Determining the Social Cost of Carbon: Under Damage and Climate Sensitivity Uncertainty

Samuel Jovan Okullo[1,2]

Abstract

This article quantifies the impact on optimal climate policy, of both damage elasticity and equilibrium climate sensitivity uncertainty, under separable preferences for risk and intergenerational inequality. The primary findings are as follows. (1) Such preferences can depress the social cost of carbon (SCC) when calibration aims at matching actual economic outcomes, countering the prevailing view that the SCC is greater with separable than with conventional entangled preferences. (2) Damage elasticity uncertainty has larger effects on climate policy than equilibrium climate sensitivity uncertainty, even under high impact tail risk of the latter. (3) Risk aversion decisively strengthens optimal climate policy under joint damage and climate sensitivity uncertainty, than with a single source of uncertainty alone. Indeed, failing to account for the interaction between damage and climate sensitivity uncertainty underestimates the cost of climate change by more than US dollars 1 trillion.

Keywords Social cost of carbon (SCC) · Epstein–Zin–Weil preferences · DICE · Climate change · Risk aversion

1 Introduction

The social cost of carbon (SCC) is a monetary measure of long-term damages from emitting the marginal ton of CO_2. Although it is usually regarded to be a comprehensive measure of the cost of anthropogenic carbon pollution to society, its estimate is highly variable depending on, among others, assumptions about societal preferences, the climate system, economic technologies, and the feed-backs between them (see e.g., Greenstone et al. 2013; Lemoine and Rudik 2017a; Newbold et al. 2013). More recently, advances in the

✉ Samuel Jovan Okullo
  s.j.okullo@outlook.com

1 School of Business Administration, Zhongnan University of Economics and Law, 182 Nanhu Avenue, Wuhan 430073, Hubei, China

2 Member of the Leibniz Association, Potsdam Institute for Climate Impact Research (PIK), P.O. Box 601203, 14412 Potsdam, Germany

climate-economics literature such as[1]: explicitly modelling optimal mitigation policy under uncertainty, accounting for possible tipping points in the climate system, and incorporating sophisticated preference specifications that better encode behavioural decision rules are leading to a consensus that plausible levels for the SCC are higher than what has been traditionally recommended.[2] Despite these advances, it is still unclear how interacting sources of uncertainty matter for optimal climate policy.

This article evaluates the impacts of both damage elasticity and equilibrium climate sensitivity uncertainty on optimal climate policy, in the presence of separable preferences for risk and inequality. More specifically, the effect of these uncertainties on the SCC is evaluated using the Epstein–Zin–Weil (EZW) (or non-expected) utility framework, and contrasted to outcomes under expected (or power) utility.[3] The core insights of the analysis are threefold: (1) relative to the conventional expected utility framework were preferences for risk and inequality are entangled, EZW preferences can actually depress the SCC when a descriptive—rather than prescriptive—calibration is adopted,[4] (2) the SCC is more responsive to damage uncertainty than to equilibrium climate sensitivity uncertainty, even under tail risk of the latter, and (3) the SCC is decisively more responsive to risk aversion when there is interaction between damage and equilibrium climate sensitivity uncertainty, than when only a single source of uncertainty is appraised.

To date, several other studies have sought to explain the impact of uncertainty on optimal climate change policy. Some that evaluate uncertainty impacts using both non-expected and expected utility and are most relatable to this article include the following. Crost and Traeger (2014) evaluate the abatement response under damage uncertainty (cf. Ha-Duong and Treich 2004). They report that mitigation effort is stronger in the non-expected (than in the expected) utility framework and that the response of abatement to damage uncertainty is minimal to moderate, depending on whether uncertainty manifests linearly or non-linearly in the damage function. Jensen and Traeger (2014) evaluate related issues as Crost and Traeger (2013, 2014), but under total factor productivity uncertainty. They document that mitigation effort is decisively strengthened under non-expected utility—relative to the expected utility case—and that abatement effort is moderately responsive to risk aversion. Ackerman et al. (2013) and also Belaia et al. (2017) focus on climate sensitivity uncertainty; they observe a higher abatement effort with non-expected (than with expected) utility and report that this effort negligibly responds to risk aversion.[5] Others such as Cai et al. (2016), while not reporting explicitly on the implications of non-expected versus expected

[1] See for instance Ackerman et al. (2013), Belaia et al. (2017), Cai et al. (2016), Crost and Traeger (2014), Lemoine and Traeger (2016), Jensen and Traeger (2014) and Traeger (2014).

[2] The baseline DICE 2013R model for instance predicts a SCC that would start about 2005 US $21 in 2020, and rise monotonically to about 2005 US $143 in 2100. In the latest version of DICE, DICE 2016R, the SCC starts at about $31 and rises at $\sim$ 3% for much of this century. The increase in SCC is primarily explained by an updated carbon cycle with a higher climate sensitivity that better tracks the deaccumulation of CO_2 over a 4000-year timescale.

[3] These preferences were initially studied by Kreps and Porteus (1978) and further elaborated upon by Epstein and Zin (1989) and Weil (1989, 1990).

[4] Contrary to a prescriptive calibration where model parameters may be chosen on normative grounds, a descriptive calibration emphasizes choosing model parameters such that the model solution is fully consistent with actual economic outcomes.

[5] In contrast to Ackerman et al. (2013) and Belaia et al. (2017) consider the potential impacts of catastrophic climate change, modelled through a collapse in the Atlantic Thermohaline Circulation, and also evaluate the consequences of inertia in abatement technology.

utility for climate policy, convey similar findings that climate policy is more stringent with non-expected (than with expected) utility.

This article differs from the above closely related literature in two main respects. Firstly, two contemporaneous sources of uncertainty are evaluated: one in the economic system and the other in the climate system. Secondly, optimal policy is investigated when both the non-expected and expected utility model are calibrated to match and reproduce observed savings behaviour or as Nordhaus (2007) calls it: to match actual economic outcomes.[6] Results indicate that the SCC is smaller under non-expected utility, countering the predominant perception that separable preferences for risk and inequality raise the SCC. To explain the seemingly contradictory result, I show that the SCC obtained in the non-expected utility framework, without realigning the model to a data consistent savings baseline, is higher because of an increased concern for future consumption welfare that is unrelated to climate policy. Realigning the model neutralizes this effect, thereby ensuring that precautionary saving in the non-expected utility model is explained principally by hedging against an uncertain future and not a structural adjustment of the preference function.

I focus on uncertainty regarding (1) economic damages from temperature change and (2) the equilibrium temperature sensitivity to accumulating CO_2, as these are possibly the most challenging to resolve and yet are of significant importance for climate policy design (cf. Ackerman et al. 2010; Burke et al. 2016; Bretschger and Pattakou 2018; Hwang et al. 2017; Revesz et al. 2014; Rudik 2019; Schmidt et al. 2013). Damage uncertainty is particularly difficult to resolve because of data paucity especially from developing countries and disagreements on how to value and assess damages across both time and space. Dell et al. (2012) and Burke et al. (2015) are some recent studies that present new perspectives on damage estimates. Dell et al. argue that atmospheric carbon accumulation has growth rate impacts that could be more severe than the level effects that the literature has traditionally considered. Burke et al. additionally demonstrate that when temperature impacts from developing countries are taken into account, then global damages can be up to an order of magnitude larger per additional warming degree than the literature indicates. Furthermore, current estimates for warming above 1 °C are at best guesstimates since global warming above this level is yet to be experienced. In the modelling, I accommodate for the planner's ignorance about temperature induced damages by treating the damage elasticity as uncertain.

Equilibrium climate sensitivity is equally hard to resolve because of inherently stochastic feedback factors. As Knutti et al. (2017) and Knutti and Hegerl (2008) report, little progress has been made in narrowing the distribution of equilibrium climate sensitivity even after fifty years of substantial advances in the understanding of climate science. A higher (lower) measure for climate sensitivity means that future temperature is very responsive (insensitive) to a doubling of atmospheric CO_2. In the modelling, I account for the possibility of low probability high impact equilibrium climate sensitivity using a right-tailed probability mass.[7] Since Weitzman's dismal theorem predicts the possibility of a runaway SCC in the presence of such right tailed climate sensitivities (cf. Millner 2013; Hwang et al. 2013, 2016), my modelling framework where: (1) preferences are such that the propensity for consumption smoothing is separate from the degree of risk aversion and (2) there is a

---

[6] To achieve this, I use the pure rate of time preference as the degree of freedom when targeting the observed savings rate.

[7] That is, when solving for the optimal policy, I account for the right-tail realizations of equilibrium climate sensitivity.

possibility for catastrophic damages (or rather, highly undesirable states of nature prevailing), partly permits elucidating complex issues as the dismal theorem.

Results indicate that climate policy is optimally more responsive to damage elasticity uncertainty than to climate sensitivity uncertainty. The reason for this is that with damage elasticity uncertainty, increasingly undesirable future states of the world are weighted more heavily because of the convexity of the damage function. And yet, under equilibrium climate sensitivity uncertainty, the undesirable states have only a mild impact because of (1) the substantial inertia present in the climate system and (2) countervailing climate sensitivity shocks that temper the long-run temperature response. This means that the planner opts for a more aggressive stance towards climate change under damage elasticity uncertainty than under equilibrium climate sensitivity uncertainty.

More importantly, in the presence of both damage and climate sensitivity uncertainty, the SCC strongly rises in the degree of risk aversion. This turns out not to be the case with only one source of uncertainty. Indeed, Crost and Traeger (2014) find, as I do, that abatement moderately responds to risk aversion under damage elasticity uncertainty. They attribute this to strong growth within the DICE modelling framework that makes future damages only marginally to moderately more costly to the planner, such that risk counts little as a cost, making it optimal to delay abatement. Ackerman et al. (2013) and Belaia et al. (2017) who focus on climate sensitivity uncertainty alone also find, once again as I do, that abatement is negligibly responsive to the level of risk aversion. Ackerman et al. (2013) conjecture this to be the result of optimistic abatement assumptions and the absence of catastrophic risk in the DICE framework.[8] Belaia et al. (2017) introduce both these dimensions;[9] they still find a negligible response even in the presence of abatement technology inertia. My analysis illustrates that interacting damage and climate sensitivity causes the planner to act decisively against climate change even for reasonable levels of risk aversion.[10]

The argument that multiple interacting sources of uncertainty can imply a more ambitious climate policy response has also been made by Ackerman et al. (2010). They, however, rely on a Monte Carlo analysis rather than a decision making under uncertainty framework. Only through a decision making under uncertainty framework—a framework that explicitly treats uncertainty during planning—can the impact of risk and risk aversion be properly understood.[11] Indeed, a Monte Carlo analysis is based on a learn-then-act view of the world, which in essence means that the planner learns about the state of the world that prevails and subsequently acts in a deterministic fashion. Along such a planning path, uncertainty and risk aversion are both completely ignored. In a decision making under uncertainty framework, i.e., act-then-learn view, the planner only sequentially learns

---

[8] Dietz and Stern (2015) and Hwang et al. (2013) also consider climate sensitivity uncertainty for various specifications of the damage function under traditional expected utility preferences. Their results suggest that abatement and the social cost of carbon can be more responsive to climate sensitivity uncertainty for very steep damage functions.

