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THE SOCIAL COST OF CARBON SHOULD NOT BE USED FOR MAKING ENERGY POLICY DECISIONS

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ABSTRACT

This paper argues that the social cost of carbon (SCC) should not be used to determine energy policies. The SCC, which is supposed to represent the avoided cost of greenhouse gas emissions, has been used to justify state and federal energy policy decisions, such as offshore wind procurements and the U.S. Environmental Protection Agency's vehicle emissions standards. This paper argues that SCC values should not be used, not because climate change is not real, but because the approaches used to estimate SCC values, primarily through integrated assessment models (IAMs) but also using expert opinions, are based on layers of arbitrary and unverifiable assumptions. The reasons why include: (i) the hubris of believing it is possible to develop accurate forecasts regarding technological developments 300 to 1,000 years into the future; (ii) the fundamental uncertainties underlying SCC estimates, such as defining the pre-industrial time period and measuring world temperatures during that period; (iii) the inherent arbitrariness of weighing the welfare of future generations versus the welfare of the current generation; and (iv) the inequity of imposing higher economic costs on today's generation to primarily benefit future generations who are expected to be far better off; and (v) that none of these policies, either individually or collectively, will have any measurable impact on world climate, given the increased emissions in developing countries whose primary focus is on economic growth and improved well-being for their citizens. The paper concludes by recommending that, as demand for energy increases over time, the most advantageous policies will focus on stimulating additional research to develop low-cost, reliable, and emissions-free energy resources. Doing so will provide greater long-term benefits than the current practice of skewing energy policy decisions to favor specific types of technologies and adopting policies that raise costs today. By raising energy costs and, thus, the costs of all goods and services, these policies impose real economic damages today while having no measurable impact on world climate.

KEYWORDS: *benefit-cost analysis, social cost of carbon, equity, uncertainty.*

1. INTRODUCTION

The social cost of carbon (SCC) is a measure of the cost of additional greenhouse gas emissions. These emissions are typically expressed in carbon dioxide equivalents (CO2-e), based on their estimated warming impact relative to carbon dioxide. Most SCC values have been developed using integrated assessment models (IAMs), which combine simple models that link forecast greenhouse gas emissions to changes in world and (depending on the IAM) regional temperatures, with models that estimate the damages resulting from those temperature changes. IAMs calculate the marginal cost of an additional metric ton of CO2 emitted today based on the estimated costs, typically in terms of reduced economic welfare measured by reductions in gross domestic product (GDP). A less common approach has been to use surveys of experts to estimate average SCC values.2 Still other approaches recommend specifying a timeframe for achieving net-zero emissions and then determining the necessary carbon taxes (and other policies) to achieve it.

SCC values derived from IAMs vary widely, from values below $0 (meaning that additional carbon emissions are beneficial) to costs over $2,000 per metric ton. This wide range of values is a consequence of differences in the models and different assumptions about fundamental parameters that cannot be observed. Alternative measures that seek to avoid the problems with IAMs, such as those based on surveys of experts, also differ widely (Pindyck 2019). Moreover, there is always uncertainty as to the basis for experts' responses. For example, if those surveyed base their responses on the results of IAMs, then surveying experts may be the equivalent of chasing one's tail. Unfortunately, what information experts base their answers on is not known. Still other alternatives, such as setting an arbitrary timeline for reducing emissions, called "Near Term to Net Zero" (NT2NZ) (Kaufman, et al. 2020), and then backing into the the SCC values needed to achieve the timeline, suffer from their own flaws.

Despite their deficiencies, IAM-based SCC estimates have been used to rationalize policies that increase energy costs, reduce consumer choice, and thus reduce economic welfare. In the U.S., for example, SCC estimates have been used to justify subsidized investments in intermittent wind and solar power, stricter vehicle mileage standards and electric vehicle mandates, low-carbon fuel standards, subsidies for so-called "green" hydrogen facilities, mandatory building electrification, energy efficiency standards for household appliances, greenhouse gas cap-and-trade programs, and others. Yet, the economic costs of these policies, especially the economy-wide costs of higher energy costs, are rarely evaluated or even considered. Moreover, because the SCC reflects global costs (or benefits), its use creates important distributional impacts for U.S. energy consumers who, as a result of these policies, face higher costs while receiving virtually no benefits from any realized emissions reductions.3

For example, the State of New Jersey has established a goal of acquiring over 11,000 megawatts (MW) of offshore wind capacity. Potential offshore wind developers submit proposals that specify the prices they propose to be paid over the duration of the projects (typically, 20 – 25 years), as well as various other "benefits" they promise to provide, such as jobs.4 The evaluations of these proposals have included benefit-cost analyses. Although these analyses are redacted based on confidentiality concerns (itself problematic for transparency), it is possible to recreate the analyses and estimate specific categories of costs and benefits. Doing so reveals that over half the claimed benefits arise from carbon reductions (O'Donnell 2024). Even if one were to accept the accuracy of other benefits (including the classification of transfer payments as benefits), the projects would fail a benefit-cost test without including the value of avoided carbon emissions.5 Moreover, the resulting increases in electric rates, amounting to billions of dollars per year, are dismissed as inconsequential (Storrow 2024).

Similarly, the US EPA's regulatory impact analysis of its proposed multi-pollutant vehicle emissions standards (EPA, 2024) showed that carbon emissions reductions were the single largest source of estimated benefits, with a present value of $1.6 trillion (2022 dollars), approximately double the estimated future fuel savings of $820 billion.6 Moreover, the EPA admitted that the estimated benefits would be realized only if all other countries base their energy policies on these same SCC estimates. Nevertheless, the EPA argues that, by imposing additional costs on its own populace, the US will encourage other countries to do the same. That argument lacks credibility, as there is no evidence that developing countries, which account for the majority of carbon emissions and whose emissions are increasing, unlike emissions from OECD countries, intend to adopt policies that prioritize reducing emissions over policies that increase economic growth and the welfare of their populations.

Because policymakers may be unfamiliar with the inherent problems with those models (and the problems with the alternatives), this paper addresses key empirical weaknesses, as well as key weaknesses with several alternatives to IAMs that have been proposed. Given the inherent uncertainty in SCC estimates of all types, a key question is whether it is appropriate to base energy policy decisions on those estimates and the resulting values of avoided CO2-e emissions.

The remainder of this paper is organized as follows. In the next section, I provide a short discussion of the most commonly used IAMs and the key parameters that drive the SCC values these models produce. Next, I focus on two areas that account for most of the damages estimated by IAMs: losses from agricultural productivity and human health impacts. Although SCC values calculated by IAMs are highly sensitive to the choice of discount rate, the literature on the "correct" discount rate is vast.7 Moreover, given the flaws in estimating future agricultural and health costs, the choice of discount rate used to convert those future costs into present values is a secondary issue.

