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Frances C. Moore, Moritz A. Drupp, James Rising, Simon Dietz, Ivan Rudik, Gernot Wagner

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Synthesis of Evidence Yields High Social Cost of Carbon Due to Structural Model Variation and Uncertainties

Abstract

Estimating the cost to society from a ton of CO2 - termed the social cost of carbon (SCC) - requires connecting a model of the climate system with a representation of the economic and social effects of changes in climate, and the aggregation of diverse, uncertain impacts across both time and space. Increasingly a growing literature has examined the effect of fundamental structural elements of the models supporting SCC calculations. This work has accumulated in piecemeal fashion, leaving their relative importance unclear. Here we perform a comprehensive synthesis of the evidence on the SCC, combining 1823 estimates of the SCC from 147 studies with a survey of authors of these studies. The distribution of published 2020 SCC values is wide and substantially right-skewed, showing evidence of a heavy right tail (truncated mean of $132). Analysis of variance reveals important roles for the inclusion of persistent damages, representation of the Earth system, and distributional weighting. However, our survey reveals that experts believe the literature is biased downwards due to an under-sampling of structural model variations and biases in damage-function and discount-rate. To address this imbalance, we train a random forest model on variation in the literature and use it to generate a synthetic SCC distribution that more closely matches expert assessments of appropriate model structure and discounting. This synthetic distribution has a mean of $284 per ton CO2, respectively, for a 2020 pulse year (5%–95% range: $32–$874), higher than all official government estimates, including a 2023 update from the U.S. EPA.

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Keywords: social cost of carbon.

*Frances C. Moore**
Department of Environmental Science and Policy, University of California Davis
Davis / CA / USA
fmoore@ucdavis.edu

Moritz A. Drupp
Department of Economics and Center for Earth System Research and Sustainability (CEN), University of Hamburg / Germany
Moritz.Drupp@uni-hamburg.de

James Rising
School of Marine Science and Policy
University of Delaware, Newark / DE / USA
jrising@udel.edu

Simon Dietz
London School of Economics
London / United Kingdom
s.dietz@lse.ac.uk

Ivan Rudik
Dyson School of Applied Economics and Management, Cornell University
Ithaca / NY / USA
irudik@cornell.edu

Gernot Wagner
Columbia Business School
New York City / NY / USA
gwagner@columbia.edu

*corresponding author

1 Introduction

Anthropogenic climate change affects the welfare of people around the world, and will continue to do so for centuries into the future. Because these costs are largely not incorporated into energy, land-use, and other economic decisions, climate change has been termed "the greatest and widest-ranging market failure ever seen" [1, p. i]. Incorporating climate costs into the prices of economic activities that emit greenhouse gases, either directly through carbon pricing or indirectly through emission-regulation or subsidies of cleaner alternatives, is essential for averting the worst climate outcomes. Quantifying these costs is extremely challenging as it involves projecting and valuing the effects of climate change in all countries and sectors far into the future, an exercise that is rife with uncertainties and contestation.

The external costs of carbon dioxide (CO_2) emissions are summarized by the 'social cost of carbon' (SCC): the present value of all future impacts from an additional metric ton of CO_2 emissions. The SCC is key for understanding the benefits of emissions-reduction policies and is used for climate and energy policy analysis in the United States, Europe, and numerous other countries and sub-national jurisdictions around the world as well as by companies and other institutions [2, 3]. Integrated assessment models (IAMs) commonly used to calculate the SCC have been criticized on various grounds, including inaccurate climate and carbon-cycle modeling, ignoring irreversibilities and tipping points in the climate system, failing to adequately model uncertainty or the potential for catastrophic outcomes, and relying on dated science in the representation of climate impacts [4–8].

The continuing importance of the SCC as a tool for climate policy analysis [2] and recognition of failings in IAMs currently used to calculate it has led to a surge of research seeking to improve, expand, and update the estimates. Major strands of this literature include: improving modeling of Earth system dynamics [9–12]; disentangling preferences over risk and time using more complex utility functions [13–15]; representing tipping points and associated uncertainties in damages [16–19]; addressing model uncertainty, ambiguity, and learning of new information [20–24]; allowing climate damages to affect the growth rate rather than just the level of economic output[11, 25–27]; calibrating aggregate climate damages on recent economic and scientific evidence [11, 20, 25, 28, 29]; modeling the distribution of climate damages and incorporating inequality aversion [30–32]; and allowing for climate damages to non-market goods, such as natural systems or cultural heritage, which are imperfectly substitutable with market-traded goods [33–36]. (Section S3 contains more detailed discussion and examples of different elements of model structures used to calculate the SCC discussed in this paper).

Although this literature is now substantial, it has accumulated piecemeal. The vast majority of papers make one or two structural adjustments to a simpler IAM and report how these alter SCC values, often with an exploration of associated parametric uncertainty. The collective implications of the full suite of issues addressed by this literature have not been assessed. Previous syntheses have quantified the distribution of SCC estimates and explored a limited set of covariates, such as publication year and discounting [37, 38], as well as the possible role of publication bias [39]. Previous modeling studies have made multiple simultaneous changes to individual IAMs [12, 40], or have undertaken systematic IAM inter-comparisons and evaluations [41, 42], albeit focusing on a limited number of IAMs with comparable model structures. Previous expert surveys have either imposed very specific structure or none at all [43–45], or have focused on carbon prices [46]. Thus, prior studies only illuminate the role of a subset of mechanisms and structural models.

This paper provides the most comprehensive assessment to date of SCC estimates, including how elements of model structure shape the SCC. It builds on two complementary approaches. First, we perform an analysis of SCC values published in the peer-reviewed literature between 2000 and 2020. After reviewing over 2800 abstracts, we identified 1823 estimates (or distributions of estimates) published in 147 studies. We recorded SCC estimates and, where reported, the distribution of parametric uncertainty, along with 31 covariates capturing details of the estimate itself (e.g., SCC year, discounting scheme, and socio-economic and emissions scenarios), important elements of model structure (e.g., growth-rate damages, distributional weighting, and representation of the utility function), and sources of parametric variation (e.g., distributions over productivity growth, climate sensitivity, discount rates and damage-function parameters). Second, to help place the literature distribution in a broader context, we conduct an expert survey of the authors of the SCC papers in our analysis. We elicit expert estimates of both the distribution of published SCC values in the peer-reviewed literature and their best estimate of the SCC distribution, all things considered. We also ask experts to break down the wedge between these two SCC estimates into component parts, generating information on what experts perceive as potentially missing from on underrepresented in the literature. Furthermore, we elicit experts' views on the degree to which various model structures as currently implemented in the literature *improve* SCC estimates, using this quality assessment to inform our final synthetic SCC estimate.

Our study therefore contains two complementary data-generating processes: a meta-analysis, which collects much richer data on published SCC estimates and their determinants than in previous studies, and an expert survey. We combine these lines of evidence to produce a synthetic SCC distribution using a random forest model trained on variation in the literature but sampled to more closely match experts' assessment of model structure and discounting parameters. The resulting SCC distribution essentially amounts to a structured re-weighting of published SCC estimates to better match expert-elicited model structure and discounting, emphasizing features identified by the random forest model as most important in driving variance in the SCC distribution. Additional details on the literature review, coding of values, data cleaning and processing, expert survey, construction of the synthetic SCC are provided in Section S2.

2 The SCC Distribution

The systematic review of the literature yields 1823 SCC estimates (or distributions) from 147 studies (full references given in Section S4). Many studies report multiple SCC estimates. For each of the 1823 estimates, we collect information on the central SCC estimate, emission pulse year, discounting, damage function, economic and emissions scenario, model structure, and distribution resulting from parametric uncertainty (where reported, specifically 832 of the 1823 estimates). Section S1 provides descriptive statistics and summary information on these estimates.

To characterize the distribution of SCC values appearing in the published literature, we sample from the dataset using a hierarchical sampling scheme. We draw 10 million SCC values sampling uniformly from the 147 studies in the dataset, then sample uniformly from the set of estimates within each paper (i.e. unique SCC year-discounting-scenario-model structure combinations), and finally from the parametric uncertainty of each estimate, if applicable. Alternate sampling schemes that account for non-independence between papers using sets of shared authors, or for different quality of studies using a normalized citation-based weighting, give quantitatively similar distributions (Table S4).

Figure 1 shows the distribution of SCC values reported in the literature, both across all estimates (top row) and split based on characteristics of the estimates and studies. The Figure gives the distribution of SCCs for pulse years between 2010 and 2030, which we use as the 2020-SCC equivalent sample from the literature. The variation in SCC values is substantial and asymmetric, exhibiting a long right tail, and a mean value (\$132 per tCO_2 after truncating the upper and lower 0.1% of values) that is several times times higher than the median (\$39). Statistical tests show evidence for a heavy tail in the SCC distribution [8], echoing Anthoff and Tol [47], with a slope of the mean excess function greater than 1 and α values between 1 and 2, indicative of a distribution with infinite variance but finite mean (see Table S5 in the SI).

