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SUPPLEMENTARY INFORMATION

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Quantifying the economic risks of climate change

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Supplementary Information

1. Table 1 Extended Background

This section extends the description of the integrated assessment model (IAM) damage functions summarized in Table 1. We focus on DICE, PAGE, and FUND, the three IAMs used by the US Government Inter-Agency Working Group (IWG) to estimate the social cost of carbon (SCC) (IAWG, 2010, 2013).[1] Aggregate damage functions have long been used in climate-economic analyses to relate projected temperature change to social costs (e.g., Cline, 1992; Nordhaus, 1991, 1992), and the IWG damage functions are remarkably similar to the earliest efforts. The typical functional form of damages is an increasing power function of mean surface temperature change, often quadratic (Kopp, Golub, Keohane, & Onda, 2011; Warren, 2011). This simple, compact (if arbitrary) functional form suited the computational constraints of cost-benefit IAMs and the analytical models that preceded them (e.g., Nordhaus 1991). Damage functions tend to be calibrated to point estimates of damages corresponding to a benchmark warming level (e.g., 2 or 3 °C), either taking a bottom-up, additive sectoral approach as in RICE (Nordhaus & Boyer, 2000) or a top-down, aggregate form as in DICE-2013 (Nordhaus & Sztorc, 2013) based on the Tol (2009) meta-analysis. For certain impact categories there exist markets that can inform estimates (e.g., agriculture, forestry, coastal property and structures), while for intangible impacts (e.g., biodiversity, environmental quality, and human health) contingent valuation or hedonic methods are used.

The three IWG models differ substantially in terms of their structure, assumptions, and parameterization, as described in Rose, Diaz & Blanford (2017). DICE has two quadratic damage functions that are driven by global mean temperature and SLR respectively, while FUND and PAGE have functions that respond dynamically to a broader set of drivers such as population, per capita income, and technological change. Here we describe the key features of the IWG damage modules, followed by a more detailed discussion of two sectors, agriculture and coastal impacts.

DICE

The DICE model was developed in 1992 by William Nordhaus (Nordhaus, 1992). DICE is an inter-temporal optimization model of economic growth for the world as a single region, balancing the cost of mitigation with the damages from climate change. The IWG did not run the DICE model in its traditional form as an

[1] Although a 2017 executive order terminated the inter-agency working group establishing official US government SCC estimates, individual federal agencies must still consider the benefits of greenhouse gas emission reductions as part of rulemaking cost-benefit analysis.

optimization model to compute the SCC, but rather as a simulation model driven by the exogenous socioeconomic scenarios.

The latest SCC estimate used the 2010 version of the DICE model (re-coded in MATLAB and run in-house by IWG). The single region DICE-2010 model is calibrated to the 12-region RICE-2010 model in terms of socioeconomic, technology, and damage parameters. RICE-2010 consists of aggregate damage functions for each region, citing the Tol (2009) meta-analysis of IAM estimates and the IPCC (2007) synthesis of the impact literature as the calibration source (Nordhaus, 2010).[2] DICE has been updated twice since the 2010 version used by the IWG. DICE-2013R also cites the Tol (2009) survey as the starting point for damage calibration, and retains the adjustment factor of 1.25 for omitted or intangible impacts. DICE-2016 uses a quadratic damage function calibrated to a meta-analysis by Nordhaus and Moffat, and implies slightly lower damages of 2.1% GDP loss at 3 °C warming (Nordhaus, 2017).

DICE-2010 was the first and only vintage of the model to explicitly include a module for sea level rise (SLR) that computes the physical extent and economic impacts. SLR is decomposed into contributions from four major processes: thermal expansion, melt from glaciers and small ice caps, Greenland Ice Sheet melt, and Antarctic Ice Sheet melt, each parameterized in accordance with the IPCC Fourth Assessment Report (Nordhaus, 2010). Coastal impacts from SLR are removed from the aggregate damage function and reformulated as a function of SLR. The remaining of climate damages are classified as non-SLR damages.

Due to DICE's highly aggregate nature, many features are accounted for in an implicit manner. For example, the effect of adaptation is included implicitly to the extent that the damage function is calibrated to estimates that report the residual damage after accounting for adaptation.

FUND

FUND is based on version 3.8 of the FUND model. FUND was developed in 1993 by Richard Tol, and since 2006 has been co-developed with David Anthoff (Tol, 1995). It is the most disaggregated cost-benefit IAM, covering 14 distinct impact sectors and 16 regions. FUND considers damages for sea level rise, agriculture, forests, heating, cooling, water resources, tropical storms, extratropical storms, biodiversity, cardiovascular respiratory, vector borne diseases, morbidity, diarrhea, and migration, each with a specific damage functional form based on or calibrated to a published impact assessment, with regional parameters based on spatial patterns of warming, estimated impacts, or other regional assumptions and adjustments (Tol, 2002a). FUND projects a positive climate impacts in certain sectors (e.g., avoided energy expenditures for space heating, increased productivity in agriculture and forestry), implying net global benefits up to roughly 2.5°C of warming.

Many of FUND's damage functions are formulated with 'dynamic vulnerability', such that vulnerability or exposure to climate impacts changes dynamically over time depending on socioeconomic metrics like population growth, income growth, and technological change. Vulnerability is projected to decrease over the long-run in many impact sectors, e.g., energy consumption declines with energy efficiency, agriculture decreases as a share of overall GDP as economies develop, and exposure to vector-borne diseases will decline

[2] Nordhaus (2010) states 'The RICE-2010 model provides a revised set of damage estimates based on a recent review of the literature', citing Tol (2009) and IPCC (2007). Nordhaus (2014) offers a somewhat different calibration basis, stating 'the most recent versions of both DICE and RICE [referring to the 2010 vintage] used the impact estimates from the 2000 RICE model (Nordhaus and Boyer 2000)'. The damage assessment in Nordhaus and Boyer (2000) was disaggregated along both region and sector dimensions, covering agriculture, coastal resources, health effects, settlements, nonmarket time use, all other vulnerable market sectors, plus the certainty equivalent of a generic catastrophic impact, and finally multiplied the additive estimate by a factor of 1.25 to account for omitted or intangible impacts.

with improved health care. Dynamic vulnerability works in both directions, however, and other impact sectors may become more vulnerable over time. For example, water resource impacts will be amplified with population growth, exposure to heat-related disorders will increase with urbanization, and willingness to pay to avoid damages to ecosystems and mortality will increase with higher per capita incomes. The income elasticities are estimated from cross-sectional data or taken from the literature in accordance with Tol (2002b). Dynamic vulnerability is distinct from the concept of climate adaptation, which is a direct response to the expected change in climate. FUND models proactive adaptation in the coastal sector, weighing the cost of retreat against those of protection in order to avoid incurring the worst impacts of SLR in the no adaptation case. FUND does not explicitly include possible high-impact, uncertain consequences of climate change but extreme outcomes are included via the long tails of uncertain parameter distributions.