[9] They model abatement inertia by putting a constraint on the growth rate of investment and catastrophic climate risk through a collapse in the Atlantic Thermohaline Circulation.

[10] Key here is that current abatement can indeed mitigate future consequences. If the planner were to end up in a highly undesirable state of the world, and abatement has little effect on mitigating future outcomes, it is possible that little to no abatement becomes the dominant strategy. These views find support in the results of Hwang et al. (2016).

[11] While the literature often uses Monte Carlo methods to approximate the impacts of decision making under uncertainty, Crost and Traeger (2013) argue and present evidence for why this can be misleading.

about the state of the world that prevails. In this case, current consumption and abatement decisions must hedge uncertain future outcomes while still contributing to the felicity of current generations. In contrast to Ackerman et al. (2010), I observe that even with less variation in the uncertain parameters, there is a decisively stronger climate policy response.

The stochastic programming technique I adopt to recover optimal policies under uncertainty resembles that of Ackerman et al. (2013) and Belaia et al. (2017). The technique is accessible even to the non-technical programmer and yet is perfectly consistent with dynamic programming (Shapiro et al. 2009). In addition, it has the benefit of not being as susceptible to the curse of dimensionality (see e.g., Tahvonen et al. 2018). This means I can obtain optimal solutions using the unabridged implementation of Nordhaus' DICE model on a generic laptop (cf., Traeger 2014).

The rest of this article is organised as follows. Section 2 discusses how damage and equilibrium climate sensitivity uncertainty are specified and introduced into the DICE model. Section 3 discusses the specification of preferences in the stochastic DICE model. Section 4 presents the numerical results and 5 concludes.

2 Economy and Climate Specification

The stochastic DICE model designed for this analysis retains the economy and climate equations of the DICE2013R (henceforth DICE) model (cf. Nordhaus 2008, 2014, 2017; Nordhaus and Sztorc 2013), but for modifications to accommodate both damage elasticity and equilibrium climate sensitivity uncertainty. A brief description of the economy-climate specification (cf. Nordhaus 2008, 2014, 2017; Nordhaus and Sztorc 2013) follows; and after that, a discussion on the representation of uncertainty.

Six endogenous state equations summarize the economy-climate system: one tracking the capital stock, three tracking the accumulation of CO_2 in the atmosphere, the upper ocean, and the lower ocean, and two tracking atmospheric and lower ocean temperature. Production activity generates emissions which enter the atmosphere and subsequently dissipate into the upper ocean and lower ocean. In the long-run, the three boxes describing the carbon sinks eventually enter a state of equilibrium. Rising CO_2 concentration in the atmosphere leads to the green house effect, and in turn, productivity losses typically referred to as economic damages. These damages represent the fraction of output that is lost as a result of the greenhouse effect. Population, and trajectories for technological improvement in production processes, emission intensity, and abatement cost are state variables that propagate exogenously. In every period, final output that remains unconsumed is saved for use as capital in future production.

2.1 Damages

DICE specifies the following damage function:

$$D\left(T_t\right) = b_1 T_t^{b_2} \tag{1}$$

where T_t denotes upper atmospheric temperature in °C above the pre-industrial baseline. The coefficient $b_1 > 0$ measures damages at 1 °C warming, whereas the elasticity $b_2 > 0$ defines the speed with which damages increase for each additional degree of warming.

$1 - D(\bullet)$, which is decreasing in $T_{a,t}$ defines the fraction of output loss due to temperature-induced damages.

Ideally, the parameters of the damage function (1) should be calibrated by regressing damage realizations on temperature realizations. Data paucity has, however, led to the practice that the elasticity b_2 is first fixed and b_1 is subsequently chosen to generate the best fit between whatever damage and temperature data there is, and the assumed polynomial fit.[12] In DICE, b_2, is set to 2 and a calibration to the available data yields a b_1 of 0.00267 (Nordhaus and Sztorc 2013). The DICE damage function thus predicts an output loss of 0.28% (2.52%) (10.08%) for $1\,°C$ ($3\,°C$) ($6\,°C$) warming. Recent findings by Dell et al. (2012) and Burke et al. (2015) suggest that these coefficients are underestimated. Burke et al. (2015) for instance report temperature damages up to 2.5–100 times larger than DICE's estimates at $3\,°C$ warming. Besides, focusing on a single estimate sidesteps the substantial ignorance that exists regarding damages.

Ackerman et al. (2010) draw the damage elasticity from a triangular distribution with a lower bound of 1, upper bound of 5, and a mode of 2. Rudik (2019) and Crost and Traeger (2014) arrive at distributions that can be approximated using a triangular distribution with a lower bound of 1, upper bound of 3, and a mode of 2. I partition such a triangular distribution in two. I then use the magnitude of the damage elasticity at the midpoint of each interval as the elasticity for that state and the area under that half of the triangle as the probability of the state. This gives a high damage state with $b_2 = 2.5$ and low damage state with $b_2 = 1.5$, each assigned a 50% probability. These values yield a 4.36% (24.69%) output loss for ($3\,°C$) ($6\,°C$) warming in the high damages state, and 1.45% (4.12%) output loss for ($3\,°C$) ($6\,°C$) warming in the low damage state. These ranges compare well with those provided in Tol (2013) and the meta-review in Howard and Sterner (2017).

2.2 Climate Sensitivity

The stock of CO_2 relative to the pre-industrial baseline is the main driver of upper atmospheric temperature forcing. Increasing radiative forcing warms the atmosphere which in turn warms the ocean layer. The atmospheric temperature equation is given by:

$$T_{t+1} = T_t + z_1\left(\left(\mathcal{F}_{t+1} - \frac{\xi}{\zeta}T_t\right) + z_2\left(T_t - T_{o,t}\right)\right) \tag{2}$$

where $\mathcal{F}_{t+1} = \xi \log_2\left(M_{t+1}/M_{pre}\right) + \mathcal{F}_{other,t+1}$. $T_{o,t}$ denotes ocean temperature, M_t is the stock of atmospheric carbon, M_{pre} the pre-industrial atmospheric CO_2 stock, $\mathcal{F}_t$ is total radiative forcing, with $\mathcal{F}_{other,t+1}$ being non-CO_2 radiative forcing. z_1 and z_2 are parameters capturing diffusive inertia in the temperature system. ξ and ζ are, respectively, parameters for forcing of equilibrium CO_2 doubling and the equilibrium temperature response for CO_2 doubling over the pre-industrial baseline. The latter is also commonly referred to as the global equilibrium climate sensitivity parameter.

Although a lot has been learned about ζ over the years, much uncertainty still exists. ζ has a broad distribution with small but finite probabilities of very large increases. Roe and Baker (2007) state that the shape of ζ's distribution is an inevitable and general

---

[12] An exception in this regard is Rudik (2019), who uses data gathered by Howard and Sterner (2017) to estimate the parameters of the damage function. He recovers an estimate for b_1 that is twice in size of that of DICE and an elasticity for $b_2 = 1.8$, which is very close to the value used in DICE.

consequence of the nature of the climate system. Uncertainties in ζ are primarily explained by uncertainties in understanding physical processes associated with snow melt, cloud cover, humidity, solar forcing, and variability in strengths of major feedback factors (Knutti et al. 2017). In the absence of feedback processes, ζ is believed to take a value of $\approx 1.2\,°C$. However, with uncertainties and variability in the strength of the major feedback factors taken in to account, its likely range is believed to be 1.5–$4.5\,°C$, with a small vanishing probability of greater than $15\,°C$ (Annan and Hargreaves 2011; Knutti and Hegerl 2008; Knutti et al. 2017).[13]

I adopt Belaia et al.'s, and before them Ackerman's, construction of a discrete probability distribution for ζ. In particular, the probability density function for climate sensitivity presented in Roe and Baker (2007), calibrated on parameters by Murphy et al. (2004), is converted into a probability mass function with five intervals. This partitioning yields the following values and accompanying probabilities for climate sensitivity: state 1, 2.43 (with probability 0.5); state 2, 3.67 (with probability 0.4); state 3, 6.05 (with probability 0.05); state 4, 8.28 (with probability 0.03); and state 5, 16.15 (with probability 0.02). This implies an expected value of 3.56, that I use if climate sensitivity is known with certainty rather than DICE's value of 2.9.[14]

2.3 Damage and Climate Sensitivity Interaction

To evaluate the effect of interactions between damage and climate sensitivity uncertainty on optimal climate policy, I construct a joint probability distribution from the above-defined probable states of nature for damages and climate sensitivity. Two probable states for damages and five probable states for climate sensitivity yields up to ten unique combinations. The first is low damages together with state 1 for climate sensitivity; the second, high damages with state 1 for climate sensitivity, and so forth. I proceed in this manner until the tenth probable state, which is, high damages and state 5 for climate sensitivity. Probabilities for each of the ten states are straightforwardly obtained as the dot product of probabilities of the corresponding parent states. With these ten states of the world in hand, it is possible to explore how the planner reacts when damages and climate sensitivity are jointly uncertain.

3 Preference Specification

The standard preference specification tightly links the dislike for deterministic intertemporal consumption fluctuations and the degree of risk aversion. It may, however, be desirable to separate these two components in order to evaluate the impact of varying one independently of the other. The generalized recursive utility representation of Kreps and Porteus (1978), Epstein and Zin (1989) and Weil (1990) very conveniently achieve this. Also commonly referred to as non-expected utility preferences, due to the non-separable

---

[13] Annan and Hargreaves (2011) show that under reasonable assumptions, much greater confidence in a moderate value for climate sensitivity is easily justified, with an upper 95% probability limit for it easily shown to lie close to $4\,°C$, and certainly well below $6\,°C$.

