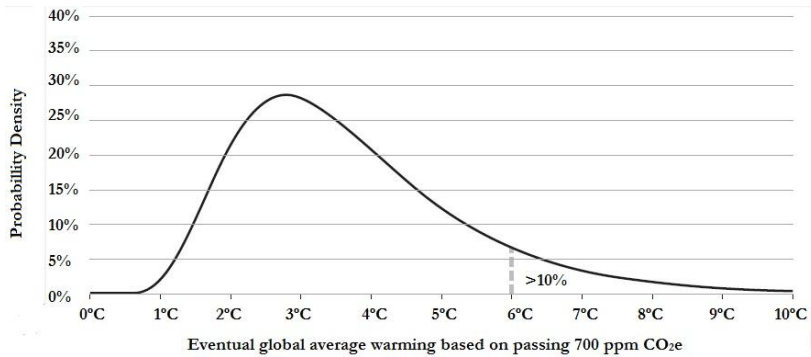
Note 2: Each curve shows the probability that the variable will be greater than the sigma shown on the horizontal axis

Source: Adapted from Nordhaus (2011)

pre-industrial level (3 million years ago) sea levels were up to 20 meters higher than today (IPCC 2013)²²

The implications of fat tails are extremely serious. Proponents of this view argue against framing climate policy in terms of BCA. Instead, they view climate change as a risk management problem (Risky Business Project 2014; Wagner and Weitzman 2015). According to them “average projections are bad enough, but it’s the small-probability, high impact events that ought to command particular attention. That possibility all but calls for a precautionary approach to climate policy” (Convery and Wagner 2015, 308). As mentioned earlier, Weitzman through his numerous papers and a book made the most persuasive case for going beyond BCA. He argued climate change is among a small list of potentially catastrophic low-probability, high impact events. Thus, it merits special attention that standard BCA (namely,

²² A 2 to 3.5°C warming above pre-industrial levels must be juxtaposed against the fact 1°C warming has already occurred. So another 1 to 1.5°C above current levels could potentially tip us over the precipice.

Figure 5: Eventual global average warming based on passing 700 ppm CO_{2e}

Source: Adapted from Wagner and Weitzman (2015)

IAMs such as Nordhaus' DICE model) cannot offer. In his view aggressive action on GHG mitigation is like buying insurance against climate catastrophe (which has a non-negligible probability of occurring).

4. CAN ECONOMIC MODELING OF CLIMATE CHANGE CATCH UP WITH CLIMATE SCIENCE?

How damaging are non-linearities and tipping points in climate change (as captured in fat tails) for BCA? Like most IAMs, DICE is a deterministic model. In order to address uncertainties (or surprises) about future costs and benefits, it uses “best guesses” (expected values) over a hypothesized probability distribution.²³ In other words, DICE attempts to incorporate abrupt climate change by calculating the expected value of low-probability, high-cost catastrophic damages. This is done by running Monte Carlo simulations after probability distributions have been assigned to various parameters. As Ackerman *et al.* (2010) put it, “DICE addresses catastrophic risk in theory, only to turn it into a deterministic guess in practice” (Ackerman *et al.* 2010, 1658).²⁴ Focusing attention on the damage function

²³ In particular, it makes the standard assumption that the climate sensitivity parameter is 3 (midpoint of the IPCC range).

²⁴ Cai and Lontzek (2019) develop a stochastic dynamic programming version of the DICE model, namely, DSICE which can, *inter alia*, model the impact of uncertainty about climate tipping points on economic policy of climate change. In an earlier paper using DSICE they show the uncertainty associated with the timing of stochastic tipping points indicates carbon taxes have to increase by at least 50% compared to the deterministic DICE model (Lontzek, Cai, Judd and Lenton 2015). For a rapid, high-impact tipping event, these

and following Ackerman *et al.* (2010) the DICE damage function (equation 3) can be rewritten as

$$d = \frac{aT^N}{1 + aT^N} \quad (5)$$

where d is climate damages as a fraction of world output and T is the increase in temperature from the base year. The use of equation (5) prevents climate damages from exceeding the value of world output.²⁵ This would be logical if damages only reduced current income as DICE assumes. However, more realistically if we assume climate damages also include loss of capital assets, damages can exceed 100% of annual output. The exponent N measures the speed with which damages increase as temperatures rise.