Figure 1 also shows how the 2020 SCC distribution differs based on particular characteristics of the estimate. The second panel shows variation across model structure, relative to a set of reference estimates with similar structure to the original DICE model (versions up to 2016). These suggest important roles for the representation of the Earth system, the persistence of damages to the economy via impacts on the growth rate, and limited substitutability between aspects of climate damages and consumption goods in the utility function. The third panel shows the well-documented sensitivity

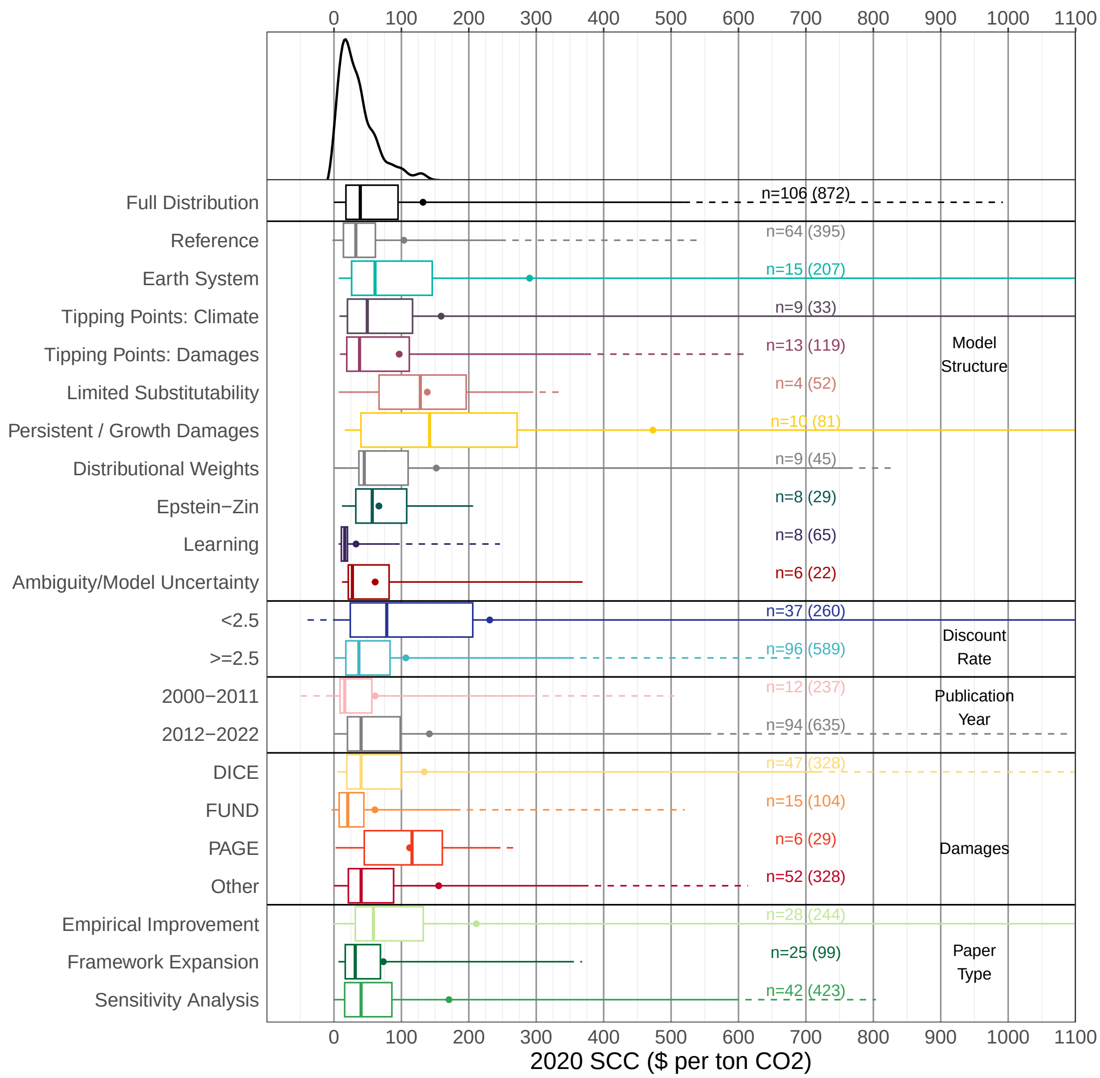

Figure 1: **Distribution of the 2020 SCC from the published literature (2020 \$ per ton CO_2).** Distribution and top boxplot show the distribution of all 2010-2030 SCC values (which we treat as the 2020-equivalent sample) from the published literature (equal weighting of all 147 papers). Other boxplots show subsets of the 2010-2030 distribution split by characteristics of published estimates, specifically model structure, discount rate, publication year, damage function, and paper type. The reference distribution refers to SCC estimates coded as not having structural changes, similar to the DICE model (versions up to 2016). Boxplots show the median (line), inter-quartile range (box), 5-95% range (solid line) and 2.5-97.5% range (dashed lines). Dots show the mean after trimming the upper and lower 0.1% of each distribution. Numbers for each plot show the number of papers and, in parentheses, the number of estimates included in each boxplot.

to discounting assumptions, with estimates using less than a 2.5% discount rate producing an SCC distribution with median and mean values twice those obtained using higher discount rates ($231 per ton CO_2 vs $107 for the truncated mean, $78 vs $37 for the median). The fourth panel documents a shift towards higher SCC values in papers published in the second half of our sample period, a finding similar to that reported previously [38].

The final panel in Figure 1 shows estimates disaggregated by whether the primary goal of the paper was one of empirical improvement (e.g., more accurately representing Earth system dynamics or improving damage function estimation), integration of new elements into SCC models (e.g., integrating model ambiguity, inequality aversion, or Epstein-Zin utility), or sensitivity analysis (e.g., SCC variation with alternate damage functions or discount rates). It shows fairly similar distributions across the three paper types, but with slightly higher SCC values in papers introducing empirical improvements.

2.1 Drivers of Variance in SCC Estimates

Figure 1 documents wide variation in published SCC estimates. The large set of covariates we record allows us to investigate how many different features of SCC modeling—including structural model features, parametric uncertainty, and other model covariates—affect SCC values. While Figure 1 shows distributions under different univariate splits of the data, multivariate analysis can better identify the effects of particular model structures and parameter values. Figure 2a shows estimated effects of structural model characteristics on SCC values after controlling for other aspects of model structure, SCC year, emissions and socio-economic scenarios, and discount rate. We plot relative changes in the SCC attributable to individual elements of model structure, relying on the fact that many papers report modeling results both with and without model changes in order to highlight relative effects. These are recorded explicitly in our data collection process and form the basis of the results shown in the figure.

Figure 2a shows large increases in the SCC (on the order of 50%) due to a number of structural model elements, specifically improvements to the representation of the Earth system, inclusion of impact tipping points, and elements of damages such as limited substitutability with consumption goods and persistent effects on economic output. Inclusion of distributional weights (typically used to represent aversion to inequality) has the largest effect on relative SCC values, on average more than doubling estimates, reflecting the regressive nature of climate-change impacts, [48, 49]. Allowing for learning over time (typically about equilibrium climate sensitivity or the damage function) tends to decrease the SCC. This is consistent with theoretical models showing that the additional emissions allowed by laxer climate policy can provide a more informative signal about uncertain parameters and lead to

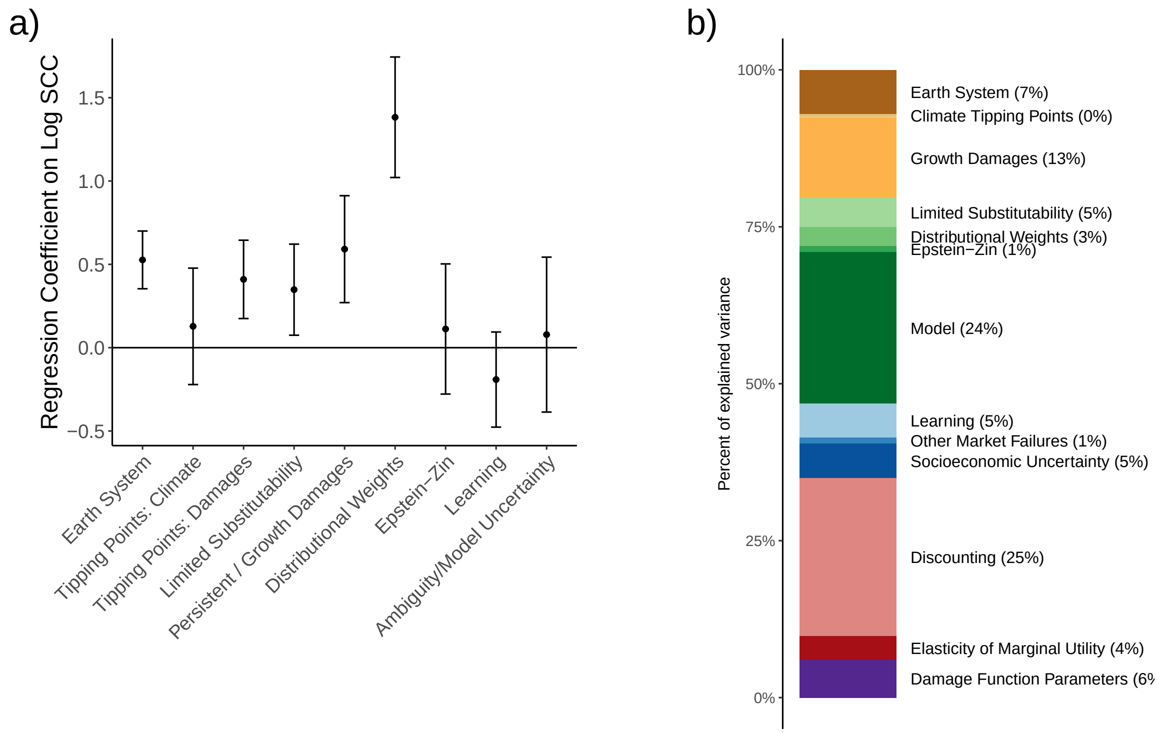

Figure 2: **Drivers of variance in published SCC estimates.** a) Effects of structural model characteristics on log SCC, controlling for other aspects of model structure, SCC year, emissions and socio-economic scenarios, and discount rate. b) ANOVA decomposition of the variance of logged SCC estimates in the literature, based on a regression of the full distribution of logged SCC estimates on the full set of covariates describing discounting, model structure, and inclusion of parametric uncertainty, as well as paper fixed-effects.

better future climate policy [24]. Additional regression models using other types of variation in the data are reported in Section S.2.1.9 and Figure S9.

Figure 2b shows results of an ANOVA decomposition of the SCC variance in the full distribution, after controlling for individual papers' mean values through the inclusion of paper fixed effects. Figure 2b shows that the single largest driver of the variance is discounting, followed by model and model uncertainty (i.e., this groups together the identity of the IAM, e.g., DICE, FUND, or PAGE, with the model uncertainty/ambiguity structural model effects), persistent/growth damages, and the Earth system representation (i.e., transient climate response, carbon cycle parametrization, equilibrium climate sensitivity, and structure of the Earth system model component). Note that the overall share of the variance explained by discounting and damage-function parameters (i.e., damage function, adaptation rates, and the income elasticity of damages) is only 35%, with most of the remainder relating to structural model choices and model uncertainty.

3 Placing the SCC Literature in Context Through Expert Surveys

Figure 1 shows the distribution of 2020 SCC values published in the scientific literature between 2000 and 2020. Although it provides a useful reference point to characterize SCC values across the full set of published studies, this distribution lacks a clear interpretation. The literature distribution may be influenced by factors such as researcher interest, model availability and tractability, and path-dependency in choices of certain model parameters such as those in the discount rate and damage function, issues discussed in more detail in S.2.2.3. Therefore, we complement the literature survey described in Section 2 with a survey of expert views on the SCC literature, placing this distribution and the set of model structures and parameters that determine it into a larger context. We distributed a survey to the population of 176 authors of SCC estimates in our literature review in May 2022, from which we received 68 partial and 48 full responses. Section S.2.2 provides further details on survey design, distribution, and analysis.

