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To cite this article: Alexander Otto *et al* 2013 *Environ. Res. Lett.* **8** 024032

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Climate system properties determining the social cost of carbon

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Abstract
The choice of an appropriate scientific target to guide global mitigation efforts is complicated by uncertainties in the temperature response to greenhouse gas emissions. Much climate policy discourse has been based on the equilibrium global mean temperature increase following a concentration stabilization scenario. This is determined by the equilibrium climate sensitivity (ECS) which, in many studies, shows persistent, fat-tailed uncertainty. However, for many purposes, the equilibrium response is less relevant than the transient response. Here, we show that one prominent policy variable, the social cost of carbon (SCC), is generally better constrained by the transient climate response (TCR) than by the ECS. Simple analytic expressions show the SCC to be directly proportional to the TCR under idealized assumptions when the rate at which we discount future damage equals 2.8%. Using ensemble simulations of a simple climate model we find that knowing the true value of the TCR can reduce the relative uncertainty in the SCC substantially more, up to a factor of 3, than knowing the ECS under typical discounting assumptions. We conclude that the TCR, which is better constrained by observations, less subject to fat-tailed uncertainty and more directly related to the SCC, is generally preferable to the ECS as a single proxy for the climate response in SCC calculations.

The 'social cost of carbon' (SCC) is the present value of the stream of future damage from one additional unit of carbon emissions in a particular year [1]. In an idealized (marginal) assessment of climate change mitigation policy, the optimal level of emissions are determined by a welfare optimization (cost–benefit analysis) that trades-off the marginal costs of reducing emissions against the SCC [2]. Hence the SCC would be equivalent to the price in a perfect carbon market (see [3–10] for the relation between SCC and other indicators in a multi-gas extension). This simple treatment of the climate mitigation problem has several limitations: persistent uncertainties in socioeconomic and biophysical processes, enduring philosophical debates on value judgements about the importance of impacts on species, ecosystems, cultures, human health and mortality, and issues around long-term decision making and discounting preclude a robust estimation of the SCC [9]. These difficulties have led parts of the scientific and political discourse to discuss the climate

problem within an alternative framework (cost-effectiveness analysis) of finding the least cost mitigation policy for staying below a global mean temperature increase relative to the preindustrial state (most prominently below 2° above preindustrial).

However, the cost–benefit framework and the SCC remain important tools, especially within the climate change economics community, which help us investigate important features of climate change such as potentially fat-tailed uncertainty [11], tipping points and learning [12], or the choice of optimal policy instruments [13–15]. In many of these analyses, it is assumed that uncertainty in the climate system's response to emissions can be represented by the equilibrium climate sensitivity, or ECS, defined as the very long-term warming resulting from a doubling of carbon dioxide (CO_2). ECS is subject to persistent, fat-tailed uncertainty [11] which can dominate expected costs. Here we argue that the SCC is usually far more strongly related to the transient climate response (TCR), which only shows thin-tailed uncertainty and can be learned about directly from observations of on-going climate change [16]. This stands in contrast to ECS which, since it is determined in part by processes with very long timescales [17, 18], is learned about much more slowly [16, 19, 20]. Using a simplified (linear) damage function, we give an analytic expression of SCC that shows direct proportionality to TCR. Allowing for more general climate damage, a numerical analysis shows that knowing the true value of TCR can reduce relative uncertainty in SCC substantially more, up to a factor of 3, than knowing ECS under typical discounting assumptions, though this result does not hold for 'outlier' [21] assumptions regarding discount rates and damage functions [22].

1. Idealized analytic example

The warming induced by a pulse injection of an idealized greenhouse gas x whose concentrations decay exponentially with rate constant k_x into an idealized climate system [23] with a linear concentration–forcing relationship, a single effective heat capacity per unit area C_e, and sensitivity parameter λ (λ is the net additional energy radiated to space per degree of warming accounting for feedbacks) is given by the absolute global temperature potential:

$$\text{AGTP}^x(t) = \frac{F_x}{C_e} \frac{(e^{-k_x t} - e^{-k_\tau t})}{k_\tau - k_x}, \tag{1}$$