PAGE

The PAGE model was developed in 1991 by Chris Hope with several updates (e.g., Plambeck 1996, Hope 2006) prior to the current PAGE09 model used by the IWG for the current SCC estimate (Hope2011a). PAGE specifies four sectors for damages: sea level, economic, non-economic and discontinuity. The SLR damage function is calibrated to Anthoff et al. (2006) and the economic and non-economic damage functions are based on Warren (2006), such that all three have an aggregate impact before adaptation of just under 2% of GDP for a temperature rise of 3 °C.[3] The discontinuity impacts are calibrated to the Nordhaus (1994) expert survey and Ackerman et al. (2009).

The PAGE damage functions for each sector are calibrated for the EU and then adjusted for other regions based on a coastline length scaling factor and assumptions about adaptive capacity. PAGE includes two types of adaptation: 'plateau' increases the tolerable level of SLR or warming without suffering any damages, and 'impact' reduces the remaining damage by a fixed percentage. The adaptation policy and capacity is prescribed for each region at the outset of the PAGE model run and does not depend on the severity of climate change.

Agriculture spotlight

Of the three models used by the IWG, only FUND has a separate damage function for the agricultural sector. Agricultural damages in FUND are a linear sum of three types of impacts: the level of warming, the CO_2 fertilization effect, and the rate of warming (Anthoff & Tol, 2014b).[4] The sum of the three components give the percent of agricultural production impacted by climate change, applied to the gross agricultural product (assumed to decline over time with economic development) to determine overall damages in absolute terms.

The effect of level of warming is a quadratic, parameterized separately for each of the 16 regions in FUND. These quadratics all give positive impacts for moderate warming that become negative at higher levels of warming. Calibration is described in Tol (2002a) and is based on economic studies from the early 1990s: Kane (1992), Reilly (Reilly, Hohnmann, & Kane, 1994), Darwin (R Darwin, Tsiga, Lewandrowski, & Raneses, 1995), Fischer (Fischer, Frohberg, Parry, & Rosenzweig, 1996) and Tsigas (Tsigas, Frisvold, & Kuhn, 1996). These are all economic studies using computable general equilibrium (CGE) or agricultural market models combined with

[3] The aggregate impact is allocated such that 'half of impacts are sea level, one-quarter economic, and one quarter non-economic' according to a comment in the model Excel file. Note that Warren (2006) is a review of four IAMs (DICE, FUND, PAGE, and MERGE), so PAGE is calibrated to the consensus of IAM output, not the impacts literature.
[4] Ackerman and Munitz (2012, 2016) quantify the relative importance of these three parts of the agriculture damage function to the total SCC value.

GCM projections of climate change and an estimate of the yield impacts. The range over which the level of warming benefits agriculture ranges from 0.75 °C in South America to 5.75 °C in Canada (Anthoff & Tol, 2014b).

The CO_2 fertilization benefit is formulated in FUND as having a declining marginal effect using a natural logarithm. The effects of CO_2 fertilization are calibrated based on average difference in damages between studies that did and did not include CO_2 effects. Benefits estimated from this meta-analysis vary between regions. A doubling of atmospheric CO_2 concentration benefits agriculture by between 16% (Small Island States) and 2.8% (Canada).

The effect of adaptation, parameterized in the damage function based on the annual rate of climate change, is based on the average difference in impacts between studies that did and did not include adaptation. Damages from the rate of climate change are strictly negative and depend on the rate of temperature change in the current time period as well as damages in the previous time period. Consistent with the observation that there is relatively little known about the rate or effectiveness of private adaptation, the parameters in this damage function are documented as educated guesses (Anthoff & Tol, 2014b).

Coastal impact spotlight

The IWG models formulate coastal damage functions in terms of the level or rate of sea level rise (SLR), which requires the intermediate translation of temperature projections into a corresponding SLR pathway. Each of the models projects SLR in its own way using a component approach or equilibrium function, and notably produce very different SLR projections to drive the damage functions, with FUND projecting twice as much SLR as PAGE in 2050 and 2100.[5]

Coastal impacts from SLR in DICE are removed from the classic DICE aggregate damage function, and reformulated as a quadratic function of SLR, $D_{SLR} = 0.00518\, SLR_t + 0.00306\, {SLR_t}^2$ implying coastal damages are 0.8% of GDP at 1m of SLR, though there is no documented basis for the point estimates used for either the SLR or aggregate non-SLR damage function calibration or the rationale for the quadratic form.

Coastal impacts in FUND are computed at the regional level using a simple process model of adaptation that trades off the cost of retreat against those of protection following the adaptation cost/benefit rule derived in Fankhauser (1995) with cost functions calibrated to Hoozemans et al. (1993), Bijlsma et al. (1995), Leatherman and Nicholls (1995), Nicholls and Leatherman (1995), and Brander et al. (2006). Net damages after adaptation expenditures can be less than half the projected damages without adaptation (Anthoff, Nicholls, & Tol, 2010). This formulation assumes perfect foresight and efficient adaptation to sea level rise, neglecting market and other institutional barriers to adaptation, allowing sea wall protection to be flexibly built each year.

SLR impacts in PAGE are a power function of the height of SLR, $D_{SLR} = w\, {SLR_t}^p$. The uncertain exponent *p* has a mode of 0.7, based on the relationship between exposed land, people, and GDP versus SLR in Anthoff et al. (2006), which finds impacts rise less than linearly with SLR, reflecting the general coastal tendency for the density of land and people to decrease with elevation. The mode of the uncertain parameter *w* is calibrated to constitute half of the aggregate impact of 3°C reported in Warren et al. (2006), which is based on SLR impacts reported in Anthoff et al. (2006). Diaz (2014) notes it is difficult to reconcile this citation: the PAGE function implies that 0.5 m of SLR in 2100 would cause a 1% loss of world GDP (i.e., $2 trillion), while Anthoff et al. find $10-20 billion in damages for 0.5 m SLR for the entire 2080 decade ($1-2 billion per year), two orders of

[5] See Diaz (2014) for details on the SLR projection modules.

magnitude smaller than in PAGE. PAGE also accounts for exogenous coastal adaptation to avoid damages from SLR, with coastal adaptation costs based on Anthoff et al. (2006).

2. Figure 2 Methods

We evaluate the IAM damage functions as stand-alone damage modules following the approach presented in Rose et al. (2017). Specifically, the damage module algorithms from the original models used for the IWG exercise (DICE-IWG in MATLAB, FUND in C#, and PAGE in Microsoft Excel) are re-coded in a common language, R, to enable controlled experiments. Damage modules are run in a deterministic mode for FUND and PAGE, using the central parameter estimates rather than their probability distributions.

In order to compare the behavior of the three damage modules, we use standardized socio-economic projections of GDP and population for 2100 that correspond to the business-as-usual scenario in Rose et al. (2017). Because damages in the IAMs are additively separable, the total damage can be decomposed into individual contributions from each region and sector. In order to derive the implied damage functions with respect to temperature in that year, we linearly scale the temperature change pathway from 2000 to 2100.