Next, I critique the alternative approaches to estimating SCC values using IAMs that have been proposed. Finally, I conclude with an entirely different policy recommendation: abandon SCC estimates of any kind when making energy policy decisions and, instead, focus on research and development efforts to develop clean, reliable, and low-cost energy resources. Doing so will reduce greenhouse gas emissions while ensuring improved well-being for all, especially energy-starved individuals in developing countries.

2. A BRIEF SURVEY OF MAJOR IAMS

IAMs are both complex and simplistic. They are complex computer models that combine projections about future changes in world temperatures stemming from increased GHG emissions with projections of the future impacts of those higher temperatures and their projected costs. These costs include impacts on human health, changes in agricultural productivity, and the costs of mitigating certain types of damages, such as the expenses associated with building higher seawalls to limit damage from rising sea levels. More detailed models also examine distributional impacts, such as the impacts on developing nations versus developed ones. They are simplistic in that the potential damages from future climate are boiled down into a few equations. Some models, such as FUND and GIVE, build up SCC estimates from individual types of damages; others (Lint and Nordhaus 2024) take a top- down approach that posits a single worldwide damage function encompassing the breadth of projected climate change impacts.

Although numerous IAMs have been developed,8 three primary models have been used to develop SCC estimates that have been by U.S. policymakers. These are: (i) Dynamic Integrated Climate and Economy (DICE) (Nordhaus 1992); (ii) Framework for Uncertainty, Negotiation and Distribution (FUND) (Tol 1997); and (iii) Policy Analysis of Greenhouse Effect (PAGE) (Plembeck, et al., 1997).

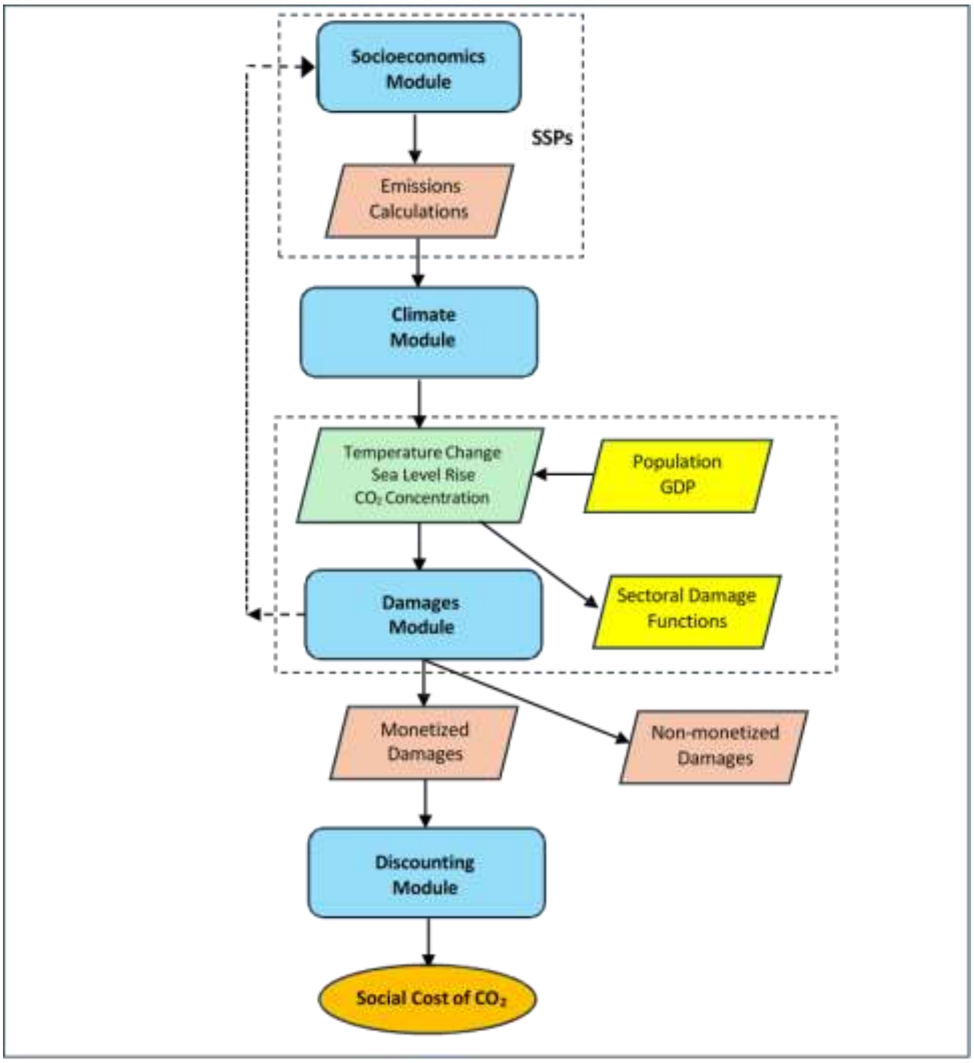
More recently, the Greenhouse Gas Impact Value Estimator (GIVE) model was developed by Resources for the Future and the University of California-Berkeley (Rennert, et al. 2022), which is similar in structure to the FUND model. Additionally, the Data-Driven Spatial Climate Model (DSCIM) developed at the University of Chicago's Climate Impact Lab (EPA 2023) has been used by the US Environmental Protection Agency (EPA) for the agency's regulatory impact analyses.9 Although the Trump Administration has rescinded the EPA guidelines, SCC estimates are still used by state policymakers, such as in setting prices for state-level emissions trading ("cap-and-trade") programs.

Of the different IAMs, the FUND model is the most detailed. It breaks the world into 16 separate regions and develops "bottom-up" estimates of damages associated with changes in agricultural production, different types of health impacts (e.g., deaths from tropical diseases, heart attacks from hot and cold weather), changes in forest cover, loss of water resources, and even extreme weather.

The academic literature is overflowing with debates over model specifications, discount rates, technological changes, future uncertainty, tipping points at which catastrophic climate impacts may occur, intergenerational equity, and other aspects.10 Most recently, SCC estimates developed with IAMs have been based on projections that extend 300 years and, in some cases, 1,000 years into the future. These three-century and longer forecasts, coupled with lower discount rates, have increased previous SCC estimates (IWG 2010, EPA 2013, EPA 2016) that were adopted by the US government by 400% or more (EPA 2023). When these new, higher SCC values are used, they can represent a majority of the benefits of different energy policies being pursued by individual US states and the US government.