[14] Over the years, DICE's estimate for equilibrium climate sensitivity has in fact been adjusted upwards with the latest 2016 version having a value of 3.1 (Nordhaus 2017).

representation of time and state of nature, Kreps-Porteus (or Epstein–Zin–Weil) preferences accommodate the expected utility framework as a special case.

Mathematically, the planner's generalized recursive welfare is:

$$W_t = \frac{1}{1-\gamma} L_t c_t^{1-\gamma} + \frac{\beta}{1-\gamma} u_t \left(\mathbb{E}_t \left((1-\gamma) W_{t+1} \right)^{\frac{1-\vartheta}{1-\gamma}} \right)^{\frac{1-\gamma}{1-\vartheta}} \tag{3}$$

where $\beta = 1/(1+\rho)$ is the discount factor and ρ is the pure rate of time preference (also known as the utility discount rate) . ρ defines the relative time value of welfare, such that a higher value expresses greater preference for earlier (rather than delayed) consumption. γ, the reciprocal of the inter-temporal elasticity of consumption substitution, measures the planner's dislike for deterministic intergenerational consumption variability. A larger γ implies a greater dislike of inequality, meaning that increased weight is placed on periods of low consumption. ϑ on the other hand is the coefficient of relative risk aversion. It measures the dislike of risk with larger values corresponding to greater risk aversion.

The variable W_t denotes discounted welfare at time t, c_t gives per capita consumption also at t, and L_t is population size at t. The objective equation (3) is maximized by choosing consumption (and abatement in case of climate policy) to maximize W_t. The expectation operator implies that current consumption is chosen under uncertainty regarding the state of the world that prevails after the current period elapses. Decisions taken at t can, therefore, be also seen as hedging options with respect to an uncertain future.

3.1 Stochastic Discount Factor

The Euler equation that describes the intertemporal consumption trade-off, derived for (3) is (see Online Appendix):

$$m_{t,t+1} = \beta L_{t+1} L_t^{-1} c_t^{\gamma} c_{t+1}^{-\gamma} \left(W_{t+1}^{\frac{1-\vartheta}{1-\gamma}} \left(\mathbb{E}_t W_{t+1}^{\frac{1-\vartheta}{1-\gamma}} \right)^{-1} \right)^{\frac{\gamma-\vartheta}{1-\vartheta}} \tag{4}$$

where $m_{t,t+1} = 1/(1 + r_{t,t+1})$ is the stochastic discount factor with $r_{t,t+1}$ being the return on capital, also sometimes referred to as the risk-free discount rate or the social discount rate.

The special case $\gamma = \vartheta$ is consistent with the expected utility framework, and in the absence of uncertainty, with Nordhaus' specification of the DICE model. Nordhaus (2014, pp. 279–278) notes that he follows a descriptive approach—also sometimes referred to as a market-based approach—in ensuring that the DICE model matches observed economic outcomes. In particular, given $\gamma(= \vartheta)$ as estimated from empirical literature and $r_{t,t+1}$ as observed from capital markets, he chooses ρ such that DICE's (base year) simulated savings rate matches actual data. This can be contrasted with the prescriptive approach of Stern (2007), where the goal is not to match actual data from capital markets per se, but rather to select ρ in order to be consistent with the present generation's ethical concern for future generations' welfare. The latter approach typically prescribes a pure rate of time preference that is much lower than that of the former[15] and leads to savings rates that are higher than what is observed in the data.

---

[15] Stern (2007) uses a pure rate of time preference of 0.1% for his analysis. This compares with 1.5% that DICE generates under a descriptive calibration.

When $\gamma \neq \vartheta$, matching observed data using the descriptive approach becomes a little demanding primarily because V_{t+1} is not directly observed. Still, one can readily obtain qualitative insights on the impact of separating γ from ϑ. To see this, first note that under expected utility, $\gamma(=\vartheta) \in [1, 4]$ (Dasgupta 2007; Thimme 2017). In contrast, EZW preferences suggest that $\gamma \in [0.5, 1)$ and $\vartheta \in [2, 10]$ (Thimme 2017). Since Nordhaus calibrates the DICE model to match observed base year savings, adjusting $\gamma(=\vartheta)$ will alter the model's simulated savings behaviour, yielding savings rates that deviate from observed economic outcomes. Consider moving $\gamma(=\vartheta)$ to 0.8 from DICE's value of 1.45. This increases the planner's propensity to save as a slanting consumption profile becomes preferable to a more evened-out one. Next, holding $\gamma = 0.8$ and moving ϑ upwards makes the planner more risk averse, which further reinforces the precautionary saving motive. What is interesting to note is that the planner is becoming more prudent, merely from parametric changes unrelated to climate change concerns. After climate change is added, the seemingly innocuous parametric adjustments can misleadingly suggest that EZW preferences prescribe a more aggressive policy response to climate change.

The impacts from separating γ and ϑ can also be clarified using a log-linearized approximation of (4).[16] That is,

$$r_{t,t+1} = \rho - (1 + \gamma)g_L + \gamma g_C - \gamma^2 \frac{\sigma_C^2}{2} - (\vartheta - \gamma)(1 + \gamma)\frac{\sigma_C^2}{2} \tag{5}$$

where g_L is the population growth rate, g_C is the consumption growth rate, and σ_C is the volatility of consumption growth. A higher risk-free rate (net of the utility discount rate) is associated with an incentive to save more in the current period, and hence a bigger jump in consumption between periods. All else constant, a higher level for risk aversion leads to greater savings when $\vartheta > \gamma$. Moreover, a larger inter-temporal elasticity of substitution (lower γ) generally increases savings, all else constant. It follows that savings—and in a way concern for future consumption welfare—increase as one moves to $\gamma = 0.8$ and $\vartheta = 10$ from $\gamma(=\vartheta) = 1.45$. Once again, this reorganization towards preference for future consumption welfare is taking place absent any climate change concerns.

Therefore, in order to coherently compare climate policy stringency between the expected utility specification and the non-expected utility specification, one needs to restrict the analysis to the same calibration technique. That is, climate policy comparisons must be made with both preference frameworks embedded either strictly within the descriptive calibration framework or alternatively within the prescriptive calibration framework. Consensus in the literature is for use of the descriptive approach. Indeed, Arrow et al. (2013, p. 349), point out that the descriptive approach prevents inconsistencies from discounting benefits and costs occurring in the same year at different rates. Moreover, Arrow (1999), Dasgupta (2007) and Nordhaus (2007) argue that the descriptive approach avoids situations where generations are predicted to save at unrealistically high levels that are inconsistent with actual economic outcomes.[17]

---

[16] The expression makes use of the assumption that consumption shocks are idiosyncratic. See the Online Appendix for derivation.

[17] There is of course some tension when calibrating the social planner framework to actual economic outcomes. Indeed, the global economy is decentralized with several distortions, imperfections, externalities, and inefficiencies in markets. Such frictions drive a wedge between the social discount rate (i.e., derived from what is socially optimal) and the investment discount rate (i.e., actual returns on risk-free capital assets), meaning that the two are generally not equalized. Should one then still calibrate the social planner model as though it were fully consistent with observed economic outcomes? Arrow (1999), Arrow et al.

These observations naturally lead to the first of this paper's contributions. While the related literature typically reports that non-expected utility implies more stringent climate policy than expected utility, the preceding paragraphs suggest that the level of the SCC, through its dependence on the social discount rate, is inadvertently larger because of a calibration technicality. That is, the SCC in the non-expected utility specification is greater in part because of parametric changes that are unrelated to the optimal response to climate change impacts. Thus, in order to restore the non-expected utility stochastic DICE model to the same market-based calibration baseline as the expected utility stochastic DICE model, impatience will typically have to be induced by adjusting ρ.[18]

The next section presents the quantitative impact on the SCC of moving from expected to non-expected utility with and without renormalization of savings behaviour. It will become apparent that without renormalization of savings, the SCC can be multiple factors larger than that in the baseline expected utility specification. With renormalization, the situation reverses and the SCC turns out to be consistently lower than in the baseline expected utility specification. These results indicate that non-expected utility, at least with regard to EZW preferences, does not necessarily give rise to a higher SCC than expected utility, unless when coupled with prescriptive considerations.

4 Numerical Results

As earlier mentioned, I employ stochastic programming to find the optimal policy under uncertainty (cf. Shapiro et al. 2009). This method is particularly convenient considering that there is only one agent in the model and the probability structure is predefined. To contain the proliferation of scenarios, while in essence preserving the DICE structure,[19] only a single shock, as in Ackerman et al. (2013) and Belaia et al. (2017)—also see Keller et al. (2004)—is introduced. The point at which the shock occurs corresponds to the point in time when the planner learns the state of nature that prevails. In other words, it corresponds to that point in time when the planner observes the random shock for which only a distribution was known up until then. All decision-making before the learning point is taken under uncertainty while that after is deterministic, adjusted to respond to the observed state of the world. Three learning points: 2040, 2080, and 2100 are evaluated. An inspection of the results shows that pre-shock (alternatively, pre-uncertainty resolution) outcomes are qualitatively and more or less quantitatively consistent across learning points. The body of this article thus focuses on the 2080 learning point with the SCC figures for the 2040 and 2100 learnings points relegated to "Appendix 1".

The consequence of moving from expected to non-expected utility, with and without renormalization of the savings rate, is discussed in the next subsection. The subsection after reports on the response of optimal climate policy to damage versus equilibrium

---

Footnote 17 (continued)

(2013), Dasgupta (2007), Drupp et al. (2018) and Nordhaus (2007) discuss this matter, and decide in favour of the descriptive approach.

[18] Since ρ is unobserved, and its value is typically assumed in empirical work, it provides the natural degree of freedom for calibrating the model when the savings rate is fixed.

[19] DICE presumes the availability of negative emission technologies sometime in the future, a feature that is terminated in this paper's version of the model.

climate sensitivity uncertainty. The final subsection discusses the influence of risk aversion on optimal policy.