We also compute damages using modified versions of the models to explore the importance of structural assumptions about dynamic vulnerability and adaptation. Specifically, we examine alternate vulnerability modes for all three IAMs. First, we implement a version of FUND with static vulnerability, fixing all income elasticities to zero.[6] Second, we introduce dynamic vulnerability into DICE and PAGE by applying an aggregate income elasticity equivalent to the implied total response in FUND, following the equations for dynamic vulnerability $\mathrm{D}_{t_{dynamic}} = f(\Delta \mathrm{T}) \cdot \left(\frac{\mathrm{ypc}_t}{\mathrm{ypc}_0}\right)^{\varepsilon}$ and static vulnerability $\mathrm{D}_{t_{static}} = f(\Delta \mathrm{T}) \cdot \left(\frac{\mathrm{ypc}_t}{\mathrm{ypc}_0}\right)^{0}$. Solving the equations for each other gives $\varepsilon = \frac{\ln\left(\frac{\mathrm{D}_{t_{dynamic}}}{\mathrm{D}_{t_{static}}}\right)}{\ln\left(\frac{\mathrm{ypc}_t}{\mathrm{ypc}_0}\right)}$, which is equal to -0.65 for the BAU scenario in FUND.

Adaptation is less of a binary toggle due to a mix of implicit and explicit representations included in each of the IAMs. In the PAGE model, we set the plateau and impact adaptation levels to zero. In the FUND model, we turn off the ability to construct protective sea walls, such that all regions must retreat in response to SLR inundation, and we do not allow any adaptation to the rate of temperature change in the agricultural sector. Note that coastal adaptation has little impact on the damage function shape because the physical driver of SLR accumulates over time and therefore damages are relatively insensitive to temperature change in a given year.

3. Table 2 Extended Background

This section extends the description of published critiques of current damage functions summarized in Table 2, and discusses related issues and implications for valuation of climate impacts.

[6] Note that dynamic vulnerability works in both directions. Some impact sectors may become more vulnerable over time (e.g., water resource impacts will be amplified with population growth, exposure to heat-related disorders will increase with urbanization, and willingness to pay to avoid damages to ecosystems and mortality will increase with higher per capita incomes), though vulnerability is projected to decrease over the long-run in many impact sectors (e.g., energy consumption declines with energy efficiency, agriculture decreases as a share of overall GDP as economies develop, and exposure to vector-borne diseases will decline with improved health care).

1. Extrapolation to high temperatures

Several authors point out that economic damages at higher levels of warming are largely unknown and that the extrapolation of damage functions beyond calibration points is essentially arbitrary (e.g., Ackerman, 2010; Dietz & Stern, 2014; Weitzman, 2012b). Most of this literature addresses the DICE damage function, which is calibrated to damages at 2.5 °C of warming but then extrapolated to higher temperatures using a quadratic functional form. However, the limited calibration basis for impacts at higher temperatures is not unique to DICE. PAGE is calibrated to damages at 3 °C of warming and the sector-specific studies underlying FUND damage functions are typically for warming of between 1 °C and 2.5 °C (Tol, 2002a).

Several authors reference the study by Sherwood and Huber (2010) showing that unabated warming will produce wet-bulb temperatures that make large areas uninhabitable as evidence that the quadratic extrapolation in DICE under-estimates damages at high temperatures (Fisher & Le, 2014; Revesz et al., 2014; Weitzman, 2012a). For example, DICE damages at 6 °C and 12 °C are equivalent to a loss of 8% and 26% of GDP respectively, yet Sherwood and Huber (2010) find that 12 °C of warming would render areas occupied by half the human population uninhabitable. Other studies point to non-linearities or catastrophes at higher temperatures that would increase the convexity of the damage-function such as the abandonment of low-lying areas and island states due to sea-level rise or the non-linear response of crop yields to warming (Fisher & Le, 2014; Hanemann, 2008). Nevertheless, very few impact analyses have been conducted at these higher temperatures.

Weitzman (Martin L Weitzman, 2012a) considers an alternative damage function that matches DICE damages in the calibration region between 0 and 2.5 °C but increases more rapidly with temperature, producing damages of 50% for a warming of 6 °C and 99% for 12°. He argues that damages at these temperatures are important because uncertainty over equilibrium climate sensitivity means the distribution over future temperature change is fat-tailed and that high-temperature damages will therefore dominate the cost-benefit analysis of climate policy (Weitzman, 2009).

The importance of these high-temperature extrapolations is largest when combined with other model structural assumptions. Since very high temperatures are not reached until the distant future, discounting means the damages therefore have little impact a measure like the SCC (Weitzman, 2012a). Ackerman and Stanton (2012) find the Weitzman damage function increases the SCC by approximately a factor of 4 when combined with a fixed 3% discount rate. It is also important when some damages fall on the growth rate rather than output (Dietz & Stern, 2015), or when combined with a fat-tailed temperature distribution to calculate expected utility, particularly with a very low pure rate of time preference and high risk aversion (Weitzman, 2012a).

2. Extrapolation to other regions

A further extrapolation critique of damage functions is that the underlying literature consists of impacts estimated for a specific region, which are then applied to other regions the world (Warren, 2011; Warren et al., 2006). van den Bergh and Botzen (2014) note that regional extrapolation is prevalent because damage cost estimates for developing countries are limited by data availability and quality, and caution that extrapolation may fail to account for their relative vulnerability.[7] Modelers often apply adjustment factors to extrapolate to developing regions (e.g., Nordhaus, 1991; Manne and Richels 1995), though this fails to fully account for geophysical and socioeconomic drivers of impacts.

[7] A distinct concept, regional equity weighting, is discussed later.

For example, PAGE defines damage functions for the EU reference region, which are then adjusted to the other regions with linear scale factors ranging from 0.4 to 0.8. Hope (2011a) explains the basis for this formulation as the fact that other regions are on average less vulnerable than the EU for the same sea level and temperature rise because of the long coastline of Europe.[8] Another example of extrapolation across regions is the FUND damage function for cardiovascular and respiratory mortality, as described in Anthoff & Tol (2014a): 'Martens (1997) assesses the increase in mortality for 17 countries. Tol (2002a) extrapolates these findings to all other countries' based on a linear function of extreme temperature.

3. Coverage of impact categories

The fact that damage functions have incomplete coverage of known impact sectors is widely acknowledged (IAWG, 2010; Marten et al., 2013; Neumann & Strzepek, 2014; Revesz et al., 2014; Tol, 2002, 2005, 2009; Warren, 2011; Watkiss & Downing, 2008; Watkiss, 2011). Some authors argue that for this reason SCC estimates should be viewed as a lower bound (Howard, 2014; van den Bergh & Botzen, 2014), however this claim must be considered alongside other known issues with SCC estimation that may cause different biases (e.g., Rose et al. 2017).