The general structure of these IAMs is shown below (Figure 1). The two topmost items – the Socioeconomics module and emissions calculations – are typically exogenous to the models. That is, they are developed independently and then used to calculate future damages from GHG emissions. The socioeconomic module provides forecasts of future world population and economic well-being, as measured by gross domestic product (GDP), and resulting GHG emissions. The rationale is that, as population and wealth increase, so will GHG emissions.

Figure 1: General Structure of an Integrated Assessment Model



Source: Adapted from National Academy of Sciences (2017).

The scenarios used by IAMs are called Shared Socio-economic Pathways (SSPs) (Riahi 2017)11 were developed by the Intergovernmental Panel on Climate Change (IPCC) in its reports provide forecasts through the year 2100. Most of these scenarios are based on ones first developed at Stanford University in the 1990s.12 However, the most recent estimates of the SCC are based on predictions extending 300 or more years into the future. Therefore, these socioeconomic forecasts must be extended. The FUND model, for example, uses population and income forecasts from these scenarios and extrapolates them through the year 3000.13 As is well known to econometrics students, forecast uncertainty increases over time (Chatfield 2001), which renders forecasts that extend 10 – 20 years into the future dubious. Accurately predicting the state of the world, including the state of technology, health care, agriculture, and so forth, 300 years or more is impossible. Imagine asking someone in 1725 (George Washington was born in 1732) to predict the state of the world today and the technologies we take for granted.

Each scenario is based on various combinations of population growth, income and economic growth, energy consumption, and carbon emissions. The scenarios include an assumed "business as usual" case, from which the social cost of carbon is derived based on the cost of mitigating the modeled climate impacts of that scenario. Importantly, the forecasts are exogenous to the IAMs, that is, they are based on hypothesized forecasts of future economic growth, population, technology, and resulting GHG emissions. One controversy has been the use by many researchers of a specific SSP, called "Representative Concentration Pathway" (RCP) 8.5, which posits an extreme future that assumes rapid population growth, accompanied by rapid increases in fossil fuel consumption and a global temperature increase over 5 ºC by the year 2100 (Hausfeather and Peters 2020).

The emissions that determine the concentrations of GHGs are based on exogenous scenarios that are inputs to the IAMs. For example, the FUND model estimates future CO2 emissions as a function of four factors: (1) the carbon intensity of energy use over time (i.e., how much CO2 is emitted per unit of energy consumption); (2) the energy intensity of the economy over time, measured as energy consumption per dollar of real GDP; (3) GDP per capita; and (4) population.14 The parameters that determine carbon intensity and energy intensity of the economy through the year 2300 for each region are guesses based on extrapolations of historical data.15 Assumptions about the quantities of methane and nitrous oxide are based on assumptions from the first IPCC report in 1992 and then extrapolated through the year 2300.16 The DICE model uses a somewhat similar approach to estimate future GHG emissions from industrial sources and land-use emissions. For both, baseline emissions are a function of total output, emissions intensity per unit of output, and the presence of emissions controls.17 The heart of all IAM-based SCC estimates is how those models determine damages related to increased concentrations of GHGs and the resulting impacts from higher temperatures. The models approach damage estimates in two different ways. The first is a "top-down" approach that aggregates different types of damages into a single damage estimate that is a function of increased temperatures.

The DICE and PAGE models employ a top-down approach, although the PAGE model categorizes damages into economic and non-economic categories, while the DICE model separates damages associated with sea level rise from those associated with other factors.18 The second approach is a "bottom-up" method that estimates damages for various categories (e.g., health, agriculture, extreme weather, energy consumption, and dryland losses). The FUND and GIVE models are examples of this second approach. The FUND Model, for example, estimates damages for 14 separate categories (Antoff and Tol 2019).

3. THE UNCERTAINTY AND UNKNOWABILITY OF KEY IAM INPUTS

On top of the exogenous assumptions about future energy intensity and carbon intensity, the sensitivity of world temperature to changes in GHG concentrations is unknown, and different IAMs make different assumptions about the relationship between GHG concentration and temperature changes (Roe and Baker 2007). The key parameter in these relationships is climate sensitivity. Roe and Baker assume climate feedback is positive and increasing, whereas the physics of warming suggests positive, but decreasing (Meinhausen 2011). More recently, research has found negative feedback owing to additional cloud formation (Eschenbach 2023).19 Another issue is the starting point temperature from which the temperature increases are measured. That starting point is taken to be an estimate of the "pre-industrial" temperature of the earth. Some IAMs, such as DICE, assume that increases in world temperature above the pre-industrial level are assumed to impose damages. Others, such as PACE and FUND, use pre-industrial temperatures as a base from which to model the impacts of temperature increases, but do not assume those temperatures are optimal.

The use of a pre-industrial temperature in IAMs raises four key questions: (1) what time period defines "pre-industrial" (2) how is the pre-industrial temperature measured for that time period; and (3) what is the basis for assuming the measured temperature is "optimal;" and (4) what does "optimal" even mean in that context? If one graphed climate damages versus average world temperature, it would show increasing damages as GHG concentrations fell. For example, plants die at CO2 concentrations below 150 parts per million, which would cause all animal life to perish.

There is no specific definition of the pre-industrial period. The IPPC defines it as the period 1850-1900; others have used the period 1720-1800. Both periods coincide with the end of the Little Ice Age, which is believed to have begun in the early 1400s. However, prior to 1850, there were few consistent temperature records, making a determination of the global average temperature uncertain.

Hence, estimates of warming since pre-industrial times are largely based on guesswork. It was not until the 1970s that satellite measurements, acknowledged to be the most accurate means of measuring atmospheric temperatures, began. Finally, even if one were to define the pre-industrial period and develop an accurate measure of the average global temperature during that time, it would still be impossible to define its optimality. The FUND model, which disaggregates the world into 16 subregions, bases damage calculations on pre-industrial temperatures in each of those subregions. We know little about the average pre-industrial world temperature; we know even less about regional variations. Hence, global climate models are calibrated to the change in temperature between an arbitrary pre-industrial period to the present.

4. AGRICULTURAL AND HEALTH IMPACT DAMAGE FUNCTIONS

Several IAMs, notably the FUND and GIVE models, disaggregate damages into specific categories. The FUND model provides the most disaggregated damage estimates, including health- related damages, agricultural losses, water losses, reductions in the amount and value of forested lands, changes in energy consumption for heating and cooling, damages from sea-level rise, damages to ecosystems, and damages from extreme weather events. These damages are estimated at least 300 years into the future.

Previous analyses using the FUND model found that increased energy consumption accounted for the overwhelming majority of estimated climate damages (Cromar, et al. 2021). However, more recent estimates, such as those using the GIVE model, indicate that the largest SCC components are health-related (including additional deaths and illnesses) and agricultural damages.20 Consequently, I focus on those two categories of damages.