where $k_\tau = \lambda/C_e$ is the thermal rate constant (inverse feedback response time [17]) and F_x is the forcing immediately after injection. Climate change damage are often assumed as $D(T) = aT^b$. We linearize economic damage for analytic simplicity by assuming a constant percentage reduction in global consumption per degree of warming, D'. This is not as restrictive as it appears, as for most baseline emissions scenarios, the impact of increasing the damage exponent on the response to a small pulse emission is similar to decreasing the discount rate: both increase the weight given to impacts further in the future when the baseline warming is higher (see appendix B). Additionally using an

exponential rate of consumption growth, g, and discount rate r (at which we discount absolute future damage), the discounted present value of climate damage attributable to that pulse emission, or SCC, is:

$$\text{SCC}^x = D' \int_{t=0}^{\infty} \text{AGTP}^x(t)e^{-k_D t}dt$$
$$= \frac{F_x D'}{C_e} \int_{t=0}^{\infty} \frac{(e^{-k_x t} - e^{-k_\tau t})e^{-k_D t}}{k_\tau - k_x}dt, \tag{2}$$

where the discount factor $k_D = r - g$ is the rate at which we discount future damage if expressed as percentage changes in consumption. In the conventional Ramsey model [24], $k_D = (\eta - 1)g + \rho$, where η is a constant representing relative risk (or inequality) aversion and ρ is the pure rate of time preference. Integration the right-hand side of equation (2) yields:

$$\text{SCC}^x = \frac{F_x D'}{C_e(k_x + k_D)(k_\tau + k_D)}$$
$$= \frac{F_x D'}{F_{2x}(k_x + k_D)[(\text{ECS})^{-1} + k_D C_e(F_{2x})^{-1}]}, \tag{3}$$

where F_{2x} is the forcing due to CO_2 doubling. The SCC is separable into a response to emissions, determined by rate of decay of the emission pulse k_x, and a response to forcing, determined by k_τ, which is inversely proportional to ECS [17]. For large values of ECS k_τ becomes small (i.e. $k_\tau \ll k_D$,) except for very low values of k_D, making SCC almost independent of ECS in this 'fat tail' situation.

A better predictor of SCC is given by the transient climate response (TCR), defined as the temperature increase following a constant compound increase in CO_2 concentrations, normalized by the percentage rate of increase per year. TCR is normally defined for a 1% increase, making 70 years the point of doubling, but like ECS the concept applies to more general scenarios. In this simple framework:

$$\text{TCR} = \text{ECS} - \frac{(\text{ECS})^2}{2T_0}\left[1 - e^{-\frac{2T_0}{\text{ECS}}}\right] \approx \frac{1}{(\text{ECS})^{-1} + T_0^{-1}}, \tag{4}$$

where $T_0 = F_{2x}t_0/2C_e$ is the TCR in the absence of any feedback ($\lambda = 0$), with $t_0 = 70$ yr (first equality in equation (4) from equation (6) in [17], approximation found from a Taylor expansion). Comparing equations (3) and (4), it is clear that SCC is approximately proportional to TCR provided the rate at which we discount future damage is equal to double the inverse timescale of CO_2 doubling: $k_D = 2/t_0 = 2.8\%$ yr^{-1}. The validity of the approximation for TCR (right-hand side of equation (4)) is tested in figure 1, which compares the functional forms of SCC and TCR (left-hand side of equation (4)) in ECS for this value of k_D and three representative values of C_e.

The right-hand side of equation (3) is the product of a term that depends on gas properties and a term that depends on climate system properties. This is potentially very useful in applying this concept to other gases. Note that the very long term response summarized by the ECS is even less relevant to the response to emissions of short-lived species like methane.

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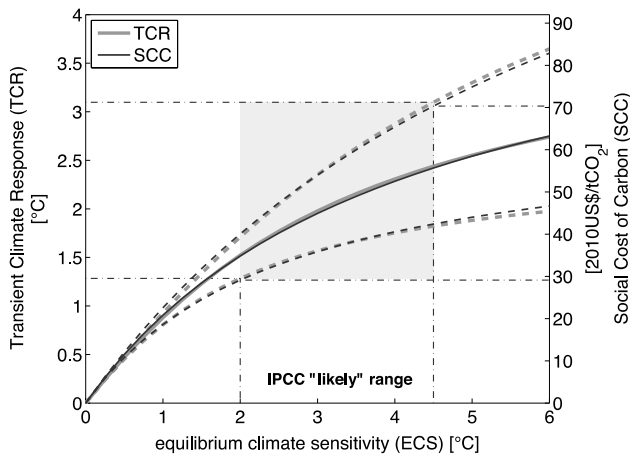
Figure 1. Transient climate response (TRC) and social cost of carbon (SCC) as a function of equilibrium climate sensitivity (ECS) under the simple analytic assumptions about the carbon climate system. Shown is the transient climate response in grey and the social cost of carbon in darker grey. Both functional relationships to ECS are nearly identical for the shown case of an effective discount rate $k_D = 2.8\%$; the constant marginal damage per degree of warming D' is calibrated towards a 2.5% loss of GDP for 3° of warming [2]. Uncertainty in effective ocean heat capacity C_e is represented by showing the expected value (solid lines, $C_e = 1$ GJ K^{-1} m^{-2}) and lower and upper bounds (broken lines, $C_e = [0.6; 1.6]$ GJ K^{-1} m^{-2}).