Of the IWG models, FUND has the most comprehensive and explicit bottom-up coverage, including climate impacts in 14 sectors: sea level rise, agriculture, forests, heating, cooling, water resources, tropical storms, extratropical storms, biodiversity, cardiovascular respiratory, vector borne diseases, morbidity, diarrhea, migration. Tol (2002a) notes that "the list of omitted impacts is long. It includes amenity, recreation, tourism, extreme weather, fisheries, construction, transport, energy supply, morbidity, and so on. The reason for omitting is that no comprehensive, quantified impact studies have been reported."

DICE accounts for common impact sectors indirectly through its RICE calibration; Nordhaus (2014) states further: "current studies generally omit several important factors (biodiversity, ocean acidification, and political reactions), extreme events (sea-level rise, changes in ocean circulation, and accelerated climate change), impacts that are inherently difficult to model (catastrophic events and very long-term warming), and uncertainty (of virtually all components from economic growth to damages)." An adjustment factor of 1.25 is applied to account for such omitted or intangible impacts. Finally, two of PAGE's four damage categories (economic and non-economic impacts) use a top-down aggregate function without specifying what is covered or omitted, though the underlying basis for calibration (i.e., Warren et al., 2006) includes both FUND and RICE damage estimates.

Impacts are typically omitted from IAM damage estimates because they are difficult to quantify and therefore lack the requisite underlying IAV and economics literature. Howard (2014) provides a detailed compilation of omitted damage categories that includes damages from acidification and warming in oceans, wildfire, large-scale migration, energy supply, labor and capital productivity, and geopolitical instability. Tol (2009) identifies saltwater intrusion to freshwater resources and tropical storm intensification as well. Neumann and Strzepek (2014) identify less-studied market sectors such as manufacturing, mining, tourism, recreation, finance, and insurance, and also note that many indirect or second-order effects (e.g., malnutrition or business interruptions) have yet to be accounted for, even in the sectors that have a deeper research base. Sussman et al. (2014) emphasize poor coverage of intangible impacts, such as the loss of cultural heritage, historical monuments, charismatic species, and disruptions to ways of life, which are thought to be socially compelling

[8] Diaz (2014) notes that this approach appears inconsistent with the fact that PAGE damage functions are calibrated to global studies of climate impacts, not European studies; it is also unclear why the same coastlength scaling factor applies to economic, non-economic, and discontinuity impacts, as well as the cost of adaptation in all four sectors.

but are challenging and controversial to quantify. Neumann and Strzepek (2014) identify omitted sectors that could potentially be included once the literature basis is more developed, noting that infrastructure, ecosystems, crime, labor, and factor productivity have a few impact estimates but may be incompletely addressed (e.g., ecosystems are largely a sample of convenience) or depend on a single thread of evidence (e.g., crime) or both (e.g., infrastructure).

Watkiss and Downing (2008) and Tol (2009) note that not all omitted impacts will be negative. Warmer temperatures in the Arctic and the corresponding loss of sea ice may afford new shipping routes and other commerce or resource opportunities. Additionally, certain negative effects of cold weather, such as winter storms and traffic disruptions, may be avoided at low levels of climate change, although these may be balanced out by increased occurrence of heat-related issues. Tourism is also expected to have heterogeneous effects, as tourist revenue is redistributed based on climatic shifts. van den Bergh and Botzen (2014) suggest that negative effects of climate change are thought to dominate omitted or unquantified positive effects, though this question illustrates large remaining research gaps in impact valuation.

4. Treatment of inter-sectoral and inter-regional interactions

Many researchers note that the IWG models fail to represent potentially important inter-sectoral and inter-regional interaction effects in their damage modules (Hitz & Smith, 2004; Howard, 2014; IAWG, 2010; Kopp & Mignone, 2012; Marten et al., 2013; Warren, 2011). Almost all damages in the three IWG model are additive in both regions and sectors, meaning there is no explicit mechanism for interactions of climate change impacts between sectors or regions. The exception is inter-regional migration in FUND that is driven by land inundation from sea level rise, with costs based on per capita income (Anthoff & Tol, 2014b). Furthermore, the underlying impacts literature basis for bottom-up damage estimates consists mostly of isolated studies of a given sector and/or region, so inter-sectoral and inter-regional interaction effects are also implicitly unaccounted for (Howard, 2014; Huber et al., 2014; Warren, 2011; Weyant, 2014). To the extent that such interactions could either exacerbate or alleviate the damage to society, the common practice of summing across sectors and regions will produce incomplete SCC estimates.[9]

Water in particular has been recognized for having critical inter-sectoral interactions (e.g., see Field et al. (2014) for discussion of the well-documented water-energy-land-agriculture nexus) that have not yet been fully captured in damage studies (Bell, Zhu, Xie, & Ringler, 2014; Warren, 2011). Water resources could affect other sectoral damage analyses through a variety of mechanisms: water availability constrains irrigated agriculture and is integral to electricity supply, affecting hydropower resources and cooling of thermal units, and conversely the water system requires energy to pump irrigation groundwater (Neumann & Strzepek, 2014). Weyant (2014) points out that finer scales of resolution (e.g., watershed or agro-ecological zone) are needed to capture these complex interactions to address questions about the magnitude and direction of economic impacts.

Warren (2011) describes the potential for climate change impacts in one region to affect another, through mechanisms which are both direct (e.g., inter-regional migration in response to desertification, drought, and flooding) and indirect (e.g., higher global food prices from declining agricultural yields in a given region). Tol (2009) notes that most impact studies estimate economic losses from direct costs, ignoring general or partial equilibrium effects. Exceptions include CGE modeling analyses, which can account for important indirect

[9] Another limitation of summing bottom-up damage estimates is the fact that impact studies produce estimates that are not comparable due to input assumptions that have not been standardized.

effects from changes in relative prices as well as inter-regional trade (see, e.g., Darwin and Tol (2001) for agriculture and Bosello et al. (2007) for sea level rise).

Related to the issue of inter-sectoral/regional interaction effects as well as omitted impact categories more broadly is the fact that climate impacts are often studied with a narrow scope of analysis, often focusing on the direct effects of climate change on economic assets or production. Oppenheimer (2013) emphasizes the importance of including human responses to climate change in assessing its net impacts, offering the examples of migration, globalization, biofuel production, and changing social vulnerability as influential factors. Calvin et al. (Calvin et al., 2013) note that the three-way interaction among impacts, adaptation, and mitigation is rarely accounted for in IAMs. Finally, many researchers point out the extreme case of interacting elements: a cascade scenario where impacts of one type trigger a response of another, and this continues to propagate across regions and sectors leading to a far-amplified impact (Huber et al., 2014; The World Bank, 2012). Sussman et al. (2014) warn that interdependencies between climatic, ecological, and human systems may lead to such cascading effects.