Figure 3a provides evidence that survey respondents perceive a substantial downward bias in the published literature. More than four fifths of experts (82.8%) report best-estimate SCC values (considering all drivers of the SCC and relevant uncertainties) that are higher than their estimates of the existing literature distribution (9.1% believe the two values are roughly equal, and the same number believe the literature is over-estimating the SCC). On average across complete responses, experts' best-estimate 2020 SCC (\$142 per ton CO_2) is more than double their literature estimate of \$60.

Experts' mean literature estimate is substantially below the mean from our literature analysis of \$132, and about 50% larger than our literature median of \$39 (Figure 1). A number of reasons could account for why experts underestimate the mean SCC in the literature, including the exclusion of papers published prior to 2000 from our literature survey (which may report lower values [38]), the prominence of focal SCC estimates around \$50 for instance from official US government guidance at the time of the survey [51], or experts being unfamiliar with some of the papers contributing to the long right tail of the SCC distribution that have a substantial effect on the mean value (see Section S.2.1.6 for further discussion).

Figure 3b shows how experts decompose the perceived downward bias in the literature into constituent elements (individual responses documenting significant heterogeneity in both the wedge magnitude and decomposition are shown in Figure S19). Damage-function and discounting parameters make up around a third of the \$82 wedge between the experts' estimates. Around two thirds of the SCC wedge is driven by structural model choices, particularly limited substitutability of non-market goods (13%),

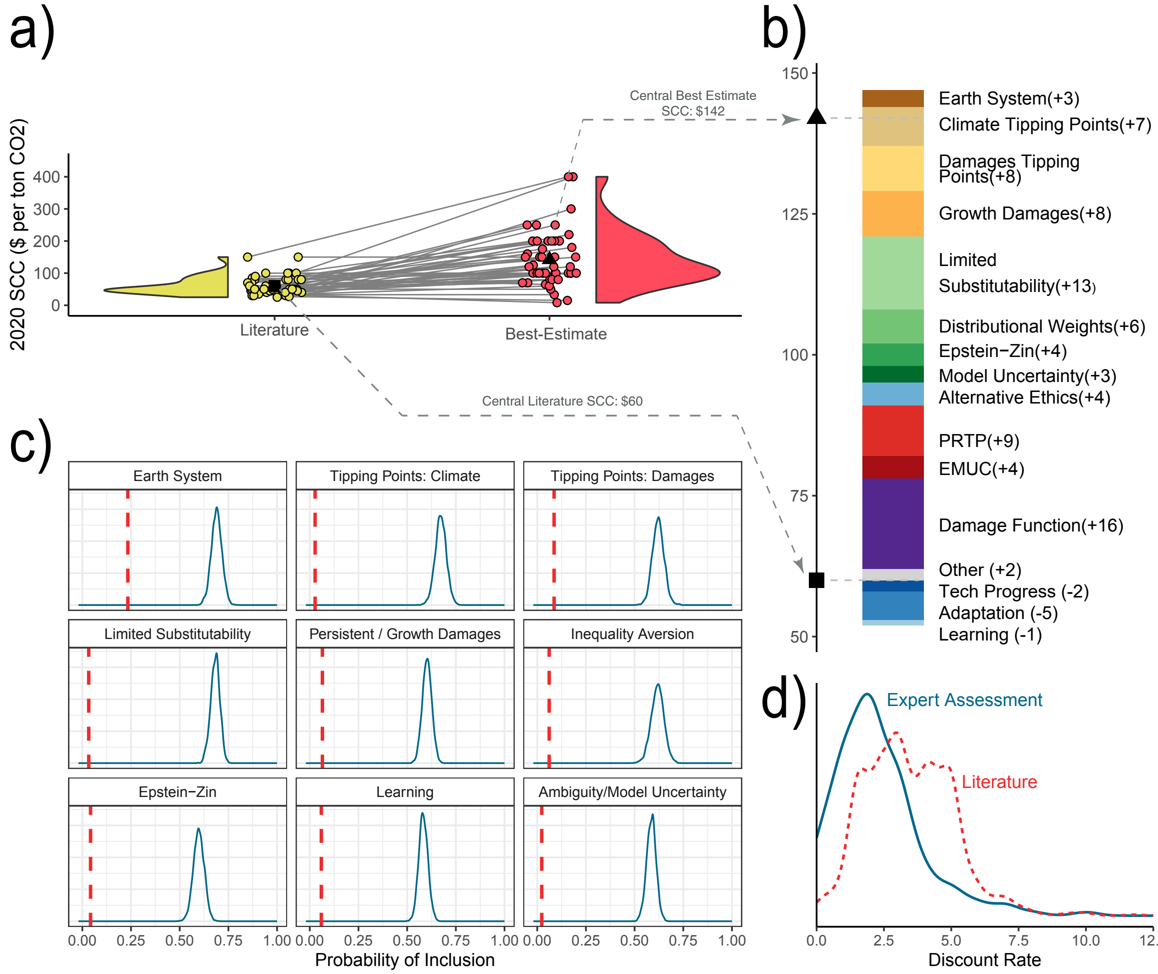

Figure 3: **Expert survey on SCC values, model structure, and discounting.** a) Expert assessment of the mean SCC value in the literature and their best estimate of the mean of the SCC distribution, accounting for any systematic biases or over- or under-representation of different model elements in the published literature. Grey lines connect estimates from the same respondent. Data shown for 48 experts providing a quantitative breakdown of the wedge between literature and best-estimate SCCs. Mean values for all 68 experts are $66 for the literature and $160 for the best-estimate. b) Experts' attribution of the difference between their estimated mean literature SCC value and the full or comprehensive SCC. Results shown averaging over all 48 expert responses, decomposing the average wedge between $60 per ton CO_2 and $142. Values in parentheses show the dollar value attributed to each element. PRTP = pure rate of time preference; EMUC = elasticity of marginal utility of consumption. c) Expert evaluation of 9 elements of model structure (blue solid line) with frequency in the published literature shown for comparison (red dashed line). Expert responses to the question "To what extent do you agree with the statement: 'Papers that include X produce better SCC estimates than those that exclude it'?" (Figure S20) are converted into model inclusion probabilities using Bayesian hierarchical modeling of expert responses (described in Section S.2.2.6) d) Distribution of discount rates in an expert assessment by Drupp et al. [50] (blue solid line) compared to the distribution in the published literature for 2020 SCC values (red dashed line).

persistent/growth damages (9%), tipping points in the climate system (8%) and in damages (8%), and distributional weights (6%). Experts also estimate a smaller upward bias in literature estimates related to an under-representation of technical progress, adaptation and learning, which contribute negatively to the SCC wedge.

Figures 3c and 3d compare expert assessment of key determinants of the SCC (specifically model structure and discounting) with their representation in the published literature. Overall, experts are positive on the 9 variations in model structure investigated. Over 50% of experts agree or strongly agree that models including these elements are preferred (over a baseline model approximating the DICE-2016 IAM [52] with a 2020 SCC of around \$40 per tCO_2) for all elements except aversion to model uncertainty or ambiguity (Figure S20). The strongest agreement is on improvements to Earth system modeling, including the integration of climate-system tipping points, and the incorporation of limited substitutability between market and non-market goods in the utility function, with some polarization over the issue of whether distributional weighting, as applied in the literature, improves SCC estimates.

Figure 3c shows these responses converted into a joint probability distribution over model structure (i.e. inclusion or exclusion of the different structural model elements) using a hierarchical Bayesian model (described further in Section S.2.2.6). Because of general agreement among experts on the value of these structural model elements, average probabilities are high, ranging from a mean of 0.58 for ambiguity or model uncertainty to 0.69 for Earth system improvements. Representation of these model structures in the published literature, however, is far lower, with values ranging from 0.23 (Earth system modeling) to 0.02 for climate tipping points and model ambiguity.

Figure 3d depicts a similar gap between expert assessment of discount rates (based on a prior expert survey reported in Drupp et al. [50]) and the distribution in the literature, with economic experts giving a mean of 2.3% (similar to recommendations by expert philosophers found in a related survey [53]), more than a percentage point lower than the literature mean of 3.4%. Figures 1 and 2 both suggest that these discrepancies in model structure and discounting between the published literature and expert assessment would push published SCCs downward, validating experts' concerns over a downward bias in the literature (Figure 3a), and the attribution of this bias (Figure 3b).

4 The Synthetic SCC Distribution

4.1 Motivation and Approach

In order to address the potential bias in the published literature documented in Figure 3c and d, we combine information from both the literature analysis and expert assessments to generate a synthetic SCC distribution that more closely matches expert assessment of discounting and model structure. This process involves first using the variance across the 1823 published SCC distributions with 31 explanatory variables to train a random forest model, then generating predictions from this model using distributions over input variables based on expert survey results shown in Figures 3c and d. This amounts to a re-weighting of the literature to produce an SCC distribution with structure and discounting characteristics closer to expert assessments (and with other desirable characteristics, such as recent publication year, inclusion of parametric uncertainty, and inclusion of non-market damages). The random forest model identifies which set of variables are most important in driving variance across SCC distributions, and should therefore be targeted for re-weighting.

The random forest model estimates a set of 500 regression trees, each based on the 31 explanatory variables and a random bootstrap of the 1823 SCC estimates. At each branch in the tree, the algorithm chooses the variable from of a random sample of 10 of the possible 31 variables that divides the sample into two groups with the largest variance between them. Our data structure is unusual in that each of the 1823 observations are a distribution (of which 54% are single-estimate point distributions). We therefore use an adapted splitting algorithm based on the Anderson-Darling k-Sample test to maximize distance between the two distributions at each split. Trees with fewer than 7 nodes or very large leaves are pruned, leaving a final 403 regression trees.

Figure S21 shows the importance of different variables from the fitted random forest. The model appropriately identifies the SCC pulse year and discount rate as the two most important variables. Elements of the damage function and the inclusion of persistent growth damages appear as important, as does the publication year (echoing previous findings from Tol [38]) and parametric uncertainty in total factor productivity growth (also identified as important in Gillingham et al. [41] and Rennert et al. [3]). Additional information on the random forest model is detailed in S.2.3.