As can be seen from figure 6 for the quadratic formulation used by Nordhaus ($N = 2$), damages rise gradually and less than half of global output is lost till $T = 19^\circ\text{C}$ — “far beyond the temperature range that has been considered in even the most catastrophic climate scenarios” (Ackerman *et al.* 2010, 1660). In contrast, as N increases, half of world output is lost at temperatures of about 7°C for $N= 3$; 4.5°C for $N= 4$; or 3.5°C for $N= 5$, implying a sense of urgency. As N tends to infinity, Eq. (5) approaches a vertical line. “This would be the appropriate shape for the damage function under the hypothesis that there is a threshold for an abrupt world-ending (or at least economy-ending) discontinuity... Thus choosing a larger N (“closer to infinity”) means moving closer to the view that complete catastrophe sets in at some finite temperature threshold. Choosing a smaller N means emphasizing a gradual rise of damages rather than the risk of discontinuous, catastrophic change” (Ackerman *et al.* 2010, 1660). Below I discuss the implications of a highly convex damage function (footnote 27).

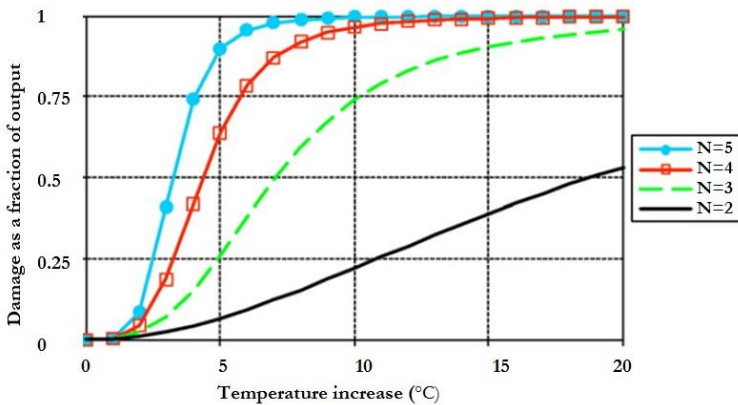
It is evident from this illustration that IAMs such as DICE are a tool and do not provide answers independent of the assumptions built into them. DICE can essentially yield results in line with Weitzman by manipulating the parameter space, modifying the damage function or introducing endogeneity in the model. For example, Ackerman *et al.* (2010) examine the implications of incorporating a fat-tailed probability distribution for ECS and modifying the damage function in the DICE model (see above). They conclude,

taxes should increase by more than 200%. They conclude the discount rate to delay stochastic tipping points is much lower than that for deterministic climate damages. In a different line of research, Kelly and Kolstad (1999) show how Bayesian learning can influence policy in a model with uncertainty.

²⁵ Unlike the case where $d = aT^N$.

[I]f either the damage function exponent remains at or near the default value of 2, or climate sensitivity remains at or near the default value of 3, then DICE projects relatively little economic harm. With plausible changes in both parameters, however, DICE forecasts disastrous economic decline and calls for rapid mitigation. The bad news is that the *optimal policy recommended by a standard IAM such as DICE is completely dependent on the choice of key, uncertain parameters*. The good news is that there is *no reason to believe that sound economics, or even the choice of established, orthodox models, creates any grounds for belittling the urgency of the climate crisis*. (Ackerman *et al.* 2010, 1664; emphasis added)

Figure 6: Damage function exponents: DICE and variants



Source: Ackerman *et al.* (2010)

I conclude this section by citing a recent significant paper by Dietz and Stern (2015), whose title says it all.²⁶ They show if DICE takes into account three essential features of the climate problem, namely, endogeneity of economic growth, highly convex damage function and climate risk (i.e., high values of ECS), “optimal policy” of DICE calls for strong controls. Dietz and Stern (2015) extend earlier work such as Ackerman *et al.* (2010) to incorporate endogenous drivers of growth and allow climate change to adversely affect these drivers. This is in sharp contrast to existing IAMs that are based on the RCK optimal growth model, where the major driver of growth is exogenous improvements in productivity and where climate change only impacts current output. Next, they assume the damage function is highly convex for a large increase in temperature like 6°C, but

²⁶ “Endogenous Growth, Convexity of Damage and Climate Risk: How Nordhaus’ Framework Supports Deep Cuts in Carbon Emissions”

not for smaller increases.²⁷ Consideration of some of the science, for example, on tipping points, leads them in this direction. Finally, they allow for explicit and large climate risks by allowing the possibility of high values of climate-sensitivity.