2. Simple numerical example

Going beyond this special case in which the social costs of carbon are directly proportional to TCR instead of ECS we apply an independent model to investigate how much could be learned about the true value of SCC from gaining perfect knowledge about either ECS or TCR. Thereby we are relaxing the strict artificial assumptions of linear damage and a linear concentration–forcing relationship and replace them by polynomial damage with variable exponents and a carbon cycle model.

It should be noted, however, that (a) we are treating the damage function and discounting as fixed and known, only investigating sensitivity in a Monte Carlo analysis, and that (b) this setup is artificial in that learning about one of the quantities via future observations would lead to gains in knowledge about the other quantity as well. However, as the difference between TCR and ECS stems from the deep ocean heat uptake on longer timescales, the uncertainty about this difference would not be reduced by mid-term observations of atmospheric conditions [25] (i.e. only the TCR part of ECS would be reduced). Nevertheless, the result will allow us to evaluate which of the two is a better predictor for the social cost of carbon.

Using a simple numerical carbon-cycle–climate model [19], we generate a large ensemble of temperature profiles for an RCP4.5 emission scenario (extended to 1765–2300) [26], representing a 'mitigation policy future', and for a RCP4.5 baseline amended by an emission pulse of 10 Gt of carbon as CO_2 in 2012. Following [19], we focus on the response to CO_2 only. Inclusion of non-CO_2 warming would increase

the effective damage exponent for the response to a pulse injection, but should not affect our overall conclusions (see appendix B for a sensitivity analysis w.r.t. stronger pulses and higher background emissions, both of which can be seen as representing additional non-CO_2 warming).

The differences between the ensemble members stem from sampling five uncertain parameters within the carbon cycle and the temperature response. The resulting 5–95% confidence intervals in ECS and TCR are 2.0–5.2 °C and 1.6–3.0 °C respectively. For each of the scenarios we calculate the social cost of carbon of the additional 10 GtC emission pulse. Figure 2 shows the SCC as a function of ECS and TCR in the resulting ensemble for a quadratic damage function and $k_D = 2.8\%$.

TCR is clearly a better predictor of SCC than ECS: on average, the 5–95% confidence interval is 50% of the mean value of SCC for each value of the abscissa in panel (a), and 11% in panel (b). Under these assumptions, learning the value of TCR reduces fractional uncertainty in SCC by 39 percentage points more than learning the value of ECS.

Figure 3 quantifies how TCR and ECS compare as predictors of SCC by plotting this relative reduction in fractional uncertainty for a range of discount rates and damage functions; e.g. a +24 means that learning about TCR instead of ECS would reduce relative uncertainty (in percentage of the mean value) of SCC by 24 percentage points more (e.g. by 54% rather than by 30%).

Using TCR as proxy for SCC is better than using ECS when the difference between discount rate and consumption growth rate is more than about 1% (un-shaded region), though this level increases as the damage exponent rises (see appendix B). Proponents of very low discount rates, and those who believe climate change threatens the levels of consumption growth that the world has enjoyed over the last two hundred years, may find ECS more relevant. Those who think consumption growth is likely to continue much as it has for the last two hundred years, who also use conventional discount rates, will find that TCR outperforms ECS as a predictor for SCC.

The markers in figure 3 represent the discount rates and damage functions used by three prominent groups within the integrated assessment community [2, 11, 22] and the settings used in figure 2. By way of context, recent work quantifying social discount rates in major OECD economies [27] implies $1.6 \leq k_D \leq 2.8$, while for major (populations over 15 million) Latin American countries [28] corresponding values are in the range $1.5 \leq k_D \leq 6.1$, even under modest, historically based assumptions about future growth. The lower bounds of these sorts of ranges would require damage exponents in excess of 6 before ECS would outperform TCR as a proxy for SCC.