4.1 AGRICULTURAL IMPACTS

The agricultural impact estimates in the FUND model are based on various studies, (Anotff and Tol 2019), which were then manipulated (Tol 2002). The agricultural impact estimates in the GIVE model are based on Moore, et al. (2017), based primarily on climate model simulations (Challinor, et al. 2014), rather than empirical observations of changes in crop yields. Moore, et al. (2017) reanalyzed the Chalinor, et al. (2014) data and determined that the agricultural losses would be even more severe.

Whereas Challinor, et al. (2014) estimate a single equation model for climate impacts,21 the FUND model evaluates the overall agricultural impact by summing up three categories for each of its 16 regions: (1) the lost production owing to imperfect adaptation; (2) the deviation from an "optimal" temperature (i.e., changing temperatures can move a region either towards or away from this optimal temperature) since 1990; and (3) the effect of CO_2 fertilization (i.e., higher atmospheric CO_2 concentrations since their pre-industrial level (assumed to be 275 parts-per-million). Impact (1) is always negative; impact (3) is always positive; and impact (2) can be either positive or negative.

Thus, the overall impact on agricultural productivity, $A_{t,r}$, for region *r* in year *t*, is:

$A_{t,r} = A^S_{t,r} + A^L_{t,r} + A^F_{t,r}$, where: $A^S_{t,r} =$ = the reduction in output because of farmers' inability to adapt to temperature changes, $A^L_{t,r} =$ the change in output as the temperature deviates from the optimal temperature, and $A^F_{t,r} =$ the increase in output because of CO_2 fertilization. The effects of CO_2 fertilization on plant growth are well-known and the FUND model assumes a logarithmic impact.

The equations for the effects of an inability to adapt to changing temperatures and deviations from an optimal temperature are

The specific equations for each are:

$$A^S_{t,r} = \alpha_r \left(\frac{\Delta T_t}{0.04}\right)^{\beta} + \left(1 - \frac{1}{\rho}\right) A^S_{t-1,r} \tag{1}$$

$$A^L_{t,r} = \delta^1_r T_t + \delta^2_r T_t^2 \tag{2}$$

$$A^F_{t,r} = \gamma_r \ln \frac{CO_{2,t}}{275} \tag{3}$$

where:

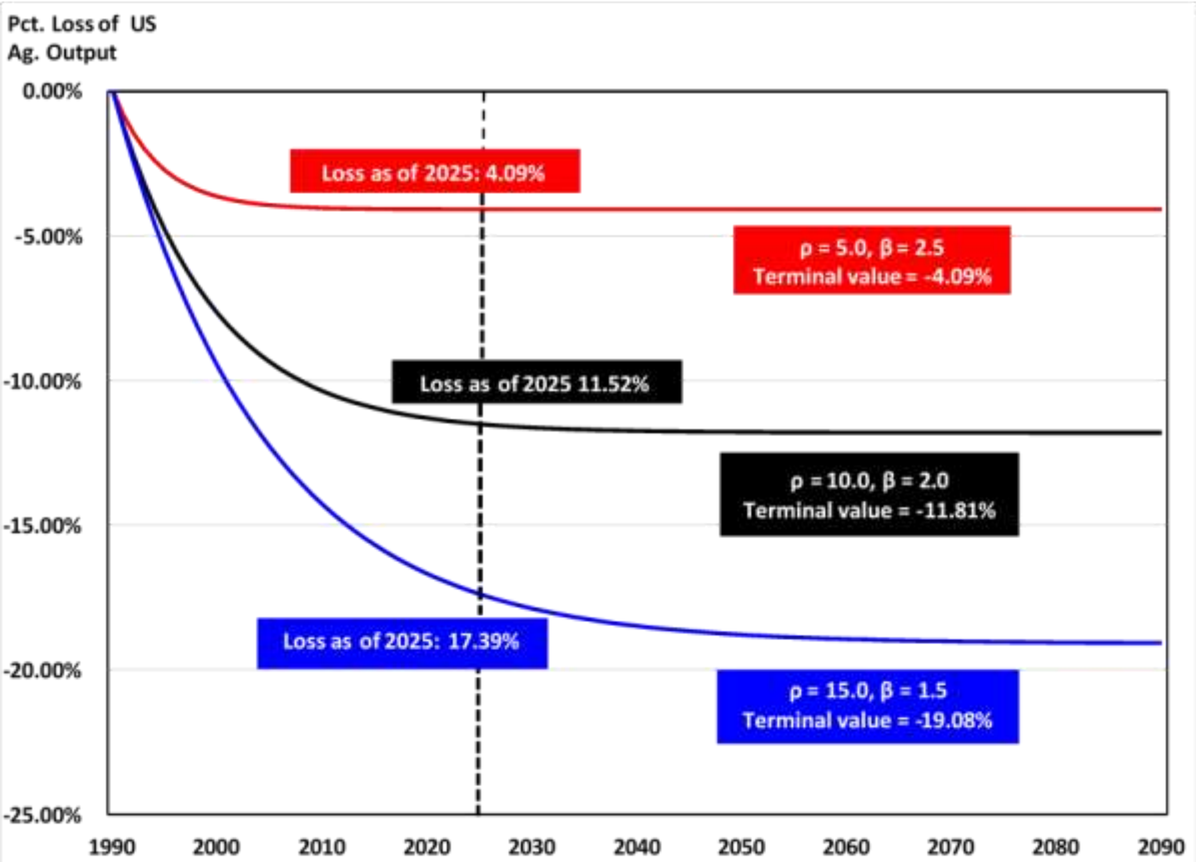
- ΔT denotes the change in the regional mean temperature (in degrees Celsius) between time t and $t-1$;
- α is a parameter, denoting the regional change in agricultural production for an annual
- warming of 0.04° C;
- β = 2.0 (1.5-2.5) is a parameter, equal for all regions, denoting the non-linearity of the reaction

- to temperature; β is an expert guess;
- ρ = 10 (5-15) is a parameter, equal for all regions, denoting the speed of adaptation; ρ is an
- expert guess.
- Tt denotes the overall change (in degree Celsius) in regional mean temperature relative to 1990;
- δ_r^1 and δ_r^2 are regional parameters that follow from the regional change (in per cent) in
- agricultural production for a warming of 2.5°C above today or 3.2°C above pre-industrial and
- the optimal temperature (in degree Celsius) for agriculture in each region; and
- γ_r are regional parameters.