5. CONCLUDING THOUGHTS

Without exaggeration climate change poses an existential threat to human civilization. What is worse, this threat is more imminent than previously believed—the phrase “climate emergency” is now part of the discourse. Climate science almost on a daily basis provides new evidence of this. Global mean temperatures are already 1.1°C more than pre-industrial levels and business as usual climate scenarios are truly horrifying. The period 2015–2019 is on track the warmest five-year period ever recorded. Undoubtedly, deep and immediate cuts in GHG emissions are required. The question then is whether standard economic analysis that weighs benefits and costs up to the task? The answer is it is possible. Economic models are useful analytical tools but what they produce depends on what goes into them. By incorporating more realistic assumptions and giving up some very limiting ones, and by incorporating science more carefully as they build their models, economists have the potential to be in sync with calls for action. Economics ‘done right’ has the potential to catch up with climate science.

ACKNOWLEDGMENTS

I would like to thank two anonymous reviewers for helpful comments and Sujayata Choudhry for her assistance. Kanchan Chopra provided the encouragement and impetus to write this essay and Kuntala Lahiri-Dutt nudged me along. Journal office was of immense help with the figures. I am grateful to all of them. This is to also acknowledge permission granted by Springer and Elsevier towards construction of figures 2 and 6, and William Nordhaus for figure 4.

²⁷ The damage function taken from Weitzman (2012) captures tipping points better. Weitzman introduced convexity in the DICE damage function by adding a third term to the quadratic specification by Nordhaus: $\Omega(t) = 1/[1 + \pi_1 T_{AT}(t) + \pi_2 T_{AT}(t)^2 + \pi_3 T_{AT}(t)^{6.754}]$. The exponent of the third term is chosen such that at $T = 6$, 50 percent of output is lost.

REFERENCES

- Ackerman, Frank, Stephen J. DeCanio, Richard B. Howarth, and Kristen Sheeran. 2009. "Limitations of Integrated Assessment Models of Climate Change." *Climatic Change* 95: 297-315.
- Ackerman, F., Elizabeth A. Stanton, and Ramón Bueno. 2010. "Fat Tails, Exponents, Extreme Uncertainty: Simulating Catastrophe in DICE." *Ecological Economics* 69 (8): 1657–1665.
- Allen, Myles *et al.* 2006. "Observational Constraints on Climate Sensitivity." In *Avoiding Dangerous Climate Change*, edited by Hans Joachim Schellnhuber, Wolfgang Cramer, Nebojsa Nakicenovic, Tom Wigley, and Gary Yohe. Cambridge, UK: Cambridge University Press
- Botzen, W.J. Wouter, and Jeroen C.J.M. van den Bergh. 2012. "How Sensitive is Nordhaus to Weitzman? Climate Policy in DICE with an Alternative Damage Function." *Economics Letters* 117: 372-374.
- Cai, Yongyang, and Thomas S. Lontzek. 2019. "The Social Cost of Carbon with Economic and Climate Risks," *Journal of Political Economy* 127 (6): 2684-2734.
- Cass, David. 1965. "Optimum Growth in an Aggregative Model of Capital Accumulation." *The Review of Economic Studies* 32 (3): 233-240.
- Comín, Francisco A. and Miguel Angel Rodríguez-Arias. 2003. "What we know about the Climate System? A brief review of current research," in *Global Climate: Current Research and Uncertainties in the Climate System*, edited by Xavier Rodö and Francisco A. Comín. New York: Springer.
- Convery, Frank J., and Gernot Wagner. 2015. "Reflections—Managing Uncertain Climates: Some Guidance for Policy Makers and Researchers." *Review of Environmental Economics and Policy* 9 (2): 304-320.
- Dietz, Simon, and Nicholas Stern. 2015. "Endogenous Growth, Convexity of Damages and Climate Risk: How Nordhaus' Framework Supports Deep cuts in Carbon Emissions." *The Economic Journal* 159 (583): 574–620.
- Gillingham, Kenneth, William Nordhaus, David Anthoff, Geoffrey Blanford, Valentina Bosetti, Peter Christensen, Haewon McJeon, and John Reilly. 2018. "Modeling uncertainty in integrated assessment of climate change: A multimodel comparison." *Journal of the Association of Environmental and Resource Economists* 5 (4): 791-826.
- Heal, Geoffrey, and Antony Millner. 2014. "Uncertainty and decision making in Climate Change Economics." *Review of Environmental Economics and Policy* 8 (1): 120-137.
- Intergovernmental Panel on Climate Change (IPCC). 2001. *Climate Change 2001: The Scientific Basis. Contribution of Working Group 1 to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.