For most of these settings, representation of climate uncertainty by the fatter-tailed ECS parameter is misleadingly pessimistic, in that it over-represents climate response uncertainty in SCC (notwithstanding other uncertainties from damage, economic projections, discounting, etc) and underestimates opportunities for reducing climate response uncertainty through future observations. We suggest that those who wish to estimate or use SCC should consider which
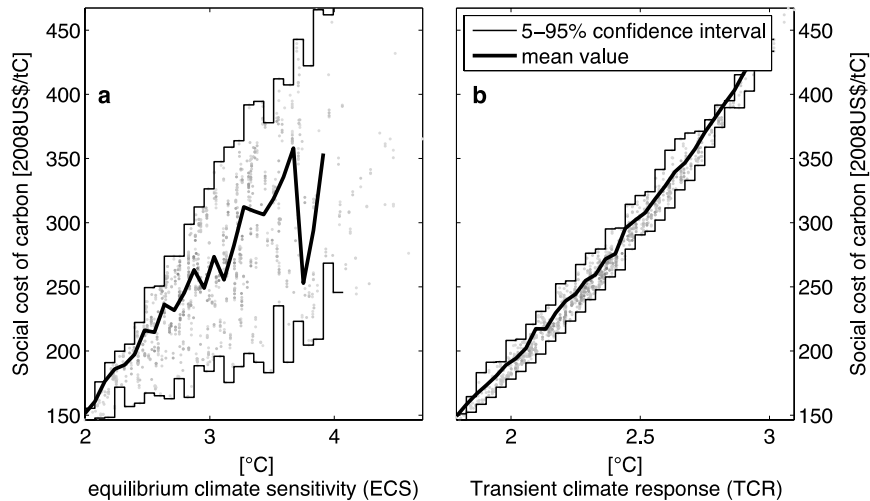
Figure 2. Social cost of carbon (SCC) depending on (a) equilibrium climate sensitivity (ECS) and (b) on transient climate response (TRC) from the ensemble simulations with the simple numerical climate model [23]. Also shown are the limits of the 5–95th percentile confidence interval of a corresponding Gaussian likelihood (thin lines) as well as the expected relationship between SCC and ECS, and TCR respectively (thick lines).
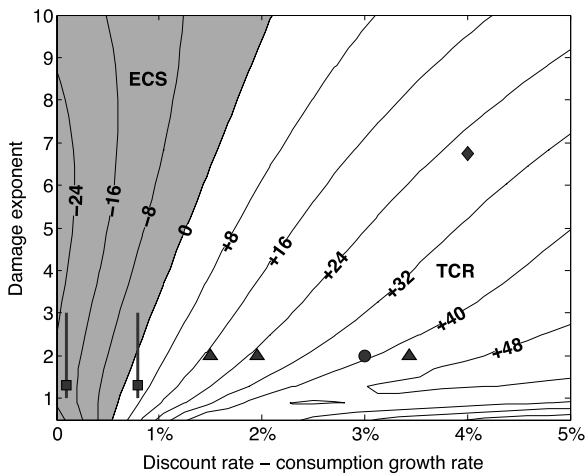
Figure 3. Benefit from perfect learning about TCR instead of ECS in terms of percentage point difference (labels) in the expected reduction in relative uncertainty about the social cost of carbon. Markers show different combinations of settings for discounting and damage function exponents. The triangles show the setting by Nordhaus [2], for different values for the constant relative risk aversion $\eta = \{1, 2, 3\}$. Squares and grey lines show the setting by Stern *et al* [22], with ranges of damage exponents and for values for relative risk aversion of $\eta = \{1, 1.5\}$. The diamond shows the setting by Weitzman [11] (although his damage function additionally includes a quadratic term). The circle shows the settings used in figure 2 ($g = 2, \eta = 2, \rho = 1\%, b = 2$). The grey shading indicates the region in which ECS is a better predictor for SCC than TCR.

climate response parameter (TCR or ECS) is most informative and appropriate, given the other assumptions under which they are working. Except where they are choosing very low discount rates or unusually high damage exponents, TCR will be the more appropriate choice.