Antoff and Tol (2019) provide the parameters and their standard deviations for each region.22 As discussed by Tol (2002), the parameters were estimated based on combining multiple analyses that all used computable general equilibrium models. In other words, the parameters are not based on empirical observation. Examining those parameters shows that most are not statistically different from zero. Furthermore, as they note β and ρ are guesses. As shown in equation (1), if the annual change in world temperature is 0.04° C, then the choice of β has no impact on the value of , $A_{t,r}^{r}$.

The model also assumes that changes in regional temperatures are all identical to the change in world temperature, even though there is no empirical evidence for this. The values of β and ρ have a noticeable impact on the calculated loss of agricultural output from imperfect adaptation. This is shown in Figure 2 using the parameters for the U.S. and assuming an annual temperature change of 0.03° C. As this figure shows, depending on the values selected for these two parameters, an annual change in temperature of 0.03° C results in between a cumulative loss of between 4.09% and 19.08% in U.S agricultural output.

Figure 2: Loss of U.S. Agricultural Output from Imperfect Adaptation (0.03° C Annual Temperature Change).



What is more curious is that, by 2025, all or most of the presumed output losses will have already taken place.23 Yet, the marginal factor productivity of U.S. agriculture has grown steadily since 1990, albeit at a slower rate than during the middle of the last century (Pardey and Alston, 2021).

Despite the observed increase in agricultural productivity, Ortiz-Bobea, et al. (2021) claim that climate change reduced agricultural output by 21% since 1961, equivalent to 7 years of productivity growth. But the loss of agricultural output is based on output models that cannot be verified. They also find that the largest impacts were in warmer regions such as Africa and Latin America.

More recently, Hultgren, et al. (2025) claim to have estimated agricultural impacts that account for the effects of adaptation by producers, even though they admit their approach does not identify the actual adaptation mechanisms. They then project future agricultural losses through the end of the century.24 Curiously, contrary to the findings of Ortiz-Bobea, et al. (2021), they determined that the worst impacts would be in more temperate regions.

Recently, McKitrick (2025) examined the Chalinor, et al. (2014) meta-analysis that is the basis for both the FUND and GIVE model impact estimates and rebuilt the dataset by including the data points that had been excluded. Incorporating these rebuilt data, he found that, contrary to the results of Chalinor, et al. (2014) and Moore, et al. (2017) that agricultural yields would either be unchanged or positive up to 5 ºC of warming.

Overall, the contrary results of various studies and the inability to measure adaptation reveal that future agricultural losses are far from certain. The models of agricultural productivity cannot adequately account for adaptation because adaptation cannot be observed directly. Moreover, claims of adverse impact of warming temperatures on agricultural productivity are clearly sensitive to the data used.

HEALTH-RELATED IMPACTS

Health-related impacts have generally focused on mortality impacts. For example, Carleton, et al. (2022) estimate a model that aggregates all forms of mortality using a function of temperatures and adaptation, represented by increases in GDP. They claim their model increases the health impact damages by an order of magnitude over previous estimates.

The FUND model uses a more granular approach to estimate health-related impacts. Specifically, FUND incorporates three categories of health impacts: (1) deaths (mortality) and illness (morbidity) from diarrheal diseases; (2) deaths and illness from vector-borne diseases (i.e., diseases spread by biting insects, specifically malaria, schistosomiasis, and dengue fever); and (3) death and illness from cardiovascular disease. Of these categories, 86% of the total impact has been attributed to diarrhea-related deaths, 12% to diarrhea-related illness, and 11% to malaria mortality (Cromar et al. 2021).25 Because the health-related impacts used in the GIVE model are also based on the results from Cromar, et al. (2021), which used the FUND model, here I focus solely on the FUND model's health impacts.

The additional number of deaths and illnesses from diarrheal diseases in region r in year t calculated in the FUND model is based on equation (4):

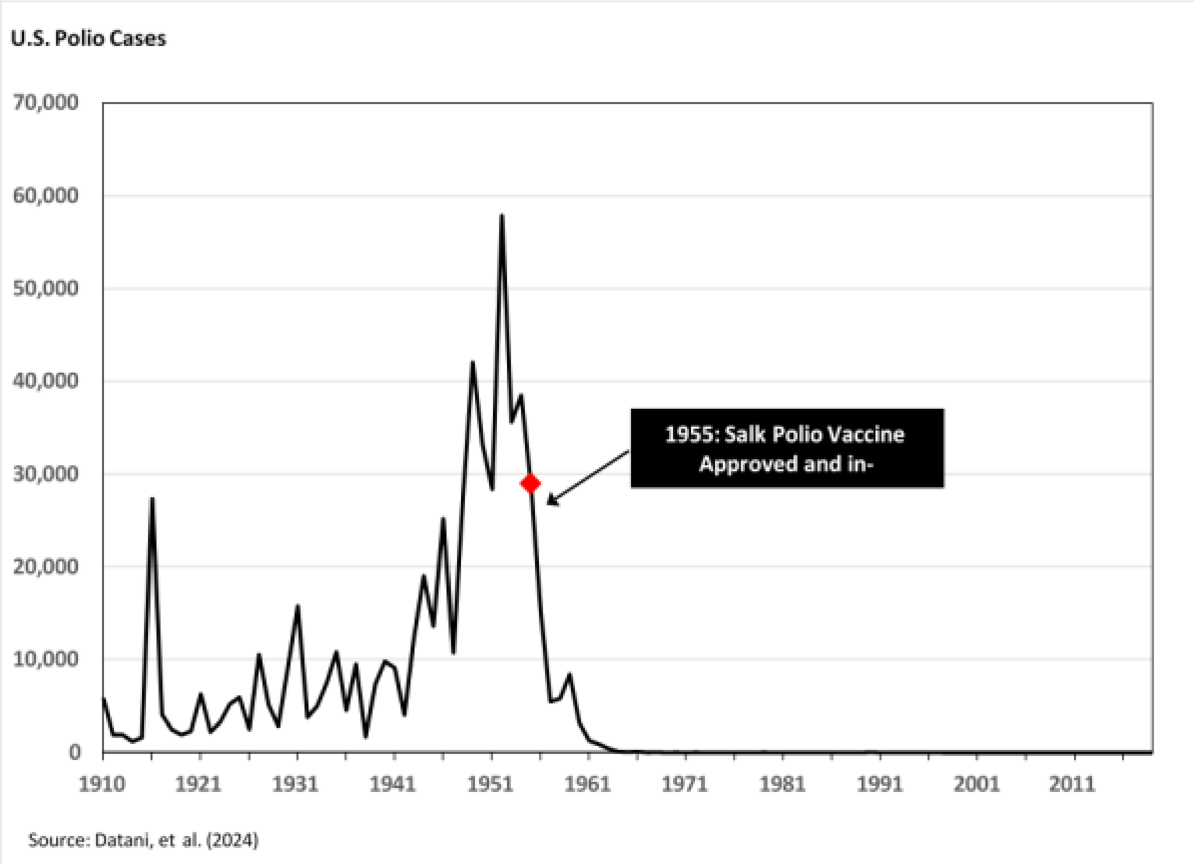
$$D^{k}_{r,t} = \mu^{d}_{r} P_{r,t} \left(\frac{y_{r,t}}{y_{r,1990}} \right)^{\varepsilon(k)} \left(\frac{T_{r,t}}{T_{r,PI}} \right)^{\eta(k)} \tag{4}$$