4.1 Expected Versus Non-expected Utility

Figure 1 presents the time path for emissions, temperature, and the expected SCC.[20] Specification '$\gamma = \vartheta = 1.45$' is labelled the baseline specification and '$\gamma = 0.8\ \vartheta = 9$' the benchmark specification. The left panels disregard renormalization of the base year savings rate for the non-baseline specifications whereas, renormalization is pursued for all non-baseline specifications showed in the right panels. '$\gamma = \vartheta = 0.8$' and '$\gamma = 0.8\ \vartheta = 0.2$' are the supplementary specifications that help clarify and explain the principal specifications. The former helps illustrate the impact of a less egalitarian attitude toward consumption variability relative to the baseline. Additionally, it clarifies the consequence of being temporally neutral to risk, as opposed to exhibiting temporal risk aversion per the benchmark specification. Specification '$\gamma = 0.8\ \vartheta = 0.2$,' by contrast, highlights the consequences of being temporally risk-loving, as opposed to being temporally risk averse per the benchmark or neutral per the first supplementary specification.[21]

Moving $\gamma(=\vartheta)$ to 0.8 from 1.45, while keeping all other parameters including the pure rate of time preference unchanged (left panels of Fig. 1), increases the model's base year savings rate from 26.9 to 32.6%.[22] This is consistent with a lower γ making the planner less averse to (deterministic) intergenerational consumption variability and, therefore, more willing to shift consumption from the present and to the relatively wealthier future. This *inegalitarian* consumption attitude also increases immediate emission abatement in order bolster the future consumption stream. Observe that under the baseline specification, emissions peak in 2045 but peak almost two decades earlier when $\gamma = 0.8$. Holding $\gamma = 0.8$ and raising $\vartheta = 9$ makes the planner more risk averse. This additional adjustment turns out to have a negligible impact on the 32.6% savings rate, but helps increase the SCC, leading to additional cuts in emissions. The lower γ, nevertheless, still has the much more substantial impact on emission policy than the larger ϑ.[23] In and of itself, the lower γ would not be a problem were it not for the distorted savings response that deviates from the baseline calibration—or observed outcomes—by nearly 7% points.[24]

---

[20] A key requirement in stochastic programming is nonanticipativity (Shapiro et al. 2009). This in essence restricts choices to depend on the current state and not on the future's yet unrealized outcomes. This requirement ensures that scenarios sharing a common history, generate similar outcomes. In stochastic DICE, this implies a single optimal outcome for consumption, abatement, emissions, and hence a unique path for all state variables prior to the realization of the shock. The reported expected SCC is obtained as the probabilistic sum over the scenario SCCs.

[21] For $\gamma < \vartheta$, the planner is willing to sacrifice welfare for the early resolution of uncertainty even if this resolution is not pay-off relevant. With $\gamma = \vartheta$, the planner is indifferent about when risk is resolved (i.e., temporally risk neutral), but prefers the late resolution of risk (i.e., temporally risk-loving) when $\gamma > \vartheta$. For further details see e.g., Epstein and Zin (1989, 1991), Kreps and Porteus (1978), Traeger (2009) and Weil (1990, 1989).

[22] The savings rate in the deterministic version of the original DICE model by Nordhaus and Sztorc (2013), is also 26.9%.

[23] Lowering γ to 0.8 explains nearly 150% of the initial increase in the SCC and increasing ϑ to 10 from 0.8 explains the remaining nearly 40%.

[24] With $\gamma = 0.8$ and recalibration of the base year savings rate disregarded, the model predicts a base year social consumption discount rate of 2.6%.
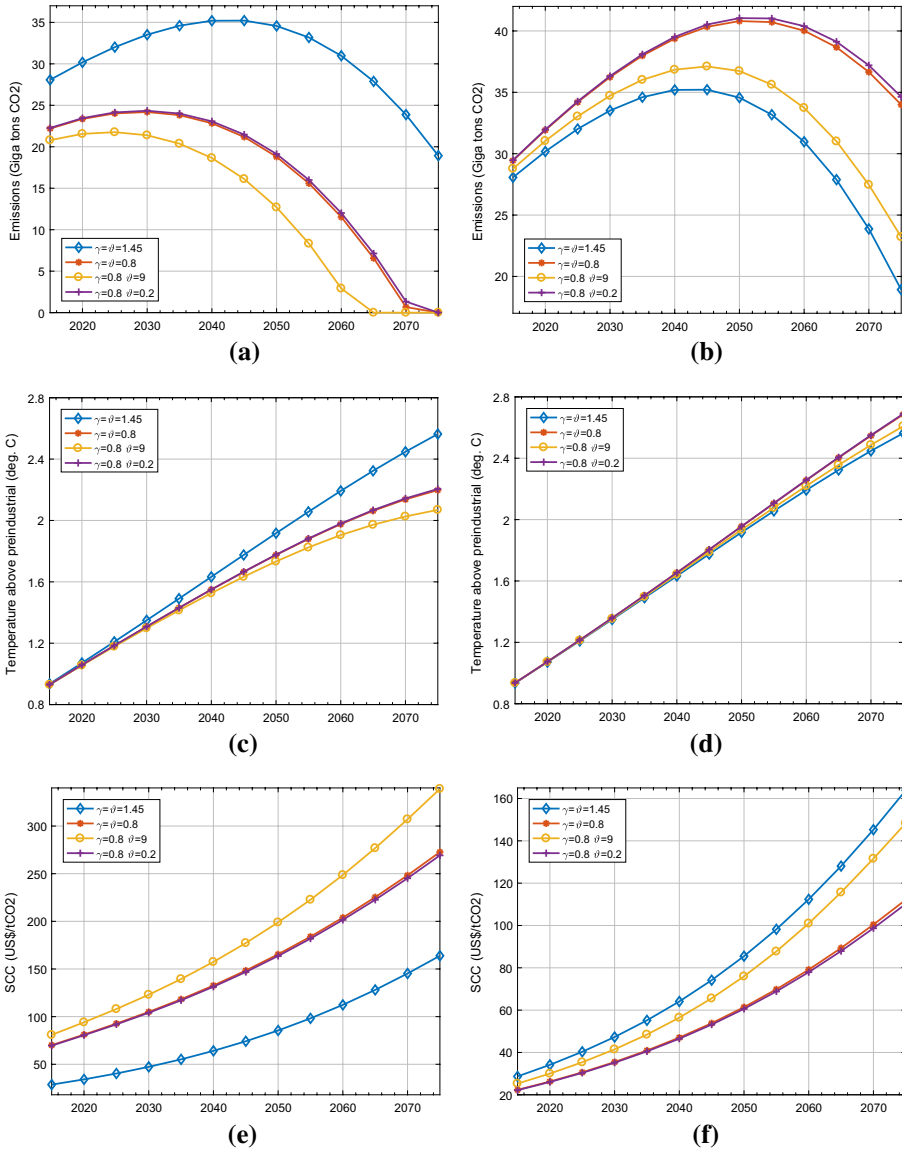
Fig. 1 Emissions, temperature, and the SCC for alternate degrees of intergenerational inequality aversion and risk aversion. *Notes*: Left panels: simulation with unadjusted pure rate of preference. Right panels: simulations with pure rate of time preference adjusted such that (base year) savings behaviour is consistent across specifications

In the right panels, ρ, is adjusted such that (base year) savings behaviour is consistent across all four preference specifications. Since the savings rate is higher when $\gamma(=\vartheta)$ is moved to 0.8 from 1.45, it is natural to induce impatience so as to lower savings to a level consistent with the baseline specification or equivalently to that observed in the data. As noted earlier, the pure rate of time preference is the natural degree of freedom for

making this adjustment since its value is typically assumed. A 1.58% increase, yielding a 3.08% pure rate of social time preference turns out to be sufficient for renormalizing savings behaviour in the non-baseline specifications. Since the figures in the right panels illustrate that the climate policy response is less ambitious in the non-baseline specifications, it is immediate that the impact of inducing impatience in order to have consistent savings behaviour across specifications, outweighs that of being less egalitarian by decreasing γ. Contrasting the findings on the right to those on the left, it is evident that even for reasonable preference parameters, EZW preferences do not necessarily recommend an aggressive climate response, as the literature has tended to suggest, unless of course when coupled with prescriptive considerations.

It is nonetheless reassuring to see that climate policy responds to the magnitude of risk aversion. This is especially important in the context of findings by Crost and Traeger (2014), Ackerman et al. (2013) and Belaia et al. (2017) that show little to no response of policy to the level of risk aversion. Clarifying which uncertainties elicit a strong climate policy response in the degree of risk aversion is important for shaping future scientific research efforts and the climate policy discourse.

4.2 Damage vis-à-vis climate sensitivity uncertainty

This subsection evaluates the optimal response of climate policy to damage elasticity uncertainty vis-à-vis equilibrium climate sensitivity uncertainty. The principle insight is that even in the presence of tail risk for equilibrium climate sensitivity, the SCC is still more responsive to damage elasticity uncertainty. The small consequences of equilibrium climate sensitivity uncertainty stem from the substantial inertia in the climate system which attenuates the severity of these shocks; and countervailing climate sensitivity shocks that over the long run temper the temperature response.[25]

Figure 2 presents the SCC under damage elasticity uncertainty (left panel) and equilibrium climate sensitivity uncertainty (right panel). In the former, the SCC rises from between 22 and 29 US\$/tCO$_2$ in 2015 to between 116 and 158 US\$/tCO$_2$ in 2075, a five-fold increase. This compares with a four-fold increase from between 20 and 25 to between 83 and 120 US\$/tCO$_2$ under climate sensitivity uncertainty. The lowest value for the SCC in 2075 under damage uncertainty, is more or less of the same magnitude as the highest value for the SCC under climate sensitivity uncertainty. Moreover, the highest value for the SCC under damage uncertainty is almost one third greater than the highest value for the SCC under climate sensitivity uncertainty. These findings convey that even in the presence of tail probabilities for equilibrium climate sensitivity, optimal climate policy is more responsive to damage elasticity uncertainty than to equilibrium climate sensitivity uncertainty.

Figure 3a, b further illustrate this point. The panels depict the difference between the expected SCC and the deterministic SCC, for otherwise identical specifications. Panel (a) illustrates that the SCC is moderately driven up due to damage uncertainty whereas panel (b) shows that it somewhat decreases due to climate sensitivity uncertainty.