We query the random forest model with just over 1800 draws from the space of model structures and discount rates obtained from expert surveys (Figure 3c and d), also including other desirable SCC characteristics such as inclusion of parametric uncertainty, accounting for non-market damages, and recent publication year (detailed in S.2.3). Figure 4 illustrates the process for generating a prediction for a single sample from the input variable space. Each tree identifies the set of published SCC estimates with characteristics corresponding to the sample's, for the set of variables chosen as splits along the path for that regression tree. The subset of published estimates for each of the 403 regression trees (the "leaves" in Figure 4) then forms the random forest's prediction for the sample. The set of published estimates contributing to this prediction will not perfectly match all characteristics of the input. For instance, some variables may not appear as splits on a given tree's path, meaning the leaf does not condition on that variable at all. Some model structures combining multiple elements are either very sparse in the literature or are not represented at all (see Figure S4). In these cases, random forest estimates will average over available relevant model structures, but cannot extrapolate interaction effects between combinations of model structures not currently represented in the published literature. However, the set of published estimates contributing to the random forest prediction will match *more* closely with the input sample than the literature as a whole and will match *most* closely on the variables with the largest effect on the SCC, since these variables will appear as splits in the regression trees more frequently.

4.2 The 2020 Synthetic SCC Distribution

Figure 5a gives the 2020 synthetic SCC. The distribution has a median value of \$185 per ton CO_2, an inter-quartile range of \$97-369 and a mean of \$283, after truncating the upper and lower 0.1% of the distribution. For comparison, Figure 5a also shows two sets of SCC estimates from the US government—values from the 2021 Interagency Working Group on the Social Cost of Greenhouse Gases (IWG) [51] and a 2023 analysis by the Environmental Protection Agency (EPA) [54] as well as official SCC estimates by the German Environment Agency (German EPA). The near-complete separation between the IWG distribution and our synthetic SCC is striking: the 75th percentile of the IWG distribution (\$52 per ton CO_2) corresponds to the 10th percentile of the synthetic distribution.

The EPA distribution has a much closer overlap with the synthetic SCC distribution, with a median value of \$157 per ton CO_2 reasonably similar to the synthetic median of \$185. Compared to the IWG values, the EPA analysis integrates a number of modeling improvements that make it more similar to the set of inputs into the synthetic SCC, including improved representation of the Earth system, discount rates closer to the expert assessment in Drupp et al. [50], and a fuller inclusion of parametric uncertainties in economic growth, climate damages, and Earth system dynamics. However, the two distributions still differ substantially at higher SCC values: the synthetic distribution places 27% probability on SCC values over \$350 per ton CO_2, compared with only 17% for the EPA distribution. This could be attributable to the integration of a wider set of model structures into the synthetic SCC distribution, particularly allowing for persistent climate damages, the inclusion of tipping points, distributional weights, and limited substitutability between climate damages and consumption goods (Figure 1). By contrast, the German EPA [55] applies distributional weighting in the FUND model and reports two SCC estimates: A lower estimate of \$223, located between our median and mean synthetic SCC, which serves as the main political benchmark, using a pure rate of time preference of 1 percent, and a higher estimate of \$777 using a pure rate of time preference of 0 percent, to be used in sensitivity analyses.

One of the advantages of the random forest model trained on the literature is that it can provide SCC estimates under a range of alternate specifications. Figure 5b uses this capability to show predicted SCC distributions under alternate input specifications, decomposing the difference between the synthetic SCC distribution and random forest predictions designed to match the DICE model [52]. Reassuringly, the random forest estimates using inputs designed to match the DICE model correspond well to published values from DICE (e.g., \$43 per ton CO_2 in 2020 US dollars from Nordhaus [52] compared to an inter-quartile range of \$25-\$71 in Figure 5b). As expected, the decomposition shows large effects of the discount rate, as well as important roles for certain elements of model structure

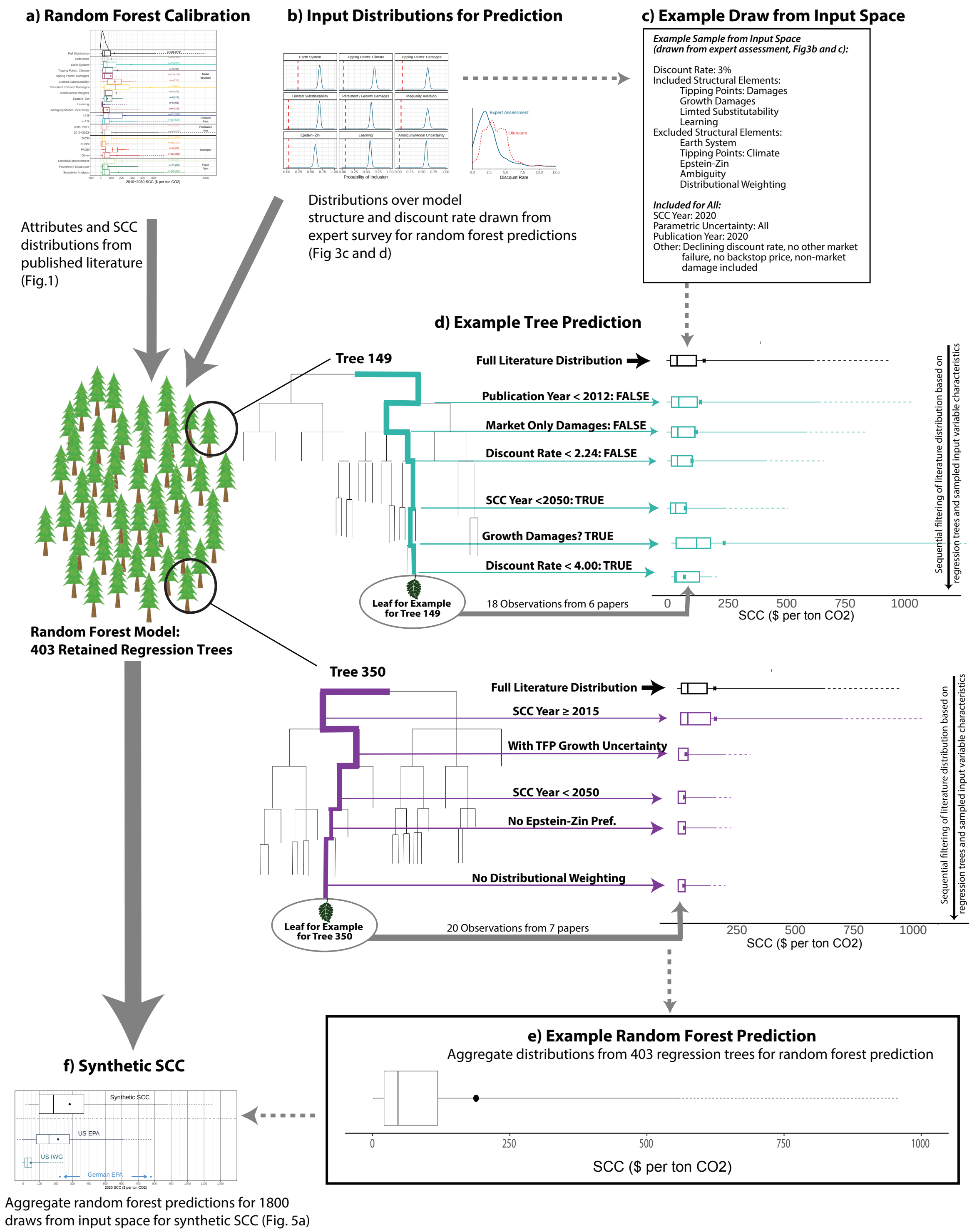

Figure 4: **Illustration of process for generating synthetic SCC distribution.** The random forest is estimated using published SCC estimates (a) then queried using draws from model structure and discount rate distributions based on expert assessments (b). Each draw (c), has a single path through each regression tree to a terminal "leaf", which contains the set of published distributions constituting that tree's prediction for that set of inputs (d). Distributions from all regression trees are aggregated to generate the random forest model's prediction for that input (e). The synthetic SCC comes from aggregating the predictions over 1800 draws from the input distribution space. Boxplots show the median (line), inter-quartile range (box), 5-95% range (solid line) and 2.5-97.5% range (dashed lines). Dots show the mean after trimming upper and lower 0.1%.

and parametric uncertainty, particularly the representation of the Earth system, inclusion of persistent damages via impacts to economic growth, and allowing for uncertainty in damages, TFP growth, and discount rate parameters.

Figure S22 shows additional distributions generated from the random forest model showing sensitivity of the synthetic SCC to structural assumptions, discount rate, publication year, pulse year, and damage function. Of note is the importance of model structure seen in Figure S22b: keeping all else equal, moving from an SCC with no differences in model structure from the standard DICE model to one with all 9 elements described in this paper included, increases the median SCC from \$124 to \$245 per ton CO_2 and the mean from \$186 to \$367.

5 Discussion and Conclusion

We present the most comprehensive synthesis to date of SCC estimates, as well as their parametric and structural drivers. Based on 1823 SCC distributions from 147 studies, we document a distribution over published 2020 SCC values that is both wide (with a 90% confidence range spanning 2 orders of magnitude) and substantially right-tailed (with a mean value of \$132 per ton CO_2 more than 4 times the median value of \$39). Analysis of variance in published SCC estimates recovers the well-known importance of discounting and damage-function parameters (explaining about one third of the variance in published SCC estimates), but also shows a critical role for key elements of model structure, including the representation of the Earth system, inclusion of persistent climate impacts to the economy, and specification of the utility function.

Published SCC values are placed in a broader context using a survey of authors of original SCC estimates in the literature. Experts on average perceive a substantial downward bias in published SCC values and attribute the majority of that bias to an under-representation of alternate model structures, as well as discounting and damage parameters. Comparison of expert elicitations with the published literature validates this assessment, with both higher discount rates and lower representation of alternate model structures in the published literature compared to expert responses.