3. Methods

The analytic results are deduced from the simplifying assumptions about the carbon cycle and temperature response

to emissions (carbon only), the exponential pulse of emissions, and the linear climate damage. For the numerical analysis of the social cost of carbon from RCP4.5 baseline emissions amended by a 10 GtC emission peak in 2012, we used a simple coupled climate carbon cycle model [19, 29] with five uncertain parameters: Climate sensitivity, ocean thermal diffusivity, ocean/biosphere carbon diffusivity, rate of advection of carbon into the deep ocean, and the carbon cycle temperature feedback parameter. The five parameters are randomly sampled within boundaries given by observations [19]. The boundary of our ensemble is chosen to represent the 5–95% confidence interval of an underlying normal distribution, representing the 'IPCC's very likely' category [30]. The panels in figure 2 are produced by calculating the social costs of carbon for all of the ensemble scenarios and for a given set of growth, discounting and damage assumptions and projecting them against the corresponding values of ECS and TCR. For quantifying the predictor quality of TCR versus ECS this calculation is repeated for a large set of damage exponents and discount and growth rates. We calculate the fractional uncertainty left when perfectly knowing ECS (or TCR), take the expected value over all possible ECS (TCR) values, and compare it to the original fractional uncertainty in the full SCC ensemble. The difference of this indicator of expected percentage reduction of fractional uncertainty in SCC between learning about TCR and ECS is shown in figure 3 (see appendix A for details).

Acknowledgment

Author contributions

MRA and DJF provided the simple climate model. MRA and BJT conceived of and developed the analytic argument. NB generated the parameter ensemble for the numeric modelling. AO ran the simple climate model, conducted the numeric SCC calculations and produced figures 2 and 3. All authors contributed to writing the paper.

Appendix A. Measuring the benefits of perfect learning about TCR instead of ECS

Throughout the paper and the appendices the terms uncertainty and risk are used synonymously, describing a random variable with a known probability distribution function or a given confidence interval.

Let $Y = Y(X)$, $X = (x_1, \ldots, x_i, \ldots, x_j, \ldots, x_n)$ represent an ensemble of values for the social cost of carbon (SCC) depending upon $n = 5$ uncertain parameters in the climate cause–effect chain, with x_i representing equilibrium (or in this case, effective [17]) climate sensitivity (ECS), and x_j representing transient climate response (TCR). The ensemble originates from constraining the uncertain parameters by observations and deriving equally probable samples within a confidence interval equivalent to the IPCC's (AR4) 'very likely' (>90%) interval. The relative uncertainty in the social costs of carbon represented by the ensemble is defined by:

$$\triangle Y = \frac{\max_X Y - \min_X Y}{\frac{1}{2}[\max_X Y + \min_X Y]}. \quad (A.1)$$

We say that x_i 'is a better proxy' for Y than x_j, if gaining perfect knowledge about x_i constrains the uncertainty in Y further than gaining perfect knowledge about x_j. More formally, we define the expected relative uncertainty of Y after perfect learning about x_i via:

$$\overline{\triangle Y|_{x_i}} = \sum_{i=1}^{m} p(x_i) \triangle Y|_{x_i}$$

$$= \sum_{i=1}^{m} p(x_i) \frac{\max\limits_{X|_{x_i}} Y - \min\limits_{X|_{x_i}} Y}{\frac{1}{2}[\max\limits_{X|_{x_i}} Y + \min\limits_{X|_{x_i}} Y]}, \quad (A.2)$$

and the expected percentage reduction in relative uncertainty about Y through perfect learning about x_i via:

$$R_{x_i}(Y) = 100 \times \frac{\triangle Y - \overline{\triangle Y|_{x_i}}}{\triangle Y}. \quad (A.3)$$

Hence, we take the difference of the expected percentage reduction in relative uncertainty about Y through perfect learning about x_i rather than about x_j as an indicator for being a better proxy for Y:

$$I_{i,j} = R_{x_i}(Y) - R_{x_j}(Y), \quad (A.4)$$

which is shown in figure 3.