Focusing on uncertainty regarding coefficient (b_1) and elasticity (b_2) of the damage Eq. (2), Crost and Traeger (2014) observe that the SCC is higher with the elasticity

---

[25] For brevity, the ensuing discussion focuses on the descriptive calibration, but impacts on the SCC for the prescriptive calibration are illustrated in Fig. 5.

uncertain than with the coefficient uncertain. Their explanation for this observation is that the world looks on average worse under damage elasticity uncertainty than under damage coefficient uncertainty, which induces the planner to abate more under the former than the latter. Evaluating climate sensitivity uncertainty, Keller et al. (2004) observe that abatement is less with the SCC uncertain. They use a weighted Monte Carlo risk analysis rather than an explicit decision making under uncertainty framework. They provide two explanations for their findings. Firstly, that risk aversion is not the dominant factor and hence the planner is willing to accept more risk even in an uncertain world. Secondly, that mitigation does not reduce the variance in pay-offs, inducing the planer to weaken rather than strengthen abatement under uncertainty. Lemoine and Rudik (2017b) as well report of small consequences on climate policy of climate sensitivity uncertainty, rationalizing this by the climate system's inertia.

An analytical expression for the SCC can provide precise insights for why climate policy responds more to damage elasticity uncertainty than to equilibrium climate sensitivity uncertainty. In "Appendix 2', a reduced version of the DICE model is set up (cf., Jensen and Traeger 2016). This model captures using three state variables—capital (K), atmospheric CO_2 (M), and atmospheric temperature (T)—the essential mechanisms present in the original DICE model. The model yields the following reduced-form expression for the expected SCC when $\gamma(=\vartheta)$:

$$\text{SCC}_t = -\frac{1}{u'(C_t)} \mathbb{E}_t \left[\sum_{\tau=t+1}^{\infty} \sum_{\iota=\tau}^{\infty} \beta^{\iota-t} u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \frac{\partial T_\tau}{\partial M_\tau} \frac{\partial M_\tau}{\partial M_{t+1}} \right] \tag{6}$$

where F_ι denotes the production function.[26] The damage elasticity shock enters through $\partial F_\iota/\partial T_\iota$ and the climate sensitivity shock through $\partial T_\iota/\partial T_\tau$.

This expression suggests that the quantitatively small consequences of equilibrium climate sensitivity uncertainty on the SCC are in part the result of: (1) significant inertia in the climate system and (2) countervailing equilibrium climate sensitivity shocks that temper the longrun temperature response. Both these impacts enter through $\partial T_\iota/\partial T_\tau$. The greater the inertia in the climate system, the smaller $\partial T_\iota/\partial T_\tau$ is, resulting in climate sensitivity uncertainty having a small impact on the expected SCC. In addition, for $\iota \gg \tau$, large and small equilibrium climate sensitivity shocks offset one another, leading to small consequences of historical temperature increases on the longrun temperature increase. The quantitative effect of using a more impactful counterfactual value for climate inertia than DICE's original value is illustrated in Fig. 6.[27] The resulting SCC is greater under uncertainty for both the baseline and benchmark specifications, and the decrease is much smaller for the two supplementary specifications.

Non-linearities also matter for the impacts of uncertainty on climate policy. Because an increase in damage elasticity links to greater expected damages at an increasing rate, and an increase in climate sensitivity uncertainty to greater expected temperature increase but at a decreasing rate, uncertainty about the former suggests a more aggressive policy to curb climate change (Jensen's inequality). Note that contrary to this article, Lemoine and Rudik (2017b), Jensen and Traeger (2016) and Hwang et al. (2017) model climate

---

[26] Because $\text{SCC}_t = \partial F_t/\partial E_t$, greater emissions correspond to a smaller gain from marginal emissions and thus a smaller expected SCC.

[27] In particular, while DICE sets the parameter that calibrates atmosphere inertia to 51 years, in this counterfactual simulation the parameter is set to 21 years.
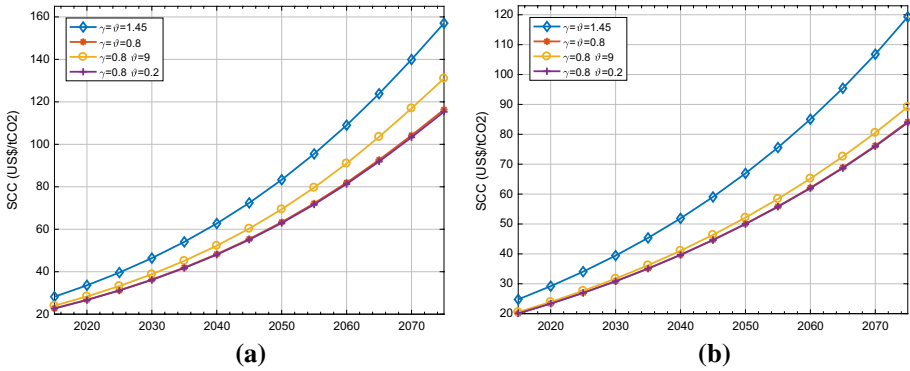
Fig. 2 SCC under damage elasticity uncertainty (left panel) and climate sensitivity uncertainty (right panel) for alternate degrees of intergenerational inequality aversion and risk aversion
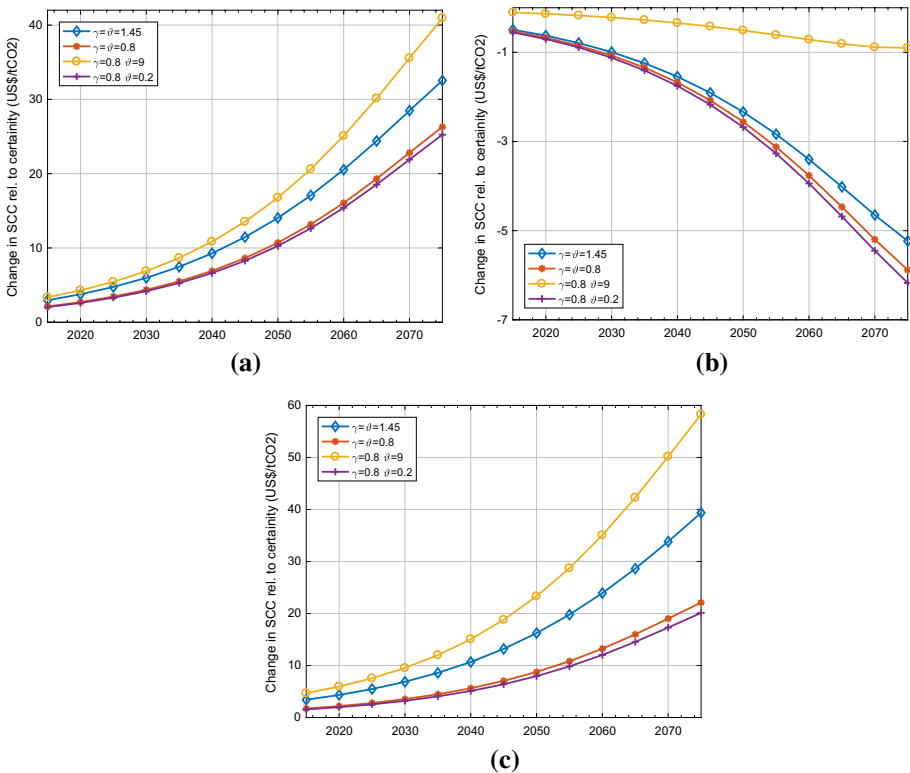

Fig. 3 Response of the SCC to damage elasticity uncertainty (**a**) and climate sensitivity uncertainty (**b**), and the interactive effects of damage and climate sensitivity uncertainty (**c**), for alternate degrees of inequality aversion and risk aversion. *Notes*: Each specification shows the difference between the expected SCC and the deterministic SCC. The deterministic SCC is obtained using the mean of the 'uncertain' damage elasticity and the mean of the 'uncertain' climate sensitivity. Renormalization of the savings rate is pursued for all specifications

sensitivity uncertainty by assuming that the climate system's feedback factor is uncertain. This implies a linear (rather than concave) relationship between atmospheric temperature and the source of uncertainty; and in the non-linear DICE model, suggests an even less aggressive policy under uncertainty than that reported above.[28] This means that the principle explanation for why they observe an increase (rather than a decrease) in the SCC under uncertainty, is likely down to their use of the mode of climate sensitivity, 3.0, rather than the expected value for recovering the optimal deterministic policy.[29,30]

Overall, these findings imply that the planner perceives the marginal ton of CO_2 emitted under damage uncertainty, as potentially more detrimental to welfare than that emitted under climate sensitivity uncertainty. And while an analytical expression for the SCC is unavailable under general disentangled preferences for risk and inequality, i.e., for general values when $\gamma \neq \vartheta$. The numerical results suggest that this extension primarily scales the impact of uncertainty for the intensity of preference for temporal risk resolution.

4.3 Uncertainty Interaction and SCC Response to Risk Aversion

Joint damage and climate sensitivity uncertainty elicit a strong response of climate policy to the degree of risk aversion than either uncertainty alone. How much welfare society is willing to sacrifice in order to contain climate change can be multiple factors greater with interacting sources of uncertainty and disentangled preferences for risk and inequality, than with a single source of uncertainty. In this section, I discuss the response of optimal climate policy to varying the degree of risk aversion.

Ackerman et al. (2013) observe that the planner's policy under climate sensitivity uncertainty marginally responds to risk aversion. They suggest that abatement is too cheap in the DICE model, which induces the planner to delay mitigation. They also argue that damages are not costly enough as to induce early action. Belaia et al. explore both dimensions by introducing a deterministic tipping point threshold with regard to thermohaline circulation, and in some scenarios consider the impact of technological inertia.[31] While they find some additional response of policy to risk aversion when inertia is present, the response is still inconsequential. They conclude that technology inertia could be modelled more elaborately and perhaps then a stronger influence of risk aversion will emerge.

Under damage elasticity uncertainty, on the other hand, Crost and Traeger (2014) observe some response of policy to increasing risk aversion. To explain why the planner does not do more, they argue that because future generations are much wealthier than present generations, the latter find it optimal to do little to abate emissions on account of damages from climate change not being catastrophic.

---

[28] The present model cannot be directly compared to the versions used by Lemoine and Rudik (2017b), Jensen and Traeger (2016), and Hwang et al. (2017). Nonetheless, when uncertainty is introduced linearly by assuming the ratio $(1/\zeta)$, rather than non-linearly by taking only the component ζ, as uncertain, the SCC is always lower under uncertainty with the former. In particular, it lower by between US$ 2-3 through out the years.