Our synthetic SCC distribution partially addresses this concern by effectively re-weighting published SCC estimates to more closely match expert assessments of model structure and discount rates (as well as other desirable qualities such as more recent publication years and inclusion of parametric uncertainties). This procedure is necessarily constrained by the published literature: some combinations of model structure and parameters simply do not exist in the literature and therefore will not appear in the synthetic SCC distribution. More original modelling studies are required to fill those

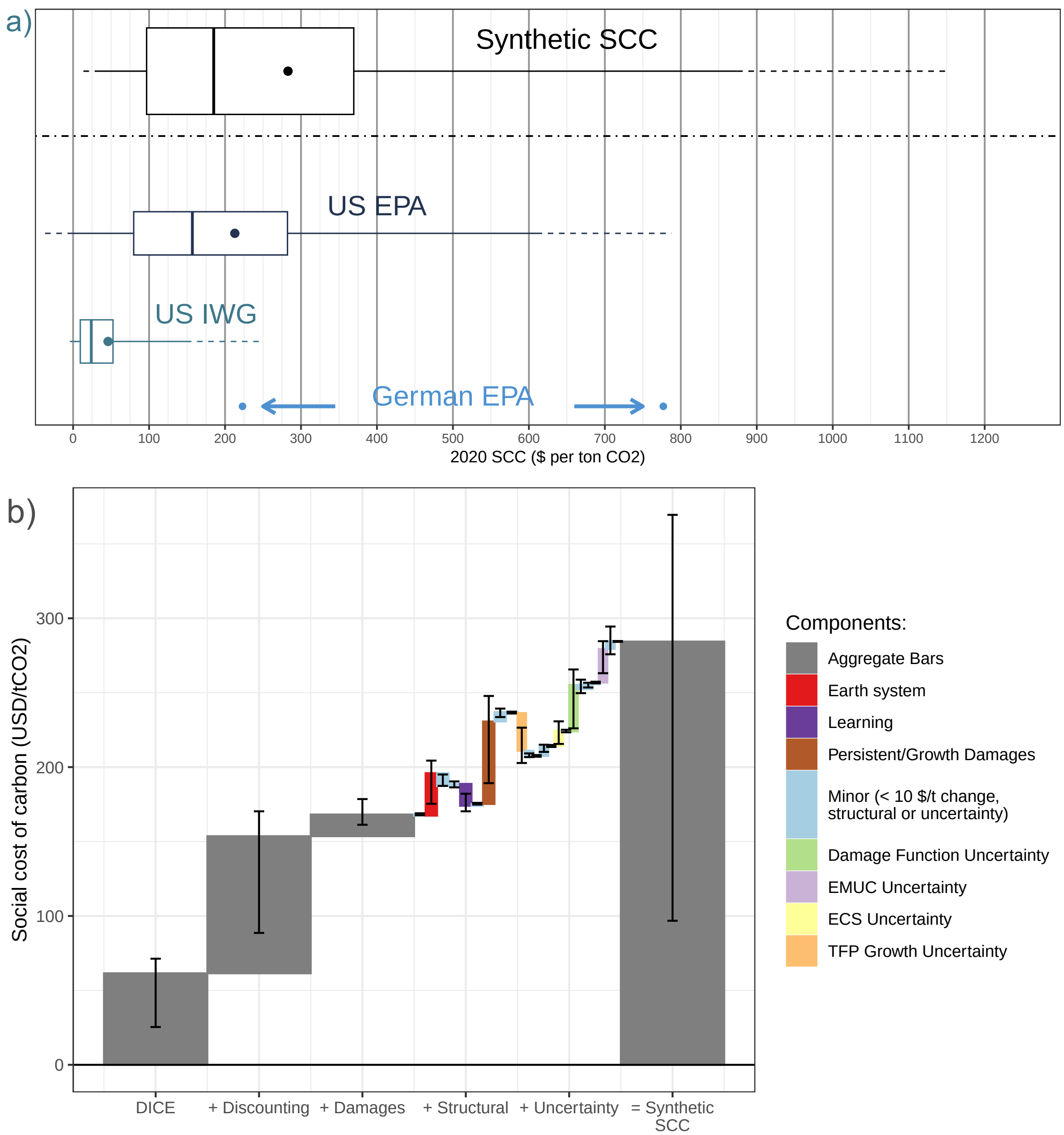

Figure 5: **Synthetic 2020 SCC Distribution and Decomposition**. a) Synthetic SCC distribution generated from the random forest model forced by input distributions over model structure and discounting shown in 3c and d. 2020 SCC distributions from two US government SCC assessments, a 2023 EPA analysis [54] and the 2021 update from the Interagency Working Group [51]. Boxplots show the median (line), inter-quartile range (box), 5-95% range (solid line) and 2.5-97.5% range (dashed lines). Dots show the mean after trimming the upper and lower 0.1% of each distribution. Dots show the two SCCs provided by the German EPA [55] under two pure rates of time preference (0% and 1%) . b) Decomposition of the difference in the synthetic SCC distribution and the random forest predictions given inputs (over model structure, discounting, damages, and treatment of uncertainty) corresponding the the DICE model [52]. Because of interactions, the decomposition depends on the order in which elements are added. Figure shows values averaging over interaction effects using 30 randomly selected different orderings. Error bars shows the interquartile range.

gaps. However, our analysis yielding synthetic SCCs does produce a distribution that is *more* similar to expert assessments than the published distribution, and is *most* similar for those variables identified in the random forest model as most important in driving SCC variance.

The resulting synthetic SCC is substantially larger than values in the published literature (median value more than 4.5 times larger, mean more than double). This relative increase (from literature to synthetic) matches how experts' average estimates more than double from their literature to best-estimate mean SCCs. The absolute value of the synthetic SCC (mean of $283) is still substantially higher than experts' best-estimate SCC. This is not surprising, given that experts substantially underestimate the mean SCC in the literature. The synthetic and expert best-estimate SCC values can be rationalized if experts underestimate the absolute value of the mean literature SCC (for reasons discussed in Section 3), while providing reasonable estimates of the proportional effects of correcting biases in the published literature. Interpreted this way, concordance between the synthetic and expert best-estimate SCCs is striking given they are generated from very different processes: both suggest that correcting biases in published SCC estimates increase mean values by just over a factor of two.

Our synthetic SCC is higher than most official government estimates, including an extensive recent update by U.S. EPA [54]. Current guidance to agencies from the IWG requires them to "use their professional judgment to determine which estimates of the SC-GHG reflect the best available evidence, are most appropriate for particular analytical contexts, and best facilitate sound decision-making." [56]. Our findings strongly suggest that the 2021 IWG estimates are unlikely to provide a sound basis for analyses requiring a valuation of climate change damages. They are inconsistent with available evidence from both the published scientific literature, expert views, and our synthetic SCC that combines key elements of both.

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Author contributions:

All authors designed the literature review and participated in data collection. FCM and JR led the data analysis of the literature values and created Figures 1, 2, 4 and 5. MAD led development and administration of the expert survey and analysis of results, including Figure 3. All authors contributed to the writing.

Competing interests:

Authors declare that they have no competing interests.

Data and materials availability:

All data, code, and materials from the literature analysis will be made available upon publication. Expert survey data is available in an anonymized format; this allows producing all main figures and results with the sole exception of supporting analyses that draw on data merged with expert characteristics in Sections S.2.2.4 and S.2.2.5.

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Supplementary Materials

Moore, Drupp, Rising, Dietz, Rudik and Wagner

April 1, 2024

Contents

S1 Dataset summary

Summary statistics are shown in Table S1, but to provide a taste of the data: the median paper has two authors and reports 6 estimates; it calculates the SCC of an emission pulse in 2020, using a pure rate of time preference (PRTP) of 1% and a elasticity of marginal utility of consumption (EMUC) of 1.45 and has a median SCC value of \$71 per ton CO_2.

The following figures describe other features of the published papers dataset collected as part of the meta-analysis.

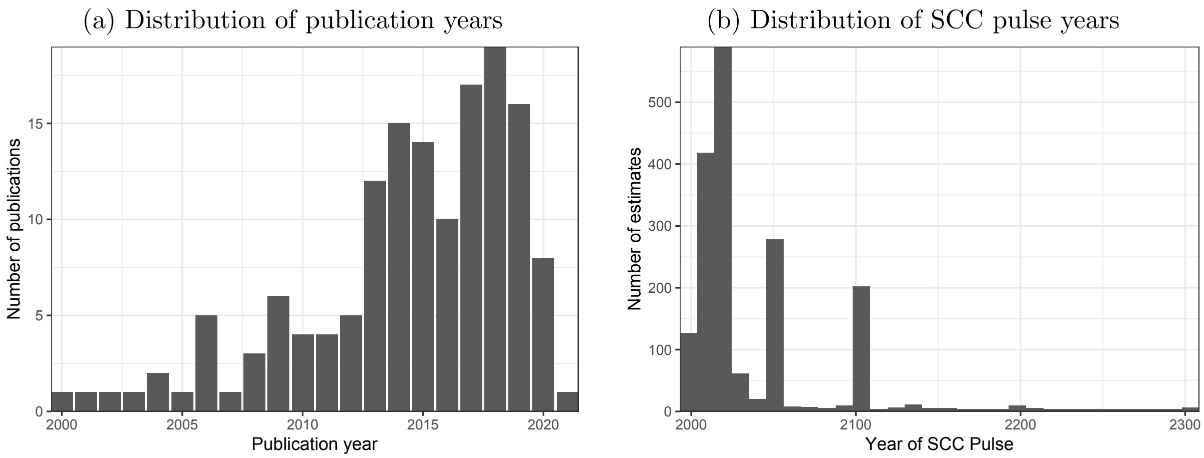

Figure S1: Distribution of (a) publication years and (b) SCC pulse years in the dataset. The distribution of publication years is per publication, while the distribution of SCC pulse years is per estimate since a publication may have multiple estimates.

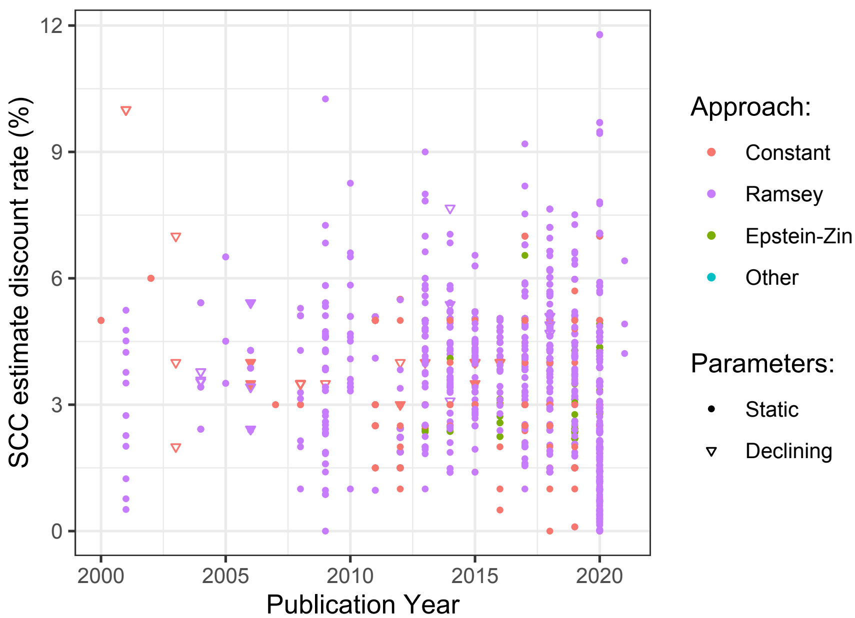

Figure S2: Discount rates used in SCC studies, by year.