5. Representation of adaptation and technological change

Representation of adaptation in all three models is highly aggregated and abstract. There are, however, important differences the role adaptation plays in determining damages in each of the models. DICE has no explicit representation of adaptation. Instead, the effect of adaptation is implicitly included to the extent that the aggregate damage function is calibrated to studies that report damages net of adaptation.[10]

FUND includes adaptation as part of the damage functions rather than a policy variable, but explicitly represents adaptation costs in the agriculture and coastal sectors (Anthoff & Tol, 2014b). In addition, FUND damage functions have a unique feature termed 'dynamic vulnerability', which captures the fact that vulnerability or exposure to climate impacts will change dynamically over time depending on socioeconomic metrics like population growth, income growth, and technological change (Tol, 2002b). Although this effect mediates the adverse impacts of changing temperatures in some sectors like health and agriculture, dynamic vulnerability is distinct from the concept of climate adaptation, which is a direct response or investment to reduce climate change impacts.

PAGE includes two types of adaptation, which are classified as plateau and impact (Hope, 2011a). The plateau adaptation increases the adapted tolerable level (e.g., amount of SLR or warming) that a region can tolerate without suffering any damages. The impact adaptation reduces the remaining impact beyond the plateau level by a fixed percentage up to a maximum threshold over the plateau beyond which impacts cannot be reduced for a given region. Net damages are given as the sum of the residual damages plus the cost of adaptation.[11]

Several authors warn that the IAM damage functions that implicitly include private adaptation (for example DICE and some FUND sectors) assume a smooth, instantaneous transition to equilibrium in a new climate state and therefore ignore transition costs that may be substantial (Farmer et al., 2015; Tol, 2009). Firms have to identify a climate signal amidst natural weather variability which may cause costly delays in adaptation (Kelly, Kolstad, & Mitchell, 2005; Schneider, Easterling, & Mearns, 2000). Other barriers or market failures may limit

[10] The argument for this approach is that since much of adaptation is a private good undertaken at the local level, adaptation will not necessarily require policy intervention but will instead largely be supplied in the private market.

[11] Diaz (2014) notes several shortcomings of this formulation of adaptation: 1) The prescribed adaptation policy is set exogenously at the outset of the PAGE model run and does not depend on the severity of climate change. 2) There is an implicit assumption that the cost of undertaking adaptation plus the residual damage is less than the unadapted damage to society, which may not necessarily be the case. 3) Adaptation expenditures could be suboptimal.

the rate of adaptation. Empirical quantification of the rate of adaptation and associated adjustment costs is extremely limited, though Hornbeck (2012) finds agricultural adjustment to productivity shocks from the US Dust Bowl took decades. Neumann and Strzepek (2014) point out that the large current 'adaptation deficit' calls into question the potential for cost-effective adaptation in the future, noting that assumptions about adaptation learning capacity and pace may be unrealistic. In general, understanding of both the rate and effectiveness of future private adaptation is extremely limited. Both empirical and process-based modeling work is beginning to address this (see Section 2).

A small group of studies has undertaken to modify existing IAMs to explicitly represent adaptation as a public decision variable by incorporating adaptation as a policy variable into DICE (de Bruin, Dellink, & Tol, 2009; Felgenhauer & Webster, 2013), RICE (de Bruin, Dellink, & Agrawala, 2009) and WITCH (Bosello, Carraro, & De Cian, 2010). In doing so, the authors parameterize adaptation cost functions or residual damage functions using information from the impacts literature. Consistent with the observation above that understanding of private adaptation is limited, several authors note the lack of data on the aggregated costs and benefits of adaptation actions required to calibrate these models.

Representation of Technological Change

While IAMs commonly represent technological change with respect to mitigation efforts, it is much less typical in damage modules (IAWG, 2010). One common approach to representing technological change is through 'learning-by-doing', the process by which accumulated experience brings about incremental improvements to production methods, allowing firms to lower costs (Arrow, 1962). This relationship can be compactly represented in a learning curve equation (Nemet, 2006). Another approach uses a heuristic to account for the energy-saving bias of technical change. The autonomous energy efficiency improvement (AEEI) parameter describes how energy intensity, energy use per unit output across the economy, decreases over time in an autonomous way, regardless of energy prices.

FUND uses the AEEI parameter to account for technological change in energy demand, which affects both the cooling demand and heating demand impact sectors. FUND uses exogenous projections for AEEI at the regional level (Anthoff & Tol, 2014a). The global average value is about 1% per year in 1990, converging to 0.2% in 2200. Tol (Tol, 1997) notes that the AEEI parameter, in conjunction with a separate parameter for carbon intensity, is roughly calibrated to match the AEEI implied by the EMF14 standardized scenario.

PAGE includes technological change in adaptation costs in a similar manner. Adaptive costs are specified as a percentage of GDP per unit of adaptation bought and benefit from autonomous technical change, such that the costs come down over time (Hope, 2011a).

6. Out of date science

Rose et al. (2017) highlight the fact that the models draw either directly or indirectly on older climate impacts literature, much dating back to the 1990s. Thus, these damage estimates fail to reflect the more recent scholarship from the impacts, adaptation, and vulnerability (IAV) community. Because many underlying impact studies are dated and because model documentation of the empirical basis for damage functions is sometimes missing, understanding exactly how damage functions were derived is often difficult.

In some cases, there is a circular basis for damage functions being calibrated to IPCC or related summary studies based on IAM results (Pindyck, 2013). Rose et al. (2017) traces the underlying studies and independence of different models, noting that damages in both PAGE09 and DICE2010 are calibrated to meta-analyses that include outputs from other IAMs, Warren (2006) and Tol (2009) respectively. These interlinkages suggest that the damage estimates produced by these three models are not independent, which has implications for the IWG experimental design, as it therefore may not be appropriate to average their results with equal weights. Questions of how to aggregate models that are not fully independent into an ensemble average have been explored within the climate science literature because similar questions arise with General Circulation Models (GCMs), many of which share common lineages and parameterizations (Tebaldi & Knutti, 2007). Although not fully resolved in the literature, several papers provide guidance on diagnosing and accounting for non-independence in multi-model ensembles (Bishop & Abramowitz, 2013; IPCC, 2010; Knutti, Furrer, Tebaldi, Cermak, & Meehl, 2010).

7. Representation of uncertainty

Damage functions have been widely criticized for failing to account for uncertainty in a number of domains (Howard, 2014; Kopp, Golub, Keohane, & Onda, 2012; Watkiss, 2011; M L Weitzman, 2009). Uncertainty can be characterized as parametric (epistemic), due to imperfect knowledge, or stochastic (aleatory), due to natural variability and inherent randomness (Kann & Weyant, 2000). Here we will describe the representation of parametric uncertainty and stochastic variability and extreme events, while uncertain climate thresholds will be discussed the next section.

Parametric uncertainty

IAMs typically deal with parametric uncertainty using sensitivity, scenario, or probabilistic propagation techniques like Monte Carlo simulation (e.g., Nordhaus 2014, Hope 2011, Anthoff and Tol 2013), yet these return a collection of possible outcomes, each corresponding to different conditions, without identifying a single result that accounts for risk, in contrast to stochastic optimization (Kann and Weyant, 2000).