[29] In their setting of fat tails, the mean is technically undefined and thus their use of the mode.

[30] Indeed, I observe a greater SCC under uncertainty, when a 'modal' value of 3.0 (rather than the mean of 3.56) is used to recover the deterministic policy. For the baseline and benchmark scenarios, the SCC under uncertainty is greater, relative to the deterministic SCC, by US$ 4.657 and 3.889 in 2020, rising to US$ 18.226 and 15.322 in 2075. In specification '$\gamma = \vartheta = 0.8$' ('$\gamma = 0.8$ $\vartheta = 0.2$') the SCC is greater by US$ 3.354 (3.322) in 2020, rising to 10.343 (10.051) in 2075.

[31] They model inertia by constraining attainable cumulative abatement per unit change in time.

Table 1 Welfare impacts of uncertainty, in trillion US$

	Climate sensitivity	Damage elasticity	Climate and damage elasticity
'$\gamma = 1.45 \vartheta = 1.45$'	−0.419	0.487	0.323
'$\gamma = 0.75 \vartheta = 0.75$'	−0.652	1.040	0.760
'$\gamma = 0.75 \vartheta = 9.0$'	−0.076	1.259	2.439
'$\gamma = 0.75 \vartheta = 0.2$'	−0.688	1.025	0.662

Welfare impacts calculated as the compensating variation required to return the planner to deterministic welfare

Interacting sources of uncertainty can induce a planner to respond decisively to climate change as the level of risk aversion increases. Figure 3c illustrates the joint effects of damage elasticity and equilibrium climate sensitivity uncertainty. In contrast to the consequences from a single source of uncertainty (panels (a) and (b)), the planner's policy is more responsive to the level of risk aversion with joint uncertainties. More specifically, the 2075 range for the SCC is US$ 38.157 with both the damage elasticity and equilibrium climate sensitivity uncertain. In contrast, it is US$ 15.674 with damage elasticity uncertainty alone, and US$ 5.271 with only equilibrium climate sensitivity uncertainty. Moreover, the SCC in the benchmark scenario is US$ 58.271 above its corresponding deterministic level with joint uncertainties. Yet, it is US$ 40.92 above (US$ 0.902 below) with only damage elasticity (climate sensitivity) uncertainty. These findings demonstrate that interacting uncertainties can justify substantially strengthening climate policy even at reasonable degrees of risk aversion.[32]

Climate policy is strengthened in the presence of interacting sources of uncertainty and increasing risk aversion because a dispersion in future welfare outcomes becomes more costly the more risk averse the planner is.[33] Table 1 presents welfare costs of uncertainty at different levels of risk aversion. The quantities correspond to how much first period consumption would have to be returned to the planner, in order to make them indifferent to uncertainty. With only climate sensitivity uncertainty, the planner gives up some consumption in order to return to the welfare enjoyed under certainty. With only damage elasticity uncertainty, the planner is compensated US$ 0.5–1.3 trillion. This compares with US$ 0.3–2.5 trillion in the presence of both damage and climate sensitivity uncertainty. Finally, observe that in the most plausible specification, the planner must be compensated the most: nearly US$ 2.4 trillion to return to the welfare received under certainty.

---

[32] Figure 5 shows that this pattern continues to hold even when the recalibration of the discount rate is disregarded for the non-baseline specifications.

[33] In fact, with an exogenous Gaussian process for consumption growth and fixed climate policy, it can be shown that the conditional variance of future welfare outcomes reduces present-day welfare for $\vartheta > \gamma = 1$.

5 Conclusions

While Stern (2007) relies on the prescriptive approach of model calibration to advocate for an ambitious response to anthropogenic climate change, the descriptive approach that has been advocated for by Arrow (1999), Dasgupta (2007) and Nordhaus (2007), and is more popular among economists, typically prescribes a much more watered-down policy response to climate change. Of late, preferences that disentangle risk and inequality aversion have been adopted in the climate change literature, not only because they yield a better fit to financial data, but also because they have the potential to reconcile the prescriptive and descriptive approaches of model calibration. In this paper, it has been argued and shown that the large SCC results associated with conventional EZW models stem from a depressed social consumption discount rate and not anything special about disentangling preferences for risk and inequality.

The paper has also contributed to an understanding of the drivers of climate policy under uncertainty. In particular, it was shown that by ignoring interacting sources of uncertainty, analysts may be severely underestimating the cost of climate change. Under joint damage elasticity and equilibrium climate sensitivity uncertainty, this cost was estimated at US$ 2.4 trillion, but was more or less negligible for climate sensitivity alone. Moreover, it was shown that some uncertainties are "more equal than others." Uncertainty about the damage elasticity was found to have a larger impact on climate policy than uncertainty about equilibrium climate sensitivity, even in the presence of risk for the latter. Finally, while it has often been found that climate policy barely responds to the level risk aversion, suggesting that the expected utility framework may be sufficient for uncertainty analysis, here was found that risk aversion features prominently in the presence of both damage elasticity and equilibrium climate sensitivity. This means that relative to expected utility framework, EZW preferences actually present both conceptual and practical benefits for understanding the consequences of uncertainty for climate policy design.

The analysis comes with caveats that can be addressed. Future extensions could for instance investigate the consequence of uncertainties using a finer mass function for the uncertain parameters and also evaluate the impacts of additional sources of uncertainty. The joint impacts of damage elasticity and climate sensitivity uncertainty could also be evaluated in a longrun risk EZW model. Longrun risks have the potential to bridge the quantitative gap between prescriptive and descriptive model calibrations since they give more weight to the degree of risk aversion in setting the risk-free discount rate.

Appendix 1: Extra Graphs

See Figs. 4, 5 and 6.

Appendix 2: Simplified DICE Model

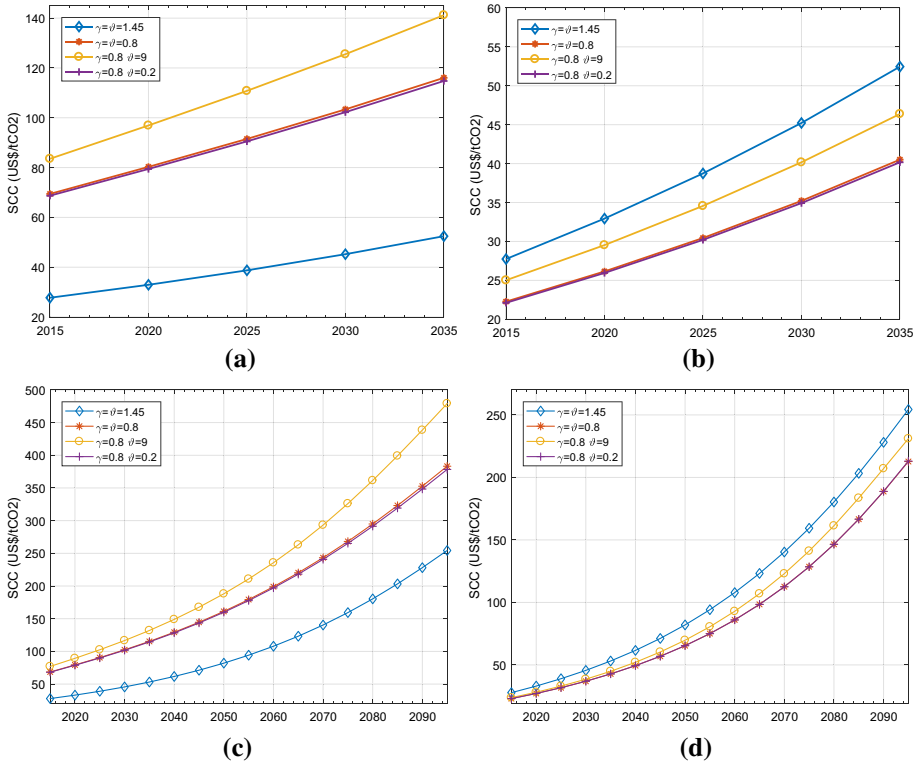DICE's atmospheric temperature Eq. (2), can be reorganized as:

Fig. 4 SCC (in US\$), for alternate degrees of intergenerational inequality aversion and risk aversion. *Notes*: Left panels: simulation with unadjusted pure rate of preference. Right panels: simulations with pure rate of time preference adjusted such that (base year) savings behaviour is consistent across specifications. Top panels: 2040 uncertainty resolution. Bottom panels: 2100 uncertainty resolution

$$T_{t+1} = \left(1 - \Delta_T\right)T_t + z_1\mathcal{F}\left(M_{t+1}\right) - z_2 T_{o,t}$$

where $\Delta_T = z_1 \xi / \zeta - z_1 z_2$. It is immediate that for $\iota > t$, T_t increases in climate sensitivity, ζ, at a decreasing rate. DICE sets $z_2 = 0.008624$, which for simplifying the derivation of the SCC can be set zero, yielding:

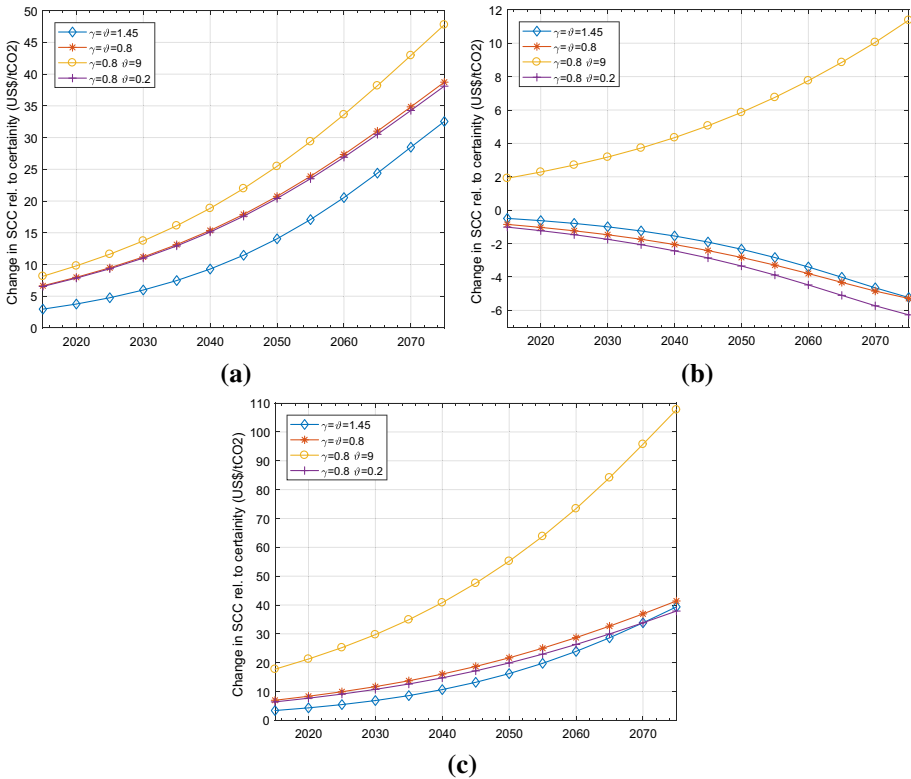$$T_{t+1} = \left(1 - z_1\frac{\xi}{\zeta}\right)T_t + z_1\mathcal{F}\left(M_{t+1}\right)$$