where

- $D^{k}_{r,t}$ = diarrheal-related deaths (k=1) and illness (k=2) in region r in year t;
- $P_{r,t}$ = the population in region r in year t;
- $y_{r,t}$ = real per capita income in region r in year t ($1995);
- $y_{r,1990}$ = real per capita income in region r in 1990 ($1995);
- $T_{r,t}$ = average temperature in region r in year t;
- $T_{r,PI}$ = average pre-industrial temperature in region *r*;
- μ^{d}_{r} =the mortality rate for diarrhea in the year 2000 in region r, based on data published by the World Health Organization;
- ε (*k*)= the income elasticity of diarrhea mortality (k=1: -1.58; k=2: -0.42); and
- $_k\eta$ = a parameter reflecting the non-linearity of response mortality to regional warming (k=1: 1.14; k=2: 0.70).

There are several problems with this specification, especially when considered over a 300-year time frame. First, reductions in deaths and illness are driven solely by changes in per capita income. There is no allowance for technological change, including the development of new vaccines and other new treatments. A good example of this is polio. As shown in Figure 3, prior to approval and production of the Salk polio vaccine in 1955, annual U.S. polio cases numbered in the thousands, peaking at just under 58,000 in 1952. In 1965, ten years after the vaccine was made available, total cases had fallen to 72. In the 30-year period, 1990 – 2019, the number of cases totaled 51, fewer than 2 each year on average.

Figure 3: Polio Cases in the United States, 1910 – 2019.



There already exist several vaccines against rotavirus, which is the leading cause of diarrhearelated deaths in young children. Moreover, as access to electricity increases in the poorest countries, basic sanitation, which is a root cause of diarrhea-related disease, will fall. Whereas the latter impact may be captured by changes in per-capita income, as the experience with polio has shown, vaccine development represents a structural change, the timing of which cannot be predicted with certainty. But it is unreasonable to assume, as the FUND and GIVE models do, that no such developments will take place over the next 300 years.

The formula used in the FUND model and by Cromar, et al. (2021) for vector-borne diseases is:[26]

$$D^v_{r,t} = D^v_{r,1990}\,\alpha^v (T_{r,t} - T_{1990})^{\beta} \left(\frac{y_{r,t}}{y_{r,1990}}\right)^{\gamma} \qquad (5)$$

Where

- $D^v_{r,t}$ – disease *v* deaths per million people in region *r* in year *t*;
- $D^v_{r,1990}$ – disease v deaths per million people in region r in 1990;
- α_v = an impact parameter, which does not vary by region, of the impact of climate change on the rate of vector-borne diseases for a one-degree global warming;[27]
- T_{1990} = the average world temperature in 1990; and

- $T_{r,t}$, $y_{r,t}$, $y_{r,1990}$ are defined as in equation (4).

As with the assumptions regarding deaths and illness from diarrheal diseases, equation (5) assumes that changes in income levels will be the sole factor in decreasing the incidence of these diseases, while changes in temperature will be the sole factor leading to increasing incidences.28 This ignores the likelihood of new health regimes to combat this disease, especially when evaluating time frames extending three centuries into the future.

5. ARE ALTERNATIVE APPROACHES BETTER THAN IAMS?

The problems with IAMs, including their reliance on parameters that are guesswork (Pindyck 2013, 2017), along with modeling issues and controversies over appropriate discount rates that should be used to estimate SCC values, has caused some researchers to instead emphasize avoidance of catastrophic climate impacts. For example, Pindyck (2019 uses this approach to estimate average SCC values instead of the marginal SCC values estimated by IAMs. Stern, et al., (2022) do not calculate SCC values at all. Instead, they emphasize a similar “guardrail” approach, which focuses on avoiding catastrophic impacts that may occur, based on the results of other climate models.

Pindyck (2019) conducted a survey of just over 6,800 economists and climate researchers. Of the 1,000 responses he received, he further narrowed the sample to exclude responses that were nonsensical or had misunderstood the survey questions. His goal was to estimate average SCC values based on the surveyed estimates of avoiding catastrophic outcomes. He asked the surveyed individuals to provide the reductions in GHGs needed to avoid catastrophic climate impacts, which he defined in terms of percentage reductions in world GDP over two different time horizons: 50 years and to the middle of the next century, about 125 years from now. Using the survey responses, he tested different probability distributions and then calculated the SCC values that would truncate those distributions to eliminate catastrophic outcomes, which he defined as a reduction in future GDP.

For example, Pindyck assumes a growth rate in real GDP of 2.0% per year. In 2023, the World Bank estimated world GDP to be $106 trillion. At a 2.0% real growth rate, 50 years from now world GDP would be $106 trillion x (1.02)50 = $275 trillion. Pindyck defines a catastrophic impact on world G as a reduction in that future GDP by 20% or more. Hence, using this definition, a catastrophic impact would mean a world GDP of about $220 trillion, still more than 100% greater than 2023 GDP. (Given forecast population growth of about 20% according to the United Nations, this means that GDP per capita would also increase.) He then calculates average SCC values as the present value reduction in future GDP divided by the present value reduction in GHGs, assuming that the cost of abatement remains constant in real dollar terms.29 The resulting SCC values averaged between $272 and $303 per metric ton, using a 3.0% discount rate. Using the probability distribution of GDP loss that best fit the responses, the overall average SCC value was $291. Pindyck then further trimmed the responses to examine values within the 5th and 95th percentiles for respondents who expressed either “low confidence” or “high confidence” in their responses. Based on that, he concluded the “right” SCC value was around $200/ metric ton for all respondents and about $80/metric ton for respondentsexpressing “high confidence” in their answers.

While Pindyck’s approach avoids the problems associated with IAMs (discussed in more detail below), it raises ther questions. First, it is not known how respondents developed the estimates they provided. Were the responsive estimates of probabilities of GDP losses based on the results of IAMs? Were they based on pure guesswork? Pindyck also disaggregated responses between those expressing “high confidence” in their answers and those who did not. But the mere fact that someone expresses high confidence in their answers does not mean those answers are any more likely to be correct than those who do not express high confidence.