The IWG experimental design accounts for parametric uncertainty in three areas (socioeconomics, climate sensitivity, and the discount rate) with inputs standardized across all models. While DICE considers no additional parametric uncertainty, FUND and PAGE explicitly capture broader parametric uncertainty because the models are run in their native probabilistic mode (IAWG, 2013). FUND and PAGE specify independent probability density functions for nearly 500 and 35 uncertainty parameters, respectively, in their damage modules, representing uncertainty around the rate of SLR as a function of temperature or the exponent on the damage function (Anthoff & Tol, 2014a; Hope, 2011a). FUND mostly uses distributions which have tails (e.g., normal, lognormal) as opposed to the truncated triangular distributions in PAGE, though the specific uncertain parameters and specifications are not readily comparable due to model structure (Rose et al., 2017). These distribution choices imply different degrees of understanding about the uncertain parameters, though their basis is not well-documented or justified by the modelers.

Stochastic variability and extreme events

Neumann and Strzepek (2014) note that impact studies typically assess gradual, mean changes in temperature and precipitation rather than fully capturing the effects of climate extremes or variability (e.g., storm surge extremes and wildfire events). For example, agricultural impacts will be driven by conditions of shorter duration related to temperature (degree days over some biophysical limit, heat wave) or precipitation (damage from intense rain, drought) not simply the annual mean temperature change. The importance of accounting for impacts due to shifts in the frequency of extreme events or increased climate variability, not just slow incremental trends in the mean of a climate variable has long been recognized (Smith & Tirpak, 1989).

Because IAM damage functions are typically formulated in terms of global or regional mean temperature, none of the IWG models explicitly account for this type of stochastic variability in climate outcomes. The effect of stochastic variability and extreme events could be included implicitly if for example the underlying studies used for calibration capture this variability, though this is generally not the case for the IWG models. For example, the coastal impact studies underlying the SLR damage functions are based on assessments of impacts due to changes in global mean sea level alone, without accounting for the additive element of variability in sea level and consequent flood risk. More recent coastal damage assessments do account for these extreme surge events (Diaz, 2016; Hinkel et al., 2014), though Diaz notes a priority for future work is to address nonstationarity in the distribution of such extremes, e.g., incorporating projections by Grinsted et al. (2013) and Buchanan et al. (2015).

8. Formulation of system dynamics and thresholds

Many researchers point out that the IWG damage functions fail to capture the risk of uncertain climate system dynamics in an explicit or credible manner (Deschenes, 2014; Hitz & Smith, 2004; Howard, 2014; IAWG, 2010; Li, Mullan, & Helgeson, 2014; Revesz et al., 2014; Sussman et al., 2014; Warren et al., 2006). Various terms are used to describe these non-marginal system dynamics, including nonlinearities, discontinuities, tipping points, tipping elements, thresholds, regime shifts, surprises, and catastrophic events, and this muddled terminology complicates discussions of already-complex concepts. Kopp et al. (2016) review the inconsistent language around ‘tipping points’ and ‘tipping elements’, and discuss the temporal dimension (e.g., abrupt or not, lag between commitment and realization), potential characteristics (e.g., hysteresis, irreversibility), and magnitude of economic shock for such events.

Known physical system thresholds include ocean thermohaline circulation disruption, methane release from the oceans or permafrost, disintegration of the polar ice sheets, albedo changes (with positive feedback), and forest die-back (Alley, 2003; Lenton et al., 2008; National Research Council, 2013). These events are non-marginal in that gradual changes in the physical climate may drive other systems over a threshold into a new equilibrium state and have the potential for one or more concerning characteristics that include being abrupt, irreversible, or exhibiting hysteresis (Sussman et al., 2014). The existence of these threats is supported by the geologic record (Alley, 2003), but the governing dynamics and thresholds are still not fully understood or quantified due to insufficient data and process models limitations. Kriegler et al. (2009) conduct an imprecise probability assessments for five tipping elements using expert elicitation. While the triggering variable, probability distribution, and consequence of such threshold responses have not yet been credibly incorporated into IAMs for reasons discussed in Diaz and Keller (2016), they are thought to drive up the SCC (Howard, 2014; van den Bergh & Botzen, 2014).

PAGE explicitly models a type of ‘discontinuity’ impact that covers a number of potential large-scale climate thresholds, which are never satisfactorily defined, as noted in Diaz (2014): Hope (2011a) only cites the Greenland ice sheet disintegration while Hope (2011b) also includes monsoon disruption and thermohaline circulation. van den Bergh and Botzen (2014) similarly comment that PAGE catastrophic outcomes reflect subjective judgements and abstract scenarios rather than well-characterized climate catastrophes. The discontinuity impact is modeled as the expected value of an uncertain event, multiplying the probability (which increases linearly with temperature above a threshold of 3C) by the consequence (mode of 15% GDP loss).

Neither DICE nor FUND attempts to directly include a climate threshold within the damage module, although DICE’s SLR module decomposes the SLR projection into components and the Antarctic Ice Sheet is assumed to have an initial discharge threshold at 3 °C, with a rate that increases linearly with temperature until a maximum rate of 2.5mm/yr is reached at 6 °C (Nordhaus, 2010). To the extent that climate threshold events are conflated with catastrophic damages, these are somewhat accounted for in the IAMs, though Kopp et al. (2016) notes a lack of clarity about what constitutes a catastrophe and recommends the term climate-economic shock instead. The bottom-up basis for the DICE aggregate damage function includes the certainty equivalent damage from a catastrophic impact, formulated such that the likelihood is 1.2% at 2.5 °C and 6.8% at 6 °C and the consequence is a loss of GDP between 22 and 44% (varies by region). These catastrophe assumptions are based on Nordhaus's own 'pessimistic' interpretation of the Nordhaus (1994) expert elicitation of the overall economic impacts of 6 °C warming, (i.e., a doubled likelihood of survey results to reflect heightened climate concerns).

FUND does not explicitly include high-impact, uncertain consequences of climate change but accounts for the possibility of extreme outcomes via the long tails of uncertain parameter distributions. However, it is worth noting that these are abstract outcomes rather than explicitly modeled feedbacks and system dynamics.

At a more fundamental level, IAM damage functions are implicitly assumed to have symmetric system dynamics in that the function behaves the same for increasing temperature as it does for decreasing temperature. Although the coupled earth and human system is complex to fully understand and model, species extinction and ice sheet loss are known cases of hysteresis or irreversibilities that cannot be 'undone' as temperatures are stabilized and then reduced from a peak level.