Fig. 5 Response of the SCC to damage elasticity uncertainty (**a**) and climate sensitivity uncertainty (**b**), and the interactive effects of damage and climate sensitivity uncertainty (**c**), for alternate degrees of intergenerational inequality aversion and risk aversion. *Notes*: Each specification shows the difference between the expected SCC and the deterministic SCC derived from the mean of the 'uncertain' damage elasticity and the 'uncertain' climate sensitivity. The renormalization of the savings rate is disregarded in the non-baseline specifications

The parameter z_1 defines the inertia in the climate system. DICE2013 sets this value to 0.098, corresponding to a duration of 51 years. In the counterfactual experiment testing the impact of climate inertia, this parameter is set to 0.25.

Furthermore, it is convenient to disregard the upper and deep ocean carbon sinks and only focus on the atmospheric stock (Jensen and Traeger 2016). The simplified stochastic DICE model becomes :

$$V\left(K_t, M_t, T_t\right) = \max_{C_t, E_t} u_t\left(C_t\right) + \beta \mathbb{E}_t V\left(K_{t+1}, M_{t+1}, T_{t+1}\right)$$

s.t.

$$K_{t+1} = \left(1 - \Delta_K\right) + F\left(K_t, T_t, E_t\right) - C_t$$
$$M_{t+1} := M_{t+1}\left(M_t, E_t\right), \quad T_{t+1} := T_{t+1}\left(M_{t+1}, T_t\right)$$
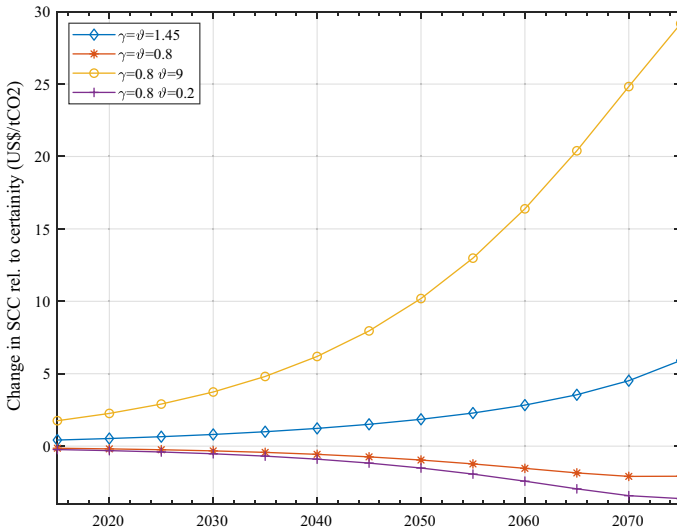
Let $V_t \equiv V\left(K_t, M_t, T_t\right)$

Fig. 6 Response of the SCC to climate sensitivity uncertainty in a counterfactual with higher climate inertia. In DICE, the climate inertia parameter is set to fifty years. In this counterfactual, the climate inertia parameter is set to 20 years. *Notes*: Each specification shows the difference between the expected SCC and the deterministic SCC. The deterministic SCC is obtained using the mean of the 'uncertain' climate sensitivity. Renormalization of the savings rate is pursued for all specifications

Taking FOC with respect to C_t yields:

$$0 = \frac{\partial V_t}{\partial C_t} = u_t'(C_t) + \beta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial K_{t+1}} \frac{\partial K_{t+1}}{\partial C_t} \right]$$

$$u_t'(C_t) = \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial K_{t+1}}$$

and with respect to E_t:

$$0 = \frac{\partial V_t}{\partial E_t} = \beta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial K_{t+1}} \frac{\partial K_{t+1}}{\partial E_t} + \frac{\partial V_{t+1}}{\partial M_{t+1}} \frac{\partial M_{t+1}}{\partial E_t} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial E_t} \frac{\partial M_{t+1}}{\partial M_{t+1}} \right]$$

$$-\frac{\partial F_t}{\partial E_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial K_{t+1}} \right] = \frac{\partial M_{t+1}}{\partial E_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial M_{t+1}} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

$$\text{SCC}_t = \frac{\partial F_t}{\partial E_t} = -\frac{\beta}{u_t'(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial M_{t+1}} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

which is an expression for the SCC.

Finding the quantities $\partial V_{t+1}/\partial M_{t+1}$ and $\partial V_{t+1}/\partial T_{t+1}$ requires differentiating the value function. First consider $\partial V_{t+1}/\partial T_{t+1}$:

$$\frac{\partial V_t}{\partial T_t} = \beta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial K_{t+1}} \frac{K_{t+1}}{\partial T_t} + \frac{\partial V_{t+1}}{\partial M_{t+1}} \frac{M_{t+1}}{\partial T_t} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial T_t} \right]$$

$$\frac{\partial V_t}{\partial T_t} = u'(C_t) \frac{\partial F_t}{\partial T_t} + \beta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial T_t} \right]$$

$$\frac{\partial V_t}{\partial T_t} = u'(C_t) \frac{\partial F_t}{\partial T_t} + \beta \mathbb{E}_t \left[u'(C_{t+1}) \frac{F_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial T_t} \right] + \beta^2 \mathbb{E}_t \left[\frac{\partial V_{t+2}}{\partial T_{t+2}} \frac{\partial T_{t+2}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial T_t} \right]$$

$$\frac{\partial V_t}{\partial T_t} = u'(C_t) \frac{\partial F_t}{\partial T_t} + \sum_{\iota=t+1}^{\infty} \beta^{\iota-t} \mathbb{E}_t \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \prod_{j=t+1}^{\iota} \frac{\partial T_j}{\partial T_{j-1}} \right]$$

$$\frac{\partial V_t}{\partial T_t} = \sum_{\iota=t}^{\infty} \beta^{\iota-t} \mathbb{E}_t \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \left(1|_{\iota=t} + \prod_{j=t}^{j=\iota} \frac{\partial T_{j+1}}{\partial T_j} \bigg|_{\iota>t} \right) \right]$$

$$\frac{\partial V_t}{\partial T_t} = \sum_{\iota=t}^{\infty} \beta^{\iota-t} \mathbb{E}_t \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_t} \right]$$

For $\partial V_{t+1} / \partial M_{t+1}$

$$\frac{\partial V_t}{\partial M_t} = \beta \frac{\partial M_{t+1}}{\partial M_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial M_{t+1}} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

$$\frac{\partial V_t}{\partial M_t} = \beta \frac{\partial M_{t+1}}{\partial M_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial M_{t+1}} \right] + \beta \frac{\partial M_{t+1}}{\partial M_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

$$\frac{\partial V_t}{\partial M_t} = \beta^2 \frac{\partial M_{t+1}}{\partial M_t} \mathbb{E}_t \left[\frac{\partial M_{t+2}}{\partial M_{t+1}} \mathbb{E}_{t+1} \left[\frac{\partial V_{t+2}}{\partial M_{t+2}} \right. \right.$$
$$\left. \left. + \frac{\partial V_{t+2}}{\partial T_{t+2}} \frac{\partial T_{t+2}}{\partial M_{t+2}} \right] \right] + \beta \frac{\partial M_{t+1}}{\partial M_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

$$\frac{\partial V_t}{\partial M_t} = \sum_{\tau=t+1}^{\infty} \beta^{\tau-t} \mathbb{E}_t \left[\frac{\partial V_\tau}{\partial T_\tau} \frac{\partial T_\tau}{\partial M_\tau} \left(\prod_{j=t}^{j=\tau-1} \frac{\partial M_{j+1}}{\partial M_j} \right) \right]$$

Recall that

$$\text{SCC}_t = -\frac{\beta}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial M_{t+1}} + \frac{\partial V_{t+1}}{\partial T_{t+1}} \frac{\partial T_{t+1}}{\partial M_{t+1}} \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \left(\frac{\partial V_t}{\partial M_t} \right) \left(\frac{\partial M_{t+1}}{\partial M_t} \right)^{-1}$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \left(\frac{\partial M_{t+1}}{\partial M_t} \right)^{-1} \sum_{\tau=t+1}^{\infty} \beta^{\tau-t} \mathbb{E}_t \left[\frac{\partial V_\tau}{\partial T_\tau} \frac{\partial T_\tau}{\partial M_\tau} \left(\prod_{j=t}^{j=\tau-1} \frac{\partial M_{j+1}}{\partial M_j} \right) \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \left(\frac{\partial M_{t+1}}{\partial M_t} \right)^{-1} \sum_{\tau=t+1}^{\infty} \beta^{\tau-t} \mathbb{E}_t$$
$$\left[\left(\sum_{\iota=\tau}^{\infty} \beta^{\iota-\tau} \mathbb{E}_\iota \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \right] \right) \frac{\partial T_\tau}{\partial M_\tau} \left(\prod_{j=t}^{j=\tau-1} \frac{\partial M_{j+1}}{\partial M_j} \right) \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \left(\frac{\partial M_{t+1}}{\partial M_t} \right)^{-1} \mathbb{E}_t$$
$$\left[\left(\sum_{\tau=t+1}^{\infty} \sum_{\iota=\tau}^{\infty} \beta^{\iota-t} \mathbb{E}_\iota \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \right] \right) \frac{\partial T_\tau}{\partial M_\tau} \left(\prod_{j=t}^{j=\tau-1} \frac{\partial M_{j+1}}{\partial M_j} \right) \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \left(\frac{\partial M_{t+1}}{\partial M_t} \right)^{-1} \mathbb{E}_t$$
$$\left[\left(\sum_{\tau=t+1}^{\infty} \sum_{\iota=\tau}^{\infty} \beta^{\iota-t} \mathbb{E}_\iota \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \right] \right) \frac{\partial T_\tau}{\partial M_\tau} \frac{\partial M_\tau}{\partial M_t} \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \mathbb{E}_t \left[\sum_{\tau=t+1}^{\infty} \sum_{\iota=\tau}^{\infty} \beta^{\iota-t} \mathbb{E}_\iota \left[u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \right] \frac{\partial T_\tau}{\partial M_\tau} \frac{\partial M_\tau}{\partial M_{t+1}} \right]$$

$$\text{SCC}_t = -\frac{1}{u'_t(C_t)} \frac{\partial M_{t+1}}{\partial E_t} \mathbb{E}_t \left[\sum_{\tau=t+1}^{\infty} \sum_{\iota=\tau}^{\infty} \beta^{\iota-t} u'(C_\iota) \frac{\partial F_\iota}{\partial T_\iota} \frac{\partial T_\iota}{\partial T_\tau} \frac{\partial T_\tau}{\partial M_\tau} \frac{\partial M_\tau}{\partial M_{t+1}} \right]$$

Letting $\frac{\partial M_{t+1}}{\partial E_t} = 1$ gives the expression in the text.