Unique values

	N	unique
Papers	1823	147
Estimates	1823	1360
Authors	1823	231
Emissions Scenario	1813	88
Socio-Economic Scenario	1702	63
Damage Function Info.	1142	91

Characteristics of Model Structure and SCC Values

	N	present
Backstop Price?	1823	19
Other Market Failure?	1823	50
Declining Discounting?	1823	72
Market Only Damages	1823	53
Carbon Cycle	1823	359
Climate Model	1823	382
Climate Tipping Points	1823	50
Damages Tipping Points	1823	168
Persistent Damages	1823	122
Epstein-Zin	1823	77
Model Ambiguity	1823	42
Limited-Substitutability	1823	60
Inequality Aversion	1823	117
Learning	1823	108
Alternative ethics	1823	16

Uncertainty assumptions

	N	present
Parametric sources of uncertainty		
TFP Growth	1823	120
Population Growth	1823	55
Emissions Growth	1823	70
Transient Climate Response	1823	74
Carbon Cycle	1823	95
Equilibrium Climate Sensitivity	1823	464
Tipping Point Magnitude	1823	130
Damage Function	1823	368
Adaptation Rates	1823	41
Income Elasticity	1823	82
Constant Discount Rate	1823	4
EMUC	1823	61
PRTP	1823	43
Risk Aversion (EZ Utility)	1823	7
Uncertainty information		
Extreme limits	1823	348
Tails ($\geq$ 95%)	1823	261
Central uncertainty (< 95%)	1823	276

Summary values

	N	mean	median	min	max
Authors per paper	1823	2.61	2.00	1.00	9.00
Estimates per paper	1823	12.40	6.00	1.00	249.00
SCC Year	1820	2039.62	2020.00	1995.00	2300.00
Central Value ($ per ton CO2)	1701	252.21	71.25	-23.79	75287.61
Reported Base Model SCC (if applicable)	837	107.00	43.74	-1.98	15063.81
Constant Discount Rate (%)	493	2.92	3.00	0.00	10.00
PRTP	1298	1.01	1.00	-1.10	5.00
EMUC	1234	1.41	1.45	0.00	5.00
RRA	78	6.84	9.50	0.00	10.00
IES	76	1.26	1.50	0.50	2.00
Tail uncertainty level	3363	91.19	95.00	50.00	99.90

Table S1: Summary statistics of the SCC dataset. The Unique values table list the number of unique

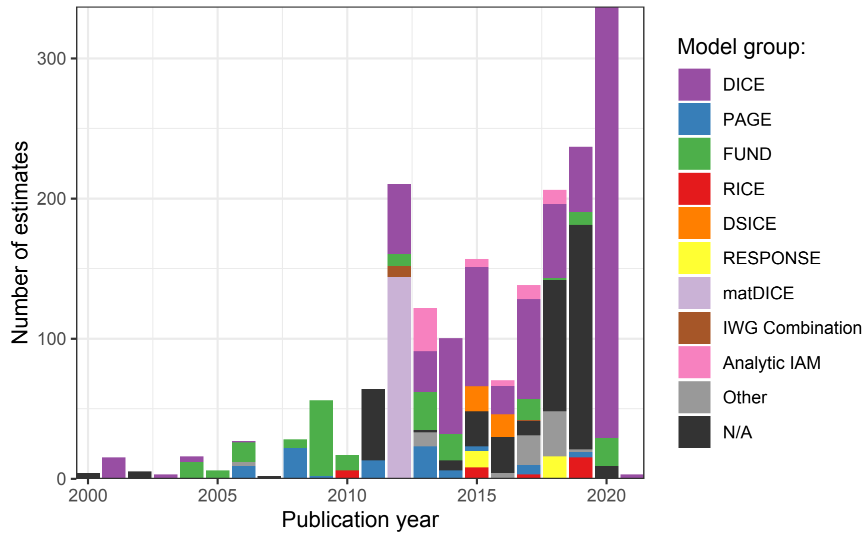

Figure S3: Integrated assessment models used in SCC studies, by year.

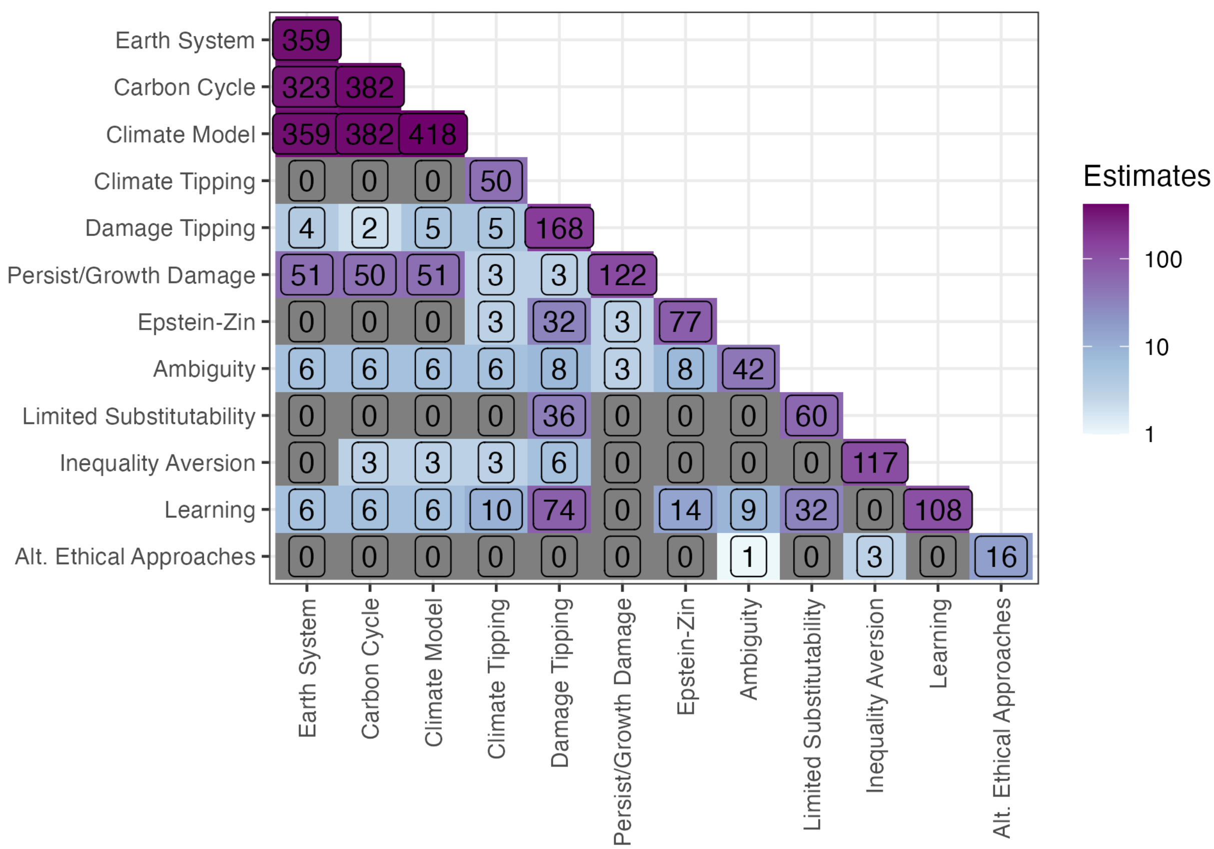

Figure S4: Number of estimates with each pair of structural changes. Numbers along the diagonal show the total number of estimates containing each change.

S2 Methods

S.2.1 Meta-analysis

S.2.1.1 Abstract Search

SCC values for use in the meta-analysis were identified from a systematic search of Web of Science, EconLit and Scopus databases. Criteria for the search were peer-reviewed papers published from 2000 to 2020 and containing one of the following search terms:

social cost of carbon, social cost of CO_2, social cost of greenhouse gases, social cost of GHG, optimal climate policy, optimal carbon price, optimal CO_2 price, optimal carbon tax

The search was conducted at the end of September 2020 and so included papers published by that end point. After removing duplicate entries, the search returned 2839 papers. These were further screened by a team of research assistants who read through the abstracts to determine whether the paper was likely to report an original, global social cost of carbon estimate. RAs were instructed to err on the side of keeping papers in the sample if in doubt to avoid dropping relevant papers. 1110 of the 2472 papers initially identified as not containing an original SCC value were re-evaluated by a second RA, an exercise that produced 98% agreement with the original coding. A further 478 abstracts were re-evaluated a third time by a different RA with 99% agreement with the second round of coding.

After the initial abstract review, 295 papers remained that potentially contained original SCC estimates. These were read by members of the author team and SCC values with details of modelling, preference parameters and uncertainty ranges were coded in an initial round of data collection. The author team identified 139 papers producing original SCC estimates of the 295. A further 8 papers meeting the inclusion criteria were identified at this stage and were also included, bringing the total number of papers included in the analysis to 147. References for these papers are givin in full in Section S4.

S.2.1.2 Data Collection and Coding

A challenge of attempting to analyze and compare variation in reported SCC across multiple papers is the variety of scenarios, model structures, and parameter values used in different papers. Authors also take different approaches in presenting results and in sampling and investigating uncertainties. A data coding template was developed to extract data on SCC and modeling covariates in a consistent, flexible, and parsimonious way to allow for comparison of values across papers.

The template developed iteratively during the initial round of paper review by the author team. Once all papers had been coded once, 18 papers were coded for a second time by a different person and SCC distributions compared. Using experience from the initial coding and comparing discrepancies and ambiguities arising from the re-coding exercise, we developed a finalized code book describing how SCC values and model covariates should be recorded from papers. All papers were re-read and coded using this finalized code book.

The coding process adopted (given in full as an addition to this Supplement) allows for recording unique SCC values from papers for particular years, discounting assumptions, socio-economic and emissions scenarios, damage functions, and model structure. If the paper reports effects of parametric variation on the SCC, this is also recorded (as distribution quantiles or min and max values) along with the nature of the parametric variation reported in the paper. The final round of coding produced 1823 unique SCC values (or distributions) arising from the 147 papers.