Several studies have integrated uncertain climate thresholds into IAMs with global stochastic optimization, beginning with Keller et al. (2004) and including more recent work that uses endogenous hazard rates linking the probability of climate catastrophes to warming (Cai, Judd, Lenton, Lontzek, & Narita, 2015; Diaz & Keller, 2016; Lemoine & Traeger, 2014; Shayegh & Thomas, 2014). Diaz (2015) and Kopp et al. (2016) note that moving beyond an abstract or stylized representation of hazard towards one that accounts for each known threat with distinct characteristics will improve the credibility of this approach. Cai Lenton & Lontzek (2016) improve upon these studies in many dimensions, using Kriegler et al.'s (2009) expert elicitation to calibrate likelihoods and the causal interactions between them, account for transition times and carbon cycle effects (e.g., ice sheet collapse could release coastal permafrost), and adjust social planner's preferences regarding risk aversion and intergenerational equity) and find that the SCC increases substantially. These particular modeling studies use stochastic and dynamic programming to solve for optimal emissions pathways and so are not directly applicable to the IWG effort, although elements of the threshold design could be implemented in a simulation approach (Diaz, 2015).

Heal and Millner (2014) warn that IAMs are not designed to treat Knightian Uncertainty (Knight 1921), which differentiates 'uncertainty' (unknown probabilities) from 'risk' (known probabilities), limiting the usefulness of damage functions and SCC estimates. Many authors point out that there are likely many climate impacts that fall into this category of 'black swans' or 'unknown unknowns' (e.g., Weitzman 2009). Furthermore, a number of conceptual challenges confront estimation of catastrophic risks, including time consistent preferences, risk aversion, and social versus private discounting.

9. Damages to growth rate, rather than level of output

Damage functions in all three models are formulated such that losses fall out the level of output, reducing production in the year that damages occur but with no persistent impacts in subsequent years. Recent literature has explored this structural assumption, introducing a number of alternative damage pathways that instead affect the growth rate of output, therefore causing persistent effects.

In the IWG implementation, the underlying factors driving growth in consumption are specified exogenously and are not directly affected by temperature. Specifically, both population and per-capita income are specified exogenously in FUND, GDP growth is given exogenously in PAGE, and growth in labor and total factor productivity (TFP) are given exogenously in DICE (Anthoff & Tol, 2014; Hope, 2006; Nordhaus & Sztorc, 2013). In the standard intertemporal optimization version of DICE, capital is determined endogenously based on the optimal savings rate so damages to output do lead to an indirect reduction in capital formation, but the IWG simulation mode did not include this endogenous feedback.

The assumption that economic growth will continue largely unaffected by climate change has been criticized in a number of recent publications (Pindyck, 2013; Revesz et al., 2014; Stern, 2013). The question is important because impacts to the growth rate have the potential to greatly increase climate damages compared to a world in which climate change only affects output. Damages to the growth rate have a permanent effect of the size of the economy whereas damages to output are transitory. This means that, if the climate permanently changes, impacts to the growth rate accumulate over time so that even small growth-rate effects will eventually dominate impacts to output (Dell, Jones, & Olken, 2012).

Moyer et al. (2014) and Dietz and Stern (Simon Dietz & Stern, 2015) both demonstrate the sensitivity of DICE output to assumptions about whether climate damages affect growth rates. Moyer et al. (2014) look at the SCC under BAU emissions when damages are allowed to affect TFP and show large sensitivity. This is driven both by higher damages but also by a lower discount rate if the standard DICE discount rate based on the Ramsey formula is used ($r = \rho + \eta g$). Because damages to TFP slow or reverse economic growth, discount rates are smaller or even negative. If instead the IWG fixed discount rate approach is used, effects on the SCC are smaller, though still large (increase by up to a factor of 10). Dietz and Stern (Simon Dietz & Stern, 2015) allow temperature to affect either TFP or the capital stock and solve for the optimal temperature trajectory, which increases the SCC by a factor of 2-3. Both papers present modified versions of the Romer growth model in which temperatures affect growth by affecting the productivity of the R&D sector and therefore the growth in TFP (Dietz & Stern, 2015; Moyer et al., 2014), the depreciation rate of capital (Dietz & Stern, 2015), and the 'knowledge-spillovers' that connect investment in capital to TFP growth (Dietz & Stern, 2015). Both papers conclude that impacts of climate change on economic growth have major implications for the SCC and the optimal mitigation pathway in DICE.

Rather than quantify impacts from the bottom-up on a sector-by-sector basis, an alternative approach is to look at temperature impacts on GDP as a whole. Although this misses important non-market impacts such as health or ecosystem services, it should capture all climate change impacts on market sectors without the need for individual sector-by-sector analysis. However, even more than with sectoral empirical results, the mechanisms through which these impacts arise are black-boxed. In addition, GDP is a measure of economic activity so the connection between changes in GDP and changes in welfare, even welfare derived from market goods, is unclear. Although much of this literature has appeared only very recently, there are some important emerging findings.

Firstly, this literature has found that the economy as a whole tends to be sensitive to temperature fluctuations, particularly in poorer countries, with the effect only partially explained by the agricultural sector (Heal & Park, 2013). Hsiang (2010) finds large effects of hot temperature shocks on economic output in Central America and the Caribbean for all economic sectors except mining and utilities. Jones and Olken (2010) find that hot temperature shocks negatively affect the growth in exports from poor countries in both agricultural and manufacturing sectors. Deryugina and Hsiang (2014) find substantial effects of hot days on annual income in the United States, including non-farm income. The mechanism driving temperature impacts in sectors not typically considered sensitive to temperature is unclear but may include effects on labor productivity or labor supply.

A second major question addressed in this literature is whether temperature shocks permanently affect the economy by affecting growth rates, which could have large implications for the SCC. Dell, Jones and Olken (2012), Lemoine and Kapnick (2016), and Burke, Hsiang and Miguel (Burke, Hsiang, & Miguel, 2015) all examine the reduced-form relationship between temperature shocks and economic growth. In general these studies find evidence that temperatures negatively affect growth in poor countries, though they differ in some important respects. Both Dell, Jones and Olken (2012) and Lemoine and Kapnick (2016) find strong interactions between temperature impacts and per-capita income, suggesting impacts are driven by poor economies being more sensitive to temperature fluctuations. Burke, Hsiang and Miguel (Burke et al., 2015) instead show evidence for a quadratic relationship between temperature and growth-rates, arguing that large impacts in poor countries arise because they are hotter than rich countries, not because they are poorer. The studies also differ in the extent to which they can confidently distinguish temporary effects of temperature on output from permanent impacts to the growth-rate. Dell, Jones and Olken (2012) use a distributed lag model to argue that warming impacts in poor countries affect the growth-rate. However, the same lag models in Burke, Hsiang and Miguel (Burke et al., 2015) have large confidence intervals that overlap zero, meaning the proportion of temperature impacts falling on growth-rates as opposed to output is unclear. Lemoine and Kapnick (2016) instead use long-differences estimation to argue that temperature changes have persistent effects on growth-rates over decadal timescales. While suggestive, there are still large uncertainties regarding whether growth-rate impacts exist, whether their magnitude depends on temperature or per-capita income, and what mechanisms are driving these effects.[12]

Two papers have incorporated the some of the new empirical literature into DICE-2013R in order to examine the implications for optimal climate policy and the SCC. Moore and Diaz (2015) create a two-region version of DICE in which temperature affects growth rates by affecting either TFP or the depreciation rate of capital, calibrating the damage functions to reproduce Dell, Jones and Olken (2012). Even with optimistic adaptation assumptions, they find the SCC along the optimal emissions pathway to be six times higher than using the standard DICE damage function. In supplementary analysis Lemoine and Kapnick (2016) incorporate their long-differences estimate of growth-rate impacts into DICE, finding they do not tend to increase the SCC relative to the standard damage function, and in some cases decreases it significantly. In both papers, the question of how temperature impacts change with per-capita income as poor regions develop is a critical one and something still unresolved in the literature.