References

Ackerman F, Stanton EA, Bueno R (2010) Fat tails, exponents, extreme uncertainty: simulating catastrophe in dice. Ecol Econ 69(8):1657–1665

Ackerman F, Stanton EA, Bueno R (2013) Epstein–Zin utility in dice: Is risk aversion irrelevant to climate policy? Environ Resour Econ 56(1):73–84. https://doi.org/10.1007/s10640-013-9645-z ISSN 1573-1502

Annan JD, Hargreaves JC (2011) On the generation and interpretation of probabilistic estimates of climate sensitivity. Clim Change 104(3–4):423–436

Arrow KJ (1999) Discounting, morality, and gaming. In: Portney PR, Weyant JP (eds) Discounting and Intergenerational Equity. Resources for the Future, Washington, pp 13–21

Arrow K, Cropper M, Gollier C, Groom B, Heal G, Newell R, Nordhaus W, Pindyck R, Pizer W, Portney P, Sterner T, Tol RSJ, Weitzman M (2013) Determining benefits and costs for future generations. Science 341(6144):349–350. https://doi.org/10.1126/science.1235665

Belaia M, Funke M, Glanemann N (2017) Global warming and a potential tipping point in the atlantic thermohaline circulation: the role of risk aversion. Environ Resour Econ 67(1):93–125. https://doi.org/10.1007/s10640-015-9978-x

Bretschger L, Pattakou A (2018) As bad as it gets: how climate damage functions affect growth and the social cost of carbon. Environ Resour Econ. https://doi.org/10.1007/s10640-018-0219-y

Burke M, Hsiang SM, Miguel E (2015) Global non-linear effect of temperature on economic production. Nature 527(7577):235–239

Burke M, Craxton M, Kolstad CD, Onda C, Allcott H, Baker E, Barrage L, Carson R, Gillingham K, Graff-Zivin J et al (2016) Opportunities for advances in climate change economics. Science 352(6283):292–293

Cai Y, Lenton TM, Lontzek TS (2016) Risk of multiple interacting tipping points should encourage rapid CO_2 emission reduction. Nat Clim Change 6(5):520–525. https://doi.org/10.1038/nclimate2964

Crost B, Traeger CP (2013) Optimal climate policy: uncertainty versus monte carlo. Econ Lett 120(3):552–558

Crost B, Traeger CP (2014) Optimal CO_2 mitigation under damage risk valuation. Nat Clim Change 4:631–636

Dasgupta P (2007) The stern review's economics of climate change. Natl Inst Econ Rev 199(1):4–7

Dell M, Jones BF, Olken BA (2012) Temperature shocks and economic growth: evidence from the last half century. Am Econ J Macroecon 4:66–95

Dietz S, Stern N (2015) Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. Econ J 125(583):574–620

Drupp MA, Freeman MC, Groom B, Nesje F (2018) Discounting disentangled. Am Econ J Econ Policy 10(4):109–34. https://doi.org/10.1257/pol.20160240

Epstein LG, Zin SE (1989) Substitution, risk aversion, and the temporal behavior of consumption and asset returns: a theoretical framework. Econ J Econom Soc 57:937–969

Epstein LG, Zin SE (1991) Substitution, risk aversion, and the temporal behavior of consumption and asset returns: an empirical analysis. J Polit Econ 99(2):263–286

Gollier C, Mahul O, Meddahi N, Nzesseu JT (2017) Term structures of discount rates: an international perspective. Technical report, Toulouse School of Economics

Greenstone M, Kopits E, Wolverton A (2013) Developing a social cost of carbon for us regulatory analysis: a methodology and interpretation. Rev Environ Econ Policy 7(1):23–46. https://doi.org/10.1093/reep/res015

Ha-Duong M, Treich N (2004) Risk aversion, intergenerational equity and climate change. Environ Resour Econ 28(2):195–207

Howard PH, Sterner T (2017) Few and not so far between: a meta-analysis of climate damage estimates. Environ Resour Econ 68(1):197–225

Hwang IC, Reynès F, Tol RSJ (2013) Climate policy under fat-tailed risk: an application of dice. Environ Resour Econ 56(3):415–436

Hwang IC, Tol RSJ, Hofkes MW (2016) Fat-tailed risk about climate change and climate policy. Energy Policy 89:25–35

Hwang IC, Reynès F, Tol RSJ (2017) The effect of learning on climate policy under fat-tailed risk. Resour Energy Econ 48:1–18

Jensen S, Traeger CP (2014) Optimal climate change mitigation under long-term growth uncertainty: stochastic integrated assessment and analytic findings. Eur Econ Rev 69:104–125

Jensen S, Traeger C (2016) Pricing climate risk. Working Paper, School of Economics and Business, Norwegian University of Life Sciences

Keller K, Bolker BM, Bradford DF (2004) Uncertain climate thresholds and optimal economic growth. J Environ Econ Manag 48(1):723–741

Knutti R, Hegerl GC (2008) The equilibrium sensitivity of the earth's temperature to radiation changes. Nat Geosci 1(11):735–743

Knutti R, Rugenstein MAA, Hegerl GC (2017) Beyond equilibrium climate sensitivity. Nat Geosci 10(10):727

Kreps DM, Porteus EL (1978) Temporal resolution of uncertainty and dynamic choice theory. Econom J Econom Soc 45:185–200

Lemoine D, Rudik I (2017a) Steering the climate system: using inertia to lower the cost of policy. Am Econ Rev 107(10):2947–57

Lemoine D, Rudik I (2017b) Managing climate change under uncertainty: recursive integrated assessment at an inflection point. Annu Rev Resour Econ 9(1):117–142. https://doi.org/10.1146/annurev-resource-100516-053516

Lemoine D, Traeger CP (2016) Economics of tipping the climate dominoes. Nat Clim Change 6(5):514–519

Millner A (2013) On welfare frameworks and catastrophic climate risks. J Environ Econ Manag 65(2):310–325

Murphy JM, Sexton DMH, Barnett DN, Jones GS, Webb MJ, Collins M, Stainforth DA (2004) Quantification of modelling uncertainties in a large ensemble of climate change simulations. Nature 430(7001):768–772

Newbold SC, Griffiths C, Moore C, Wolverton A, Kopits E (2013) A rapid assessment model for understanding the social cost of carbon. Clim Change Econ 4(01):1350001

Nordhaus WD (2007) A review of the stern review on the economics of climate change. J Econ Lit 45(3):686–702

Nordhaus WD (2008) A question of balance: weighing the options on global warming policies. Yale University Press, New Haven

Nordhaus W (2014) Estimates of the social cost of carbon: concepts and results from the DICE-2013R model and alternative approaches. J Assoc Environ Resour Econ 1(1/2):273–312

Nordhaus WD (2017) Revisiting the social cost of carbon. Proc Natl Acad Sci 114(7):1518–1523. https://doi.org/10.1073/pnas.1609244114

Nordhaus W, Sztorc P (2013) DICE 2013R: introduction and users manual. Technical report, Yale University. http://aida.wss.yale.edu/~nordhaus/homepage/Web-DICE-2013-April.htm. Accessed June 2018

Revesz RL, Howard PH, Arrow K, Goulder LH, Kopp RE, Livermore MA, Oppenheimer M, Sterner T (2014) Global warming: improve economic models of climate change. Nature 508(7495):173–175

Roe GH, Baker MB (2007) Why is climate sensitivity so unpredictable? Science 318(5850):629–632

Rudik I (2019) Optimal climate policy when damages are unknown. SSRN

Schmidt MGW, Held H, Kriegler E, Lorenz A (2013) Climate policy under uncertain and heterogeneous climate damages. Environ Resour Econ 54(1):79–99. https://doi.org/10.1007/s10640-012-9582-2

Shapiro A, Dentcheva D, Ruszczynski A (2009) Lectures on stochastic programming. MPS-SIAM series on optimization, vol 9. SIAM, Philadelphia, p 3

Stern N (2007) The economics of climate change: the Stern review. Cambridge University Press, Cambridge

Tahvonen O, Quaas MF, Voss R (2018) Harvesting selectivity and stochastic recruitment in economic models of age-structured fisheries. J Environ Econ Manag 92:659–676

Thimme J (2017) Intertemporal substitution in consumption: a literature review. J Econo Surv 31(1):226–257

Tol RSJ (2013) Targets for global climate policy: an overview. J Econ Dyn Control 37(5):911–928

Traeger CP (2009) Recent developments in the intertemporal modeling of uncertainty. Annu Rev Resour Econ 1(1):261–286

Traeger CP (2014) A 4-stated dice: quantitatively addressing uncertainty effects in climate change. Environ Resour Econ 59(1):1–37

Weil P (1989) The equity premium puzzle and the risk-free rate puzzle. J Monet Econ 24(3):401–421

Weil P (1990) Nonexpected utility in macroeconomics. Q J Econ 105(1):29–42

Weitzman ML (2009) On modeling and interpreting the economics of catastrophic climate change. Rev Econ Stat 91(1):1–19