S.2.1.3 Data Cleaning and Standardization

Following the systematic collection of raw data from the papers, we undertook a series of steps to make values comparable across papers. Firstly, SCC dollar values were adjusted to 2020 dollars using the GDP Implicit Price Deflator from the St Louis Fed (*1*) . If a paper did not report the dollar year of the SCC, we first attempted to infer a dollar year based on that used by the baseline model modified or re-calibrated in that paper (e.g DICE2016 or FUND3.9). If this was also unavailable then we assumed a dollar year of 5 years prior to the publication date.

A second important standardization involved imputing comparable discount rates across all values. Approximately 30% of our entries use a constant discount rate to calculate the SCC. The vast majority of the remainder use Ramsey discounting, which depends on two preference parameters (the pure rate of time preference and the elasticity of marginal utility of consumption) and the consumption growth rate. To infer an effective discount rate for SCC values using the Ramsey rule, we merge in information on the consumption growth rate for the relevant time-period under the socio-economic scenario used in the paper. Consumption growth rates from 2020 to 2200 (if available) were identified for multiple different integrated assessment models (10 versions of DICE, RICE 2010, 13 versions of FUND, the SSP scenarios and the older SRES scenarios). After merging in the per-capita consumption growth rate, we calculate the effective discount rate for that SCC value using the Ramsey rule given the reported preference parameters. If we are unable to match a consumption growth rate to a particular SCC value, we impute an estimate based on the average consumption growth rate across all scenarios for that SCC year.

S.2.1.4 Distribution Fitting

We record quantiles of the probability distribution for each SCC value, to the extent that this information is provided by the underlying papers. The full set of quantiles recorded across paper consist of 0.1%, 1%, 2.5%, 5%, 10%, 17%, 25%, 50%, 75%, 83%, 90%, 95%, 97.5%, 99%, 99.9%. Where SCC sensitivity to non-probabilistic parameter changes are reported, we record the minimum and maximum of these. The number of SCC observations reporting each of these quantiles is shown in Table S2.

Quantile	Count	Percent
Min	309	17%
0.1th	3	0.2%
1th	4	0.2%
2.5th	4	0.2%
5th	224	12.3%
10th	23	1.3%
17th	72	3.9%
25th	21	1.2%
50th	377	20.7%
75th	21	1.2%
83rd	72	3.9%
90th	29	1.6%
95th	257	14.1%
97.5th	4	0.2%
99th	36	2%
99.9th	7	0.4%
Max	324	17.8%

Table S2: The quantiles recorded across SCC distributions. The number of SCCs with information on each quantile is shown in the Count column, and this as a percent of all SCCs is shown in the Percent column. The Min and Max entries are recorded when sensitivity tests are described with no probabilistic information, while the remaining are used when recording probabilistic analyses (e.g. confidence intervals).

Depending on the available quantiles, we fit different probability distribution functions. The following conditions are applied to each observation:

1. If only the central value is given, the SCC is treated as deterministic.
2. If only the minimum and maximum are given with the central value, a triangular distribution over the provided values is used.
3. If other quantiles are given along with a minimum (maximum), the distribution is bottom-coded (top-coded) to this value.
4. If a 0.1% or 99.9% value is given, the distribution is truncated to these values.

5. If a central value (mean or median) and one other (non-truncating) quantile is given, the distribution is assumed to be Gaussian.
6. If a central value (mean or median) and two other (non-truncating) quantiles are given, the distribution is assumed to be either a Skew normal or a exponentially modified normal, whichever produces a better fit to the quantiles.
7. Otherwise, the distribution is assumed to be a mixture of up to k - 2 Gaussians, where k is the number of fitting values (quantiles and the mean SCC value).
8. If cases 2 - 6 are used, an alternative model consisting of a piecewise uniform distribution with weights from the spans between quantiles is tried as an alternative, and the best-fitting distribution is returned. We also fit a left and right tail extending beyond the most extreme reported quantiles, selecting either a Gaussian, triangular, or exponential distribution based on which best fits the quantiles reported above (right) or below (left) the mean.

In cases where no analytical solution exists to the parameters of the distribution, we evaluate the fit of a potential distribution as

$$\text{RMSE} = \sqrt{(\mu - \hat{\mu})^2 + \sum_k (a_k - \hat{a}_k)^2}$$

where μ is the reported central value, $\hat{\mu}$ is the distribution mean, a_k is the k^{th} reported quantile, and $\hat{a}_k$ is the corresponding estimated quantile. This is used both to estimate parameters for distributions and to select the preferred distribution according to the rules above. The distributions selected are shown in Figure S5 and in Table S3.

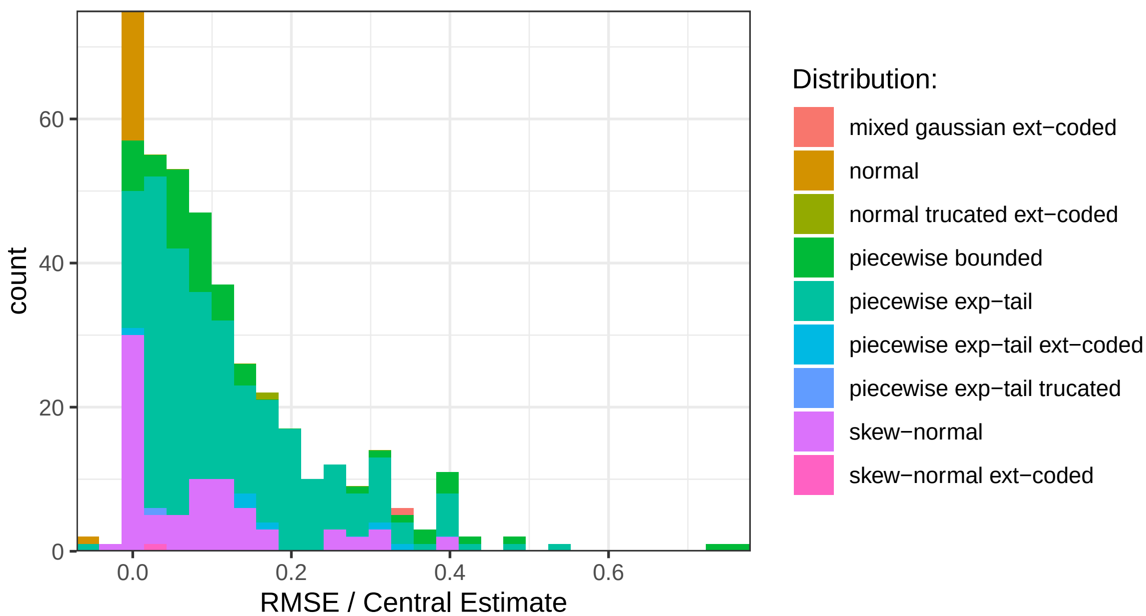

Figure S5: Histogram of the continuous distributions used to fit the quantile information. The solutions are plotted against the degree of miss-fit, described by the ratio of the RMSE to the reported central SCC value.

S.2.1.5 Sampling

Describing the distribution of SCC values in the literature requires sampling over papers and reported values. We investigate three different approaches to sample over the set of SCC papers:

1. **Equal Paper Weighting:** Each paper in the data-set receives equal weighting

(a) Count of distributions fit to data

Distribution	Unbounded	Truncated
Delta	1140	
Triangle	273	
Gaussian	19	1
Skew-Normal	102	2
Piece-wise Uniform	225	61
Total stochastic	683	

(b) Count of tails fit to piece-wise distributions

Distribution	Left-Tail	Right-Tail
Triangle	139	99
Gaussian	88	97
Exponential	3	34
Total piece-wise tails	230	230

Table S3: Information about the distributions fit to the reported SCC information. (a) The general distribution applied, and whether it is truncated or not. Delta, Triangle, and Gaussian distributions are applied in particular cases, while Skew-Normal and Piece-wise Uniform distributions are chosen based on goodness-of-fit. The Total stochastic row excludes Delta distributions. (b) For piece-wise uniform distributions, the tails fit based on quantile information. In total 230 piece-wise uniform distributions have tail information, including 5 which are truncated; the remaining 56 are bounded (uniform to the minimum and maximum).

2. **Informational Weighting:** Papers more likely to contain more independent estimates are weighted more heavily than papers likely to have estimates highly correlated with other papers in the dataset. We operationalize this by calculating a shared co-author index that compares the average number of co-authors shared between paper i and paper j compared to an estimated null value based on 250 random draws that fix the number of authors in the sample and the number of authors on papers, but randomly reshuffles co-authors. Papers with average shared authorship less than the mean of the null distribution receive full weight while those with higher values receive lower weights that gradually decline with higher levels of shared authorship across the 147 papers in the dataset.
3. **Citation Weighting:** Papers with higher citation counts (based on Google Scholar) are weighted more heavily. To avoid mechanically placing higher weight on older papers, weighting is based on the average citations per year since publication

After sampling a paper, using any of the three alternate sampling schemes, we treat all all SCC observations reported by the paper as equally likely to be sampled. If the sampled SCC observation is a point estimate, then we draw that value. If it is a distribution (37% of the total) then we sample a single draw from the fitted distribution.

Table S4 gives quantiles from the three alternate sampling schemes and shows relatively small differences across the distributions at the median and lower half of the distribution. But the co-author weighted and citation-weighted sampling schemes have substantially more probability mass in the upper tails, particularly the citation-weighted distribution. For simplicity, analysis and discussion in the paper focuses on the distribution using equal paper weighting.

S.2.1.6 Sensitivity Analysis

Figure S6 shows the change in the mean SCC value for the full literature distribution after iteratively dropping each paper in the dataset, for the 15 papers with the largest effect. By far the highest-leverage paper is Nordhaus (*2*), largely because this paper includes a value of over $70,000 per ton CO_2 under a "super-low" discounting scheme with a constant 0.1% discount rate (Table J-1 in that paper). Dropping this paper reduces the mean 2020 SCC by $136. Only two other papers (*3, 4*) change the mean SCC by more than $10 and one (*5*) changes it by between $5 and $10. The remaining 143 papers affect the mean SCC value by less than $5 each. Because of the extreme effect of a single supplementary value, we drop this most extreme value from Nordhaus (*2*) in all subsequent analysis,

Quantile	Equal-Weighting	Co-Author Weighted	Citation Weighted
0.01	-4.7	-3.2	-18.4
0.025	0.1	1.2	0.2
0.05	2.3	4.4	3.1
0.1	6.5	9.1	6.9
0.25	17.7	22.8	17.8
0.5	45.8	56.1	51.5
0.75	127.9	153.9	177.3
0.9	292.4	354.8	596.5
0.95	622.7	662.0	1046.2
0.975	959.3	1046.2	1524.1
0.99	1509.8	1669.5	3199.5

Table S4: Quantiles of the full SCC distribution using alternate weighting schemes to sample papers. Results in the main text sample uniformly from all papers (Equal-Weighting). Here we compare quantiles from this distribution with alternate weighting schemes. Co-Author Weighted down-weights papers that share large numbers of co-authors with other papers in the dataset on the basis that the information content of these papers may be not fully independent. Citation Weighted weights the sampling of papers based on citation counts, normalized by the number of years since publication. The central 5% - 75% of the distributions are very similar, but citation weighting in particular results in more probability mass on SCC values above $200 per ton CO_2.

including all results reported in the main text. To reduce sensitivity of findings to extreme outliers we report truncated means that drop the upper and lower 0.1% of the distribution for all literature and synthetic SCC distributions and report median values in addition to the mean throughout the paper.