- Intergovernmental Panel on Climate Change (IPCC). 2013. “Summary for Policymakers,” in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.
- Intergovernmental Panel on Climate Change (IPCC). 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva.
- International Energy Agency (IEA). 2013. World Energy Outlook. Available at http://www.wec-france.org/DocumentsPDF/Evenements/06-12-13_AIE.pdf
- Kelly, David L., and Charles Kolstad. 1999. “Bayesian learning, growth, and pollution.” *Journal of Economic Dynamics and Control* 23(4): 491–518.
- Koopmans, Tjalling C. 1965. “On the Concept of Optimisation Economic Growth” in *The Economic Approach to Development Planning*. 225-287. Chicago: Rand McNally.
- Lemoine, Derek, and Christian P. Traeger. 2016. “Economics of Tipping the Climate Dominoes.” *Nature Climate Change* 6 (5): 1-23.
- Lenton, Timothy M., Johan Rockström, Owen Gaffney, Stefan Rahmstorf, Katherine Richardson, Will Steffen, and Hans Joachim Schellnhuber. 2019. “Climate Tipping Points - Too Risky to Bet Against.” *Nature* 575: 592-595.
- Lontzek, Thomas S., Yongyang Cai, Kenneth L. Judd, and Timothy M. Lenton. 2015. “Stochastic Integrated Assessment of Climate Tipping Points Indicates the Need for Strict Climate Policy.” *Nature Climate Change* 5: 441–444.
- McKibbin, Warwick. 2014. [Review of the book “Climate Economics: The State of the Art.” by Frank Ackerman and Elizabeth A. Stanton] *Journal of Economic Literature* 52 (2): 559-562.
- Meinshausen, Malte, Nicolai Meinshausen, William Hare, Sarah C. B. Raper, Katja Frieler, Reto Knutti, David J. Frame, and Myles R. Allen. 2009. “Greenhouse-gas Emission Targets for Limiting Global Warming to 2 °C.” *Nature* 458 (7242): 1158-1163.
- Millner, Antony, Simon Dietz, and Geoffrey Heal. 2013. “Scientific Ambiguity and Climate Policy.” *Environmental and Resource Economics* 55 (1): 21-46.
- Newbold, S. C. 2010. “Summary of the DICE Model.” *Improving the Assessment and Valuation of Climate Change Impacts for Policy and Regulatory Analysis*. [https://yosemite.epa.gov/ee/epa/cerm.nsf/vwan/ee-0564-114.pdf/\\$file/ee-0564-114.pdf](https://yosemite.epa.gov/ee/epa/cerm.nsf/vwan/ee-0564-114.pdf/$file/ee-0564-114.pdf)
- Nordhaus, William D. 1977a. “Strategies for the Control of Carbon Dioxide.” Cowles Foundation Discussion Paper No. 443, Yale University.
- Nordhaus, William D. 1977b. “Economic Growth and Climate: The Carbon Dioxide Problem.” *The American Economic Review* 67 (1): 341-346.

Nordhaus, William D. 1992a. "The 'DICE' Model: Background and Structure of a Dynamic Integrated Climate-economy Model of the Economics of Global Warming." Cowles Foundation Discussion Paper No. 1009, Yale University.

Nordhaus, William D. 1992b. "An Optimal Transition Path for Controlling Greenhouse Gases." *Science* 258 (5086): 1315-1319.