10. Assumption of perfect substitutability of environmental services

All three IAMs assume that temperature damages only affect utility through their effect on consumption of goods. Both Weitzman (2009) and Sterner and Persson (Sterner & Persson, 2008) point out that this implies the types of damages caused by climate change can be substituted on a one-for-one basis with increased consumption. This may be appropriate if the primary impact of climate change is on consumption of material goods, but is inappropriate if damages fall on goods that are imperfectly substitutable with higher consumption such as biodiversity or health. This perfect substitutability, combined with exogenously specified

[12] In addition to evidence for temperature shocks on economic growth, Hsiang and Jina (2014) use a distributed lag model to show cyclone strikes negatively affect economic growth, not just output. Even accounting for the fact that climate change will decrease cyclone risk in some areas, these growth impacts imply very large negative impacts of climate change.

growth, almost ensures that absolute welfare will increase over time, despite climate change damages. If instead material goods are imperfectly substitutable with the environmental services affected by climate change, the relative price of impacted sectors will rise with climate change, causing larger impacts than under perfect substitutability.

Sterner and Persson (Sterner & Persson, 2008) investigate the importance of this effect by altering the DICE utility function to include the effects of non-market damages that are only imperfectly substitutable with market goods using a CES utility function. They find that if climate damages are imperfectly substitutable with consumption of material goods, then the optimal emissions pathway in DICE is similar to that implied by the very low pure rate of time preference used in the Stern Review (Stern, 2006; Sterner & Persson, 2008). Results are sensitive to parameters that may be difficult to estimate, however, such as the degree of substitutability between material goods and environmental services, and the fraction of utility today derived from environmental services. The authors also point out that though there may be a range of substitutability between environmental and material goods, calculations will be dominated by goods with lowest substitutability as these will have the largest relative price increase and come to dominate welfare calculations.

Weitzman (2009) points out that the question of how substitutable material goods are with climate damages is empirically difficult to determine but has a very large impact on IAM results, particularly when combined with high temperatures (resulting from fat-tailed probability distributions) and low discount rates (resulting from uncertainty in the discount rate). In a later paper (Weitzman, 2012b) he shows how both the multiplicative damages currently used in IAMs, the CES damages used by Sterner and Persson (Sterner & Persson, 2008), and a utility function in which temperature enters additively are members of a general class that can be derived from two axioms: constant relative risk aversion and an analogous constant temperature risk aversion. Giving a numerical example, he shows that choosing an additive utility function rather than the standard multiplicative function increases willingness to pay (WTP) to avoid climate change by a factor of seven, even when damages are calibrated to give the same number for a warming of 2°. He argues the strong dependence of IAM results on obscure details of how temperature enters the utility function that are impossible to determine empirically is an example of deep structural uncertainty that requires caution in interpreting the SCC values.

This issue is identified by the IWG as a reason why the current functional form of damages in the IWG IAMs may be inadequate for accurately representing climate change damages (IAWG, 2010).

11. Utility Function and handling of risk aversion

In the IWG report, models were run to produce monetary damages with and without an additional pulse of CO_2 that were then discounted to give the SCC (IAWG, 2010, 2013). This process is consistent with the standard versions of FUND and PAGE which report damages simply in dollar values, leaving aggregation of damages in individual regions to a global value and the conversion to utility to the user.[13] The standard version of DICE however includes a constant elasticity of substitution (CES) utility function with the elasticity of marginal utility of consumption (η) set to 1.45, which was not used in the IWG process (Nordhaus & Sztorc, 2013). Much of the literature regarding risk-aversion in IAMs concerns this utility function and therefore is less relevant to the IWG process which simply uses monetary damages, implicitly using a linear utility function with no risk aversion.

[13] An exception is that parts of damages in the coastal sector in FUND use a discount rate derived from the Ramsey rule that implies logarithmic utility (i.e. η=1) (Anthoff & Tol, 2014b).

The simple utility function in DICE combined with a single representative agent means that the same η parameter represents preferences over consumption at different time periods, risk aversion, and preferences over income inequality within a given time period. Weitzman (Martin L Weitzman, 2012a) points out that in the standard DICE model, higher risk aversion tends to lower the SCC because it increases the discount rate. If instead damages are based on an expected utility calculation over a fat-tailed probability distribution of future temperatures, then higher risk aversion substantially increases the SCC. Anthoff, Tol and Yohe (2009) and Newbold and Daigneault (2009) find a similar sensitivity to the risk aversion parameter when climate damages are uncertain in sensitivity analyses using FUND and a modified version of the DICE model respectively.

Recent papers have begun incorporating findings from the asset-pricing literature that show large differences between time and risk preferences by incorporating Epstein-Zin preferences into IAMs. In addition to changing preferences, these papers also allow for the explicit representation of uncertainty in DICE, either over the climate sensitivity (Ackerman & Stanton, 2012), damage function (Crost & Traeger, 2011; Daniel, Litterman, & Wagner, 2015), or future growth rates (Jensen & Traeger, 2014). Because Epstein-Zin utility adds significant computational complexity, this work typically relies on simplified models derived from DICE. Preference parameters derived from asset price returns typically indicate much higher risk aversion (9.5-10) than would be indicated in the standard DICE CES utility function (1.45), and therefore these papers find that disentangling time and risk preferences tends to increase the SCC substantially.

Because the η parameter also captures preferences over intra-temporal inequality, it arises in questions of how to aggregate climate damages occurring to people at different income levels. Several authors have pointed out that using a declining marginal value of consumption for the purposes of time discounting but not in evaluating the importance of damages to different populations is inconsistent and could disguise important distributional impacts (Farmer et al., 2015; Sterner & Persson, 2008). Since climate damages tend to fall disproportionately on poorer regions, weighting monetary damages by their importance for utility will tend to increase estimates of global damages, a practice sometimes referred to as 'equity weighting'. Lemoine and Kapnick (2016) aggregate up heterogeneous country-level impacts into global damage functions using different η values and show large differences over a range of plausible values. For regional models, the within-region distribution of climate impacts, as well as the between-region distribution is important for an inequality-averse decision-maker as shown in Anthoff, Hepburn and Tol (2009) for FUND and Dennig et al. (2015) for RICE.

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