Second, Pindyck’s selection of experts was based on publications in peer-reviewed journals.But if academic journals are more likely to reject contrary viewpoints that challenge conventional wisdom, then the experts sampled will be biased. Third, because even catastrophic losses still leave future generations significantly better off based on GDP per capita, a broader question remains: the equity of forcing the current generation to

endure welfare losses in order to enrich future generations even more. While that is more a philosophical issue than a purely economic one, debates over current policies, such as subsidies for electric vehicles that are primarily purchased by wealthier consumers, and which are paid for by lesswealthy ones raise the same issue. However, that issue, and the broader one of whether the current generation's welfare should be reduced to benefit future generations, and, if so, by how much, are rarely addressed.

Kaufman, et al. (2020) recommend an entirely different approach, called Near-term to Net Zero (NT2NZ). Rather than attempting to estimate an SCC directly using IAMs, they propose setting a date for achieving net-zero GHG emissions and then determining the required emissions tax to achieve this goal. They claim this avoids the inherent uncertainties in estimating SCC values using IAMs. Yet, NT2NZ uses another IAM to estimate the carbon taxes that will be needed, along with other, unspecified, policies to achieve net-zero by the specified time. It also ignores the arbitrary specification of a net-zero date, which may be based on assumed climate tipping points, risk aversion,and so forth, none of which can be observed.

Still more recently, Stern, et al. (2022) proposed an approach that incorporates aspects of NT2NZ with what they term a "guardrail approach." They focus on the potential for catastrophic risk owing to climate tipping points, based on limiting temperature increases below 1.5 ºC. Ultimately, however, they do not suggest any specific policies to be adopted.

Arguments for adopting NT2NZ and "guardrails" focus on assumed climate "tipping points" (Lenton, et al 2023) and climate catastrophes, however defined. These arguments lack any empirical basis and are instead based on modeling assumptions that cannot be verified. There is no evidence of climate "catastrophes" caused by increased GHG levels in earth's past, even though atmospheric CO2 concentrations have been far higher previously.

Weitzman's "Dismal Theorem" (Weitzman 2009, 2014) assumes that, under certain conditions, we would be willing to spend an infinite amount of money to avoid a catastrophic outcome lacks practicality. For example, there is geologic evidence of cataclysmic events in the earth's past, such as the asteroid impact that caused the Cretaceous–Paleogene extinction event about 66 million years ago, which led to the extinction of the dinosaurs and three-quarters of plant and animal species.

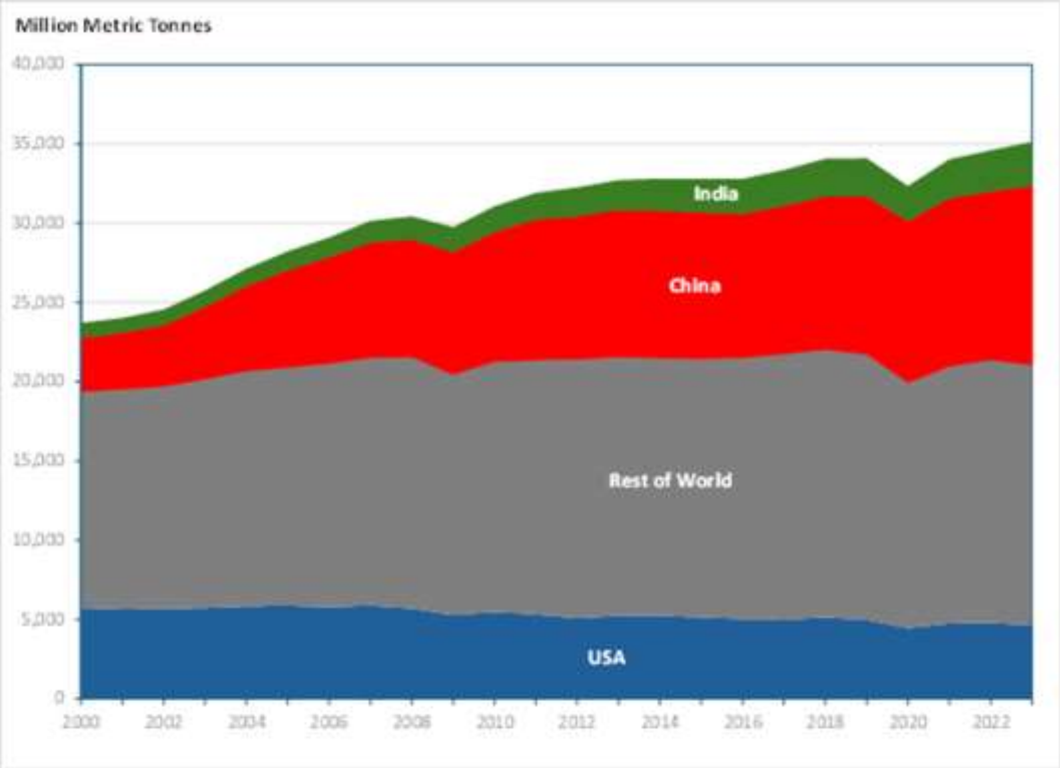
(Five other mass extinctions occurred before then, such as the Permian-Triassic extinction that took place about 252 million years ago and is believed to have been caused by volcanic activity.) That event clearly had a catastrophic impact on the climate. Such an event would fit well into Weitzman's theorem. Given limited resources, it is impossible to devote infinite resources to preventing a single potential catastrophe, much less several. And there is no guarantee that the adopted spending level would avoid the catastrophe.

6. CONCLUSIONS AND POLICY IMPLICATIONS

The only certainty about long-term predictions is that they will ultimately prove to be incorrect. Yet, IAMs now rely on forecasts that extend 300 years or more into the future. Just as an individual living 300 years ago could not forecast the technologies we take for granted today, it is unreasonable to assume that we can accurately forecast the future centuries from now. New technologies will undoubtedly emerge, some of which we may not even conceive of today.

Of course, it is impossible to devote infinite resources to address a single issue, much less multiple potential catastrophes (e.g., a civilization-ending asteroid strike or nuclear holocaust). Although we cannot completely rule out potential future catastrophes (of any sort), the reality is that society has limited resources and must make decisions about how best to allocate them. Hence, the question is whether SCC estimates should be used to drive energy policies and, if so, how. Answering that question requires confronting several economic and physical realities. First, global increases in GHG emissions are being driven by China and India (Figure 4). U.S. energy-related emissions fell by 20% between 2000 and 2023. (On an inflation-adjusted basis, U.S. energy-related emissions per dollar of GDP fell by 50% over this same time.) In 2023, U.S. emissions accounted for just 13% of world emissions. That percentage has been decreasing for decades.