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

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

Nordhaus, William D. 2010. "Economic Aspects of Global Warming in a post-Copenhagen Environment." *Proceedings of the National Academic of Sciences* 107 (26): 11721-11726

Nordhaus, William D. 2011. "The Economics of Tail Events with an Application to Climate Change." *Review of Environmental Economics and Policy* 5 (2): 240-257.

Nordhaus, William D. 2013. "Integrated Economic and Climate Modeling" in *Handbook of Computable General Equilibrium Modeling*. First Edition, 1069-1131. Amsterdam: Elsevier.

Nordhaus, William D., and Zili Yang. 1996. "A Regional Dynamic General Equilibrium Model of Alternative Climate Change Strategies." *American Economic Review* 86 (4): 741-765.

Pindyck, Robert S. 2013. "Climate Change Policy: What Do the Models Tell Us?" *Journal of Economic Literature* 51 (3): 860-72.

Pindyck, Robert S. 2017. "The Use and Misuse of Models for Climate Policy." *Review of Environmental Economics and Policy* 11 (1): 100-114.

Ramsey, F. P. 1928. "A Mathematical Theory of Saving." *Economic Journal* 38 (152): 543-559.

Risky Business Project. 2014. "Risky Business: The Economic Risks of Climate Change in the United States."

https://riskybusiness.org/site/assets/uploads/2015/09/RiskyBusiness_Report_WEB_09_08_14.pdf

Roe, Gerard H., and Marcia B. Baker. 2007. "Why is Climate Sensitivity So Unpredictable?" *Science* 318 (5850): 629-632.

Stanton, Elizabeth A., Frank Ackerman and Sivan Kartha. 2009. "Inside the Integrated Assessment Models: Four issues in climate economics." *Climate and Development* 1 (2):166-184.

Stern, David I., Frank Jotzo, and Leo Dobes. 2013. "The Economics of Global Climate Change: A Historical Literature Review." CCEP Working Paper No. 1307. Available at <https://ageconsearch.umn.edu/record/249412/files/ccep1307.pdf>.

- Stern, Nicholas. 2014. "Ethics, Equity and the Economics of Climate Change Paper 1: Science and Philosophy." *Economics and Philosophy* 30 (3): 397-444.
- Stocker, Thomas F., Qin Dahe, Gian-Kasper Plattner. 2013. "Technical Summary." In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley. USA: Cambridge University Press.
- Wagner, G., and Martin L. Weitzman. 2015. *Climate Shock*. USA: Princeton University Press.
- Weitzman, Martin L. 2007. "Role of Uncertainty in the Economics of Catastrophic Climate Change." *AEL-Brookings Joint Center Working Paper* 07-11. Available at <https://pdfs.semanticscholar.org/9ebd/87c605d31a59545cca2699a584068515522c.pdf>.
- Weitzman, Martin L. 2009. "On Modeling and Interpreting the Economics of Catastrophic Climate Change." *The Review of Economics and Statistics* 91 (1): 1–19.
- Weitzman, Martin L. 2011. "Fat Tailed Uncertainty in the Economics of Catastrophic Climate Change." *Review of Environmental Economics and Policy* 5 (2): 275-292.
- Weitzman, Martin L. 2012. "GHG Targets as Insurance Against Catastrophic Climate Damages." *Journal of Public Economic Theory* 14 (2): 221–44.
- Weyant, John. 2014. "Integrated Assessment of Climate Change: State of the Literature." *Journal of Benefit-Cost Analysis* 5 (3): 377-409.
- Weyant, John. 2017. "Some Contributions of Integrated Assessment Models of Global Climate Change." *Review of Environmental Economics and Policy* 11 (1): 115-137.
- Wieners, Claudia Elisabeth. 2018. "God does not play DICE – but Bill Nordhaus does! What can models tell us about the economics of climate change?" *Climate: Past, Present & Future* (blog) December 3, 2018. <https://blogs.egu.eu/divisions/cl/2018/12/03/god-does-not-play-dice-but-bill-nordhaus-does-what-can-models-tell-us-about-the-economics-of-climate-change/>
- Wikipedia contributors. 2020. "Radiative forcing." *Wikipedia, The Free Encyclopedia*. Accessed January 26, 2020. https://en.wikipedia.org/w/index.php?title=Radiative_forcing&oldid=936693346