Appendix B. Sensitivity analysis of the benefit of perfect learning about TRC instead of ECS

The social cost of carbon (SCC) is a marginal concept for calculating the monetized impact of the 'next' ton of emissions (or rather a pulse of emissions, but small relative to the emission baseline). The result of TCR being a better proxy for SCC than ECS, over a wide range of effective discount rates and damage functions might depend on the baseline emission scenario. Another effect impacting upon
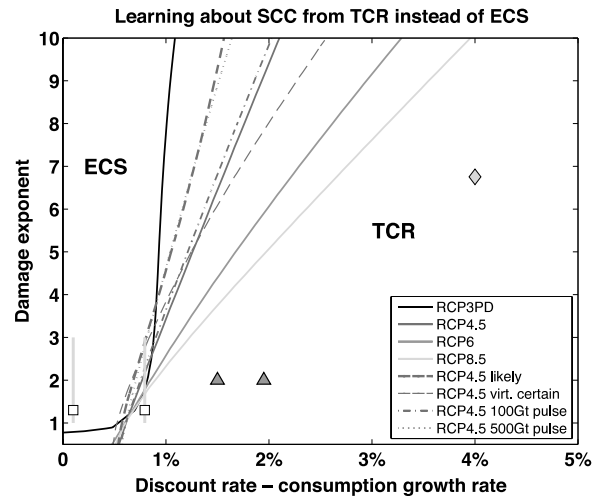
Figure B.1. Sensitivity analysis of the benefit of perfect learning about TCR instead of ECS, shown is the boundary between the regimes in which TCR is a better (right-hand side) or worse (left-hand side) proxy for SCC than ECS. Sensitivity is investigated for four different RCP baseline emission scenarios (solid lines, shades of grey), for three different levels of constraining the ensemble representing the confidence intervals of an underlying Gaussian distribution, with levels corresponding to the IPCC ranges of 'likely', 'very likely' (default), and 'virtually certain', and finally for three different amplitudes of the emission pulse used for calculating the SCC: 10 GtC (default), 100 GtC, and 500 GtC. The markers representing discounting and growth assumptions are equivalent to figure 3.

the comparison of TCR versus ECS might come from the cut-off introduced in the ensemble design process, where only samples are kept that lie within a given confidence interval of an underlying Gaussian distribution, where the default value of taking the 5–95th percentile represents the IPCC category of taking the 'very likely' boundaries of the ensemble.

Finally, the limits of the marginal approximation were tested by investigating the impact of bigger, potentially non-marginal, emission pulses, as a small pulse size 'linearizes' any damage function.

Hence the investigation of the expected reduction in relative uncertainty of SCC by perfect learning about TCR, or ECS was repeated for four different baseline emission scenarios, which represent the CO_2-only emissions from the RCP scenarios [26], for three different amplitudes of the additional emission pulse (10 GtC, 100 GtC, 500 GtC), and for different confidence intervals of an underlying Gaussian distribution representing the IPCC's categories of 'likely' (>66%), 'very likely' (>90%), and 'virtually certain' (>99%), whereby we always started from RCP4.5 as a base case and changed one property at a time. The resulting boundary between the regimes in the space, spanned by effective discount rate and damage function exponent, in which TCR or ECS are 'better proxies' for the social cost of carbon are shown in figure B.1.

While TCR remains the better proxy for SCC for the majority of combinations of published damage exponents and observed social time preference rates, we note a general tendency of ECS being the 'dominant' proxy for a larger

range of discount rates and damage functions the higher the baseline emission scenario. Higher emissions scenarios make ECS more relevant for rapidly rising damage functions because those damage functions are extremely sensitive to small changes in larger numbers. Likewise, increasing the fraction of the distribution covered in the analysis makes ECS more relevant, again at higher damage functions, for the same reason: because the combination of higher numbers raised to powers greater than four somewhat offsets more of the effect of the discounting. However this effect is pronounced only for rather high damage exponents, within the range of exponents broadly used (<3) TRC remains a better proxy for SCC, given that the effective discount rate is $>1\%$. Changing the ensemble design by demanding a higher level of confidence (i.e. including more ensemble members) induces the same tendency of extending the regime in which ECS is a better proxy towards higher effective discount rates. Again, this tendency is only significant for high damage function exponents.

Testing the limits of the marginal approximation shows that higher amplitudes of the emission pulse added to the baseline have the opposite effect to a higher level of confidence and a higher emission baseline, by shifting the boundary between the TCR and ECS regimes towards lower effective discount rates.

Our main conclusion is that TCR is a better proxy for SCC than ECS for a wide range of effective discount rates ($>1\%$) and damage function exponents, including many settings used in prominent integrated assessment studies. This result is robust under changes to the emission baseline, ensemble design, and the amplitude of the emission pulse, up to about quadric damage functions. Damage of this order or higher is rare in the integrated assessment literature.

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