Figure 4: Energy Related CO2 Emissions, 2000 – 2023



Source: Statistical Review of World Energy 2024; illustration by the author.

China's and India's focus, like the developing nations in Africa, is on economic development. China alone is permitting hundreds of new coal-fired power plants, which will emit billions of metric tons of GHGs. Policies enacted by the U.S. and Europe that increase domestic energy costs or force consumers to purchase more expensive electric vehicles, install electric heat pumps, and more expensive appliances will reduce U.S. economic growth and well-being; it will not change the developing world's focus on economic growth and improved well-being for their existing residents.

Using SCC estimates to justify these policies will not alter that fact. Nor will adopting arbitrary NT2NZ timelines or imposing specific emissions guardrails. Although the development and use of complex models to estimate the SCC is an interesting academic exercise, the resulting estimates are impractical for actual policy analysis. Moreover, the costs of these policies – such as the impact of higher energy prices on economic growth and consumer welfare – have been ignored.

Fossil fuels still account for over 80% of total world energy consumption despite the trillions of dollars spent on green energy resources such as wind and solar, and the world will continue to depend on fossil fuels for the foreseeable future. Although the development and use of complex models to estimate the SCC is an interesting

academic exercise, the resulting estimates are impractical for actual policy analysis. Rather than use arbitrary SCC estimates to justify green energy subsidies and mandates, a better focus for the U.S. would be to prioritize research and development of lower-cost, emissions-free, and nuclear power plants that use standardized designs. Doing so is likely to have a greater long-run impact on GHG emissions. Moreover, that technology can be transferred to developing nations to provide them with the reliable energy supplies they require for economic growth. Using SCC estimates to evaluate domestic energy policies will have no measurable impact on world climate. Hence, a more effective policy approach would be to prioritize access to ample supplies of clean, reliable, and affordable energy to enhance societal well-being today. Rather than justify highcost policies to reduce carbon emissions by incorporating benefits based on arbitrary estimates of the SCC, policymakers can focus on funding basic research on clean energy technologies that will be able to provide the increasing quantities of affordable and reliable energy that society requires and enable developing countries to meet their demand for improved welfare. This approach will ensure more low-carbon energy is available while eliminating costly regulations based on either flawed IAMs or arbitrary net-zero timelines.

7. BIBLOGRAHPY

1. I thank Iddo Wernick and Richard O. Zerbe for their comments and suggestions.
2. The approach used by Pindyck (2019) is discussed in Section 6.
3. This paper is not a debate about whether climate change is real.
4. In many cases, what the proposals promise are not true benefits, but rather wealth transfers.
5. For ease of exposition, I focus on CO2 emissions. Other greenhouse gases (GHGs) lead to estimates of CO2 equivalent (CO2-e) emissions, based on the estimates of radiative forcing of these other GHGs. For a discussion of radiative forcing values, see Hodenbrag et al., (2020).
6. EPA (2024), Tables 9-4 (fuel savings) and 9-10 (GHG reduction benefits).
7. See, e.g., Lind, et al. (1982), Toth (1995), Cropper, et al. (2014), Greaves (2017), Rennert, et al. (2022).
8. Weyant (2017) provides a survey of the different models.
9. A regulatory impact analysis is the term used by EPA to describe a benefit-cost analysis. The EPA has also used a meta-analysis, based on the work of Howard and Sterner (2017).
10. For a summary of some of the issues, see Weyant (2015).
11. See also (Bauer, et al., 2017). “Shared Socio-Economic Pathways of the Energy Sector – Quantifying the Narratives,”
12. See Jeremy Leggett, et al., 1922. “Emissions Scenarios for the IPCC: An Update,” in Climate Change 1992 -The Supplementary Report to the IPCC Scientific Assessment, Volume 1, J.T. Houghton, B.A. Callander, and S.K. Varney (eds.) (Cambridge: Cambridge University Press, 1992), pp. 71-95; see also Nebjosa Nakicenovic and Rob Swart, 2000. “Emissions Scenarios: IPCC Special Report,” (Cambridge: Cambridge University Press 2000) 13.
13. See the FUND model documentation under “Science,” Section 2. The model assumes population remains constant after that year and that per capita income grows at the same rate as assumed for the year 2300.
14. FUND 3.9 Documentation, Section 3.1. The calculation is known as the “Kaya identity,” named after Yoichi Kaya.
15. Antoff and Tol (2019).
16. Leggett, et al., 1992.
17. Lint Barrage and William Nordhaus, 2024. “Policies, projections, and the social cost of carbon: Results from the DICE-2023 model,” PNAS 121. https://doi.org/10.1073/pnas.2312030121
18. The DICE model has a regional counterpart, RICE.
19. Clouds have been acknowledged as one of the great uncertainties in climate modeling (Ceppi, et al. 2017).
20. For example, in the year 2100, the GIVE model results show an overall SCC of $663 per metric ton. Of that total, agricultural damages are $262 per metric ton, and health-related damages are $360 per metric ton. Additional energy consumption is $31 per metric ton and coastal impacts from sea level rise are just $4 per metric ton. The calculations can be found on the GIVE model website: https://www.rff.org/publications/data-tools/scc-explorer/
21. The supplementary information for Challinor, et al. (2017) does not report the results of their entire regression model. Instead, they report only four variables. One of those, a dummy variable for on-farm adaptation is never defined. In other words, from the article one does not know what “on-farm adaptation” even means, nor whether such adaptation is based on changes in temperature (the assumption in the model) or something else (e.g., changes in commodity prices, changes in fertilizer prices, crop rotation).
22. The parameters and their standard deviations are shown in Table A of their model documentation.
23. Equation (1) is a standard difference equation, which reaches a terminal value.

24. The losses they estimate are incorporated into DSCIM.
25. The FUND model also incorporates estimates of additional deaths associated with more intense tropical storms, although this clearly is a different form of health-related impact.
26. The equation in Antoff and Tol (2009) does not show temperature defined by region, but the narrative states it refers to regional temperature in year t. I have modified equation (5) to reflect this.
27. The malaria impact parameter reported by Antoff and Tol (2019) are not statistically different from zero. Interestingly, the impact factor for schistosomiasis is negative, meaning that, as temperatures increase, the rates of this disease fall.
28. Snow, et al. (2017) contend that temperature changes alone do not account for changes in malaria incidence rates in Africa, which accounts for the majority of malaria deaths.
29. Pindyck argues there are two countervailing factors. First, improved technology reduces abatement costs over time. But, second, the marginal cost of reducing additional emissions increases. Pindyck assumes these two factors balance out.

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COMPETING INTERESTS

The author declares he has no competing interests relevant to this paper.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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