S.2.1.7 Tail Behavior

One of the most notable features of Figure 1 is the long right tail, extending well above $500 per ton of CO_2. The question of the role that low probability but very bad outcomes (i.e., the "right tail" of climate damages) should play in driving climate policy has been written about extensively. In developing his "dismal theorem", Weitzman described the potentially high sensitivity of expected climate damages to behavior in the far tail of the distribution (*6, 7*). In extreme cases, the presence of fat tails may lead to unlimited downside exposure and a distribution with an infinite mean. Even in less extreme cases, substantial probability mass in the tails may cause the expected value to be highly sensitive to necessarily subjective judgements regarding the probability of very bad outcomes (*7*).

Previous work in the literature has shown evidence for a long-right tail in climate damages. Anthoff and Tol (*8*) for example, looking only at parametric uncertainty included in the FUND model, find evidence for fat tails as the mean of the distribution continues to increase with the number of Monte Carlo runs. Other work looking at parametric uncertainty across multiple variables and several IAMs also typically shows a right tail on the SCC distribution (*9, 10*). Recently, Anthoff and Tol (*11*) examined evidence for fat tails in both the parametric distribution of DICE, PAGE and FUND, as well as across published estimates of the SCC, again finding support for fat tails in the FUND model but only mixed evidence in the other models and in the meta-analysis.

The presence of fat tails in a distribution can be tested using the mean excess function (MEF) – the mean of the distribution conditional on being above some threshold (*12–14*). If the mean above the threshold is increasing faster than the threshold itself – then it indicates the presence of a fat tail. The slope of the mean excess function can be used to find the value of the shape parameter for the Generalized Pareto Distribution (GPD) that best fits the distribution (*12*), and the tail index (α) of the distribution. A tail index greater than 2 indicates a thin-tailed distribution, $1 < \alpha < 2$ is a thick tailed distribution with finite mean but infinite variance, while $\alpha < 1$ is a fat tailed distribution with infinite mean and variance. Table S5 shows estimates of the tail index using multiple threshold quantiles for the estimation. Regardless of how we weight observations or set a minimum threshold for inclusion in the sample, we consistently find mean excess function slopes greater than 1, and α values between 1 and 2. This is indicative of a fat-tailed distribution with infinite variance but finite mean.

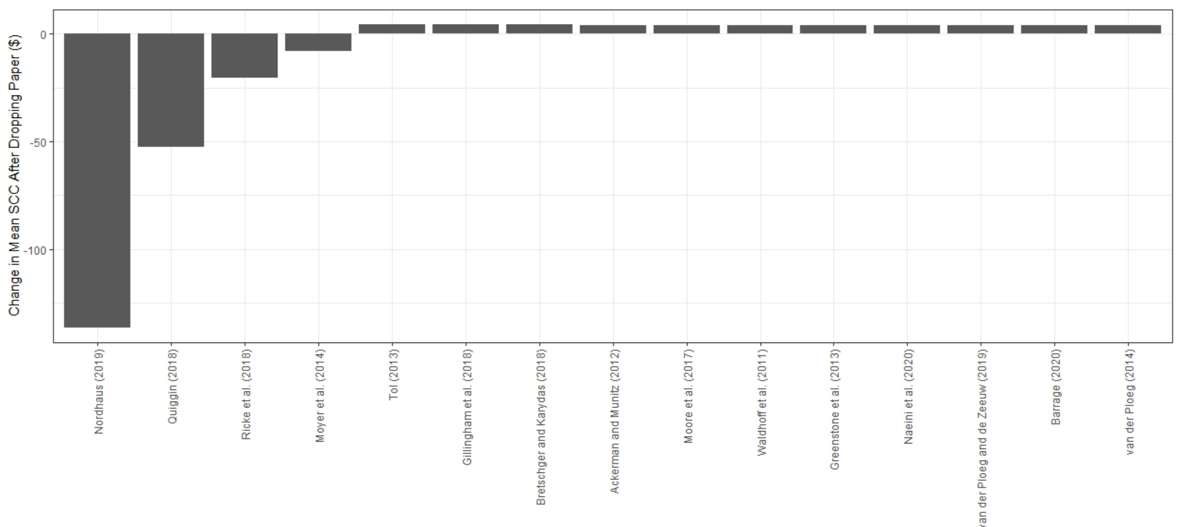

Figure S6: 15 Papers with Largest Effect on Mean 2020 SCC, Calculated as the Change in Mean SCC Value after Dropping the Paper from the Distribution

Table S5: Estimates of the Mean Excess Function slope, the Generalized Pareto Distribution shape parameter, and tail index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MEF Slope	1.731***	1.661***	1.315***	1.477***	2.856***	2.746***	2.624***	1.477***
	(0.085)	(0.043)	(0.022)	(0.006)	(0.094)	(0.060)	(0.035)	(0.006)
Num.Obs.	67	135	338	1316	67	135	338	1316
Minimum Threshold Percentile	95	90	75	0	95	90	75	0
Observational Weights	Num. Obs.	Num. Obs.	Num. Obs.	Num. Obs.	1/Num. Obs.	1/Num. Obs.	1/Num. Obs.	1/Num. Obs.
GPD Shape Parameter	0.63	0.62	0.57	0.6	0.74	0.73	0.72	0.6
Estimated Tail Index	1.58	1.6	1.76	1.68	1.35	1.36	1.38	1.68

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note:

Standard errors are robust to heteroskedasticity. All estimates are from a sample that excludes Nordhaus (2019). Columns 1-4 weight observations of the mean excess by the number of SCC observations used to compute it. Columns 5-8 weight observations with the inverse.

S.2.1.8 Damage function based SCCs

For 46% of the SCC observations, we are able to construct a simple functional representation of the underlying damage relationships. These consist of 13 versions of DICE damage functions across 241 estimates, 7 versions of FUND across 83 estimates, 2 versions of the Howard & Sterner function across 261 estimates, 5 estimates using PAGE damages, 68 estimates using Weitzman damages, 11 estimates using Dietz & Stern damages, and 168 estimates where another explicit functional form was used. A heat map of these various damages is shown in Figure S7.

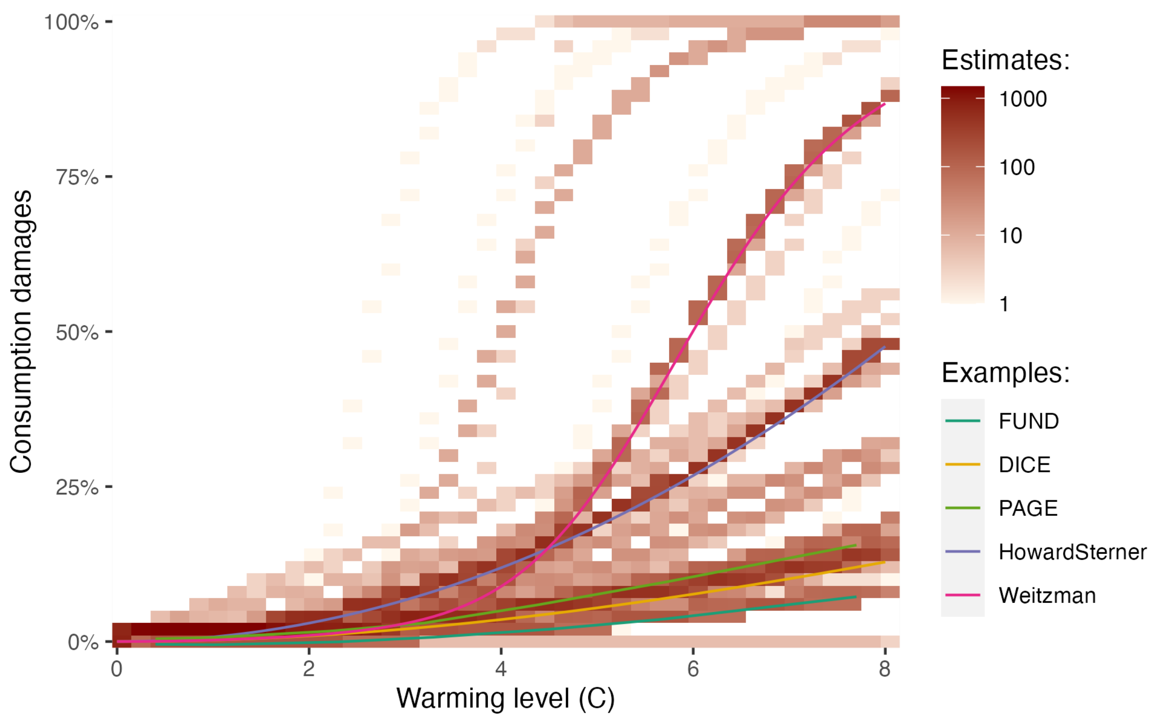

Figure S7: Damages projected across temperatures, shown as a heat map of the occurance of the given damages across studies. Illustrative common damage functions shown as curves.

The SCCs that result from these damage functions are dependent upon not only the structural features of interest in this paper, but also the climate and socioeconomic scenario, discounting, and baseline assumptions.

As a simple proxy for damages, we generate a damage function based SCC under identical conditions, only varying the damage function. This is done by simulating temperatures under DICE 2013 for a baseline RCP 8.5 scenario and an additional emissions pulse in 2020. Damages are calculated as fractional losses of GDP in each year and totaled under a 3% discount rate. These total damages are translated into dollars per ton assuming a constant global GDP of $84.54 trillion.

Figure S8 shows the damage function based SCC compared to reported SCCs (shown here as just the central values). Reported SCCs show a spread around each damage function based SCC, based on the range of model structures and parameters associated with particular damage functions in the literature. However, damage function based SCCs increase steadily with reported SCCs, on average. A regression explaining reported central SCC as a function of SCC year, discount rate, and damage function based SCC achieves an R^2 of 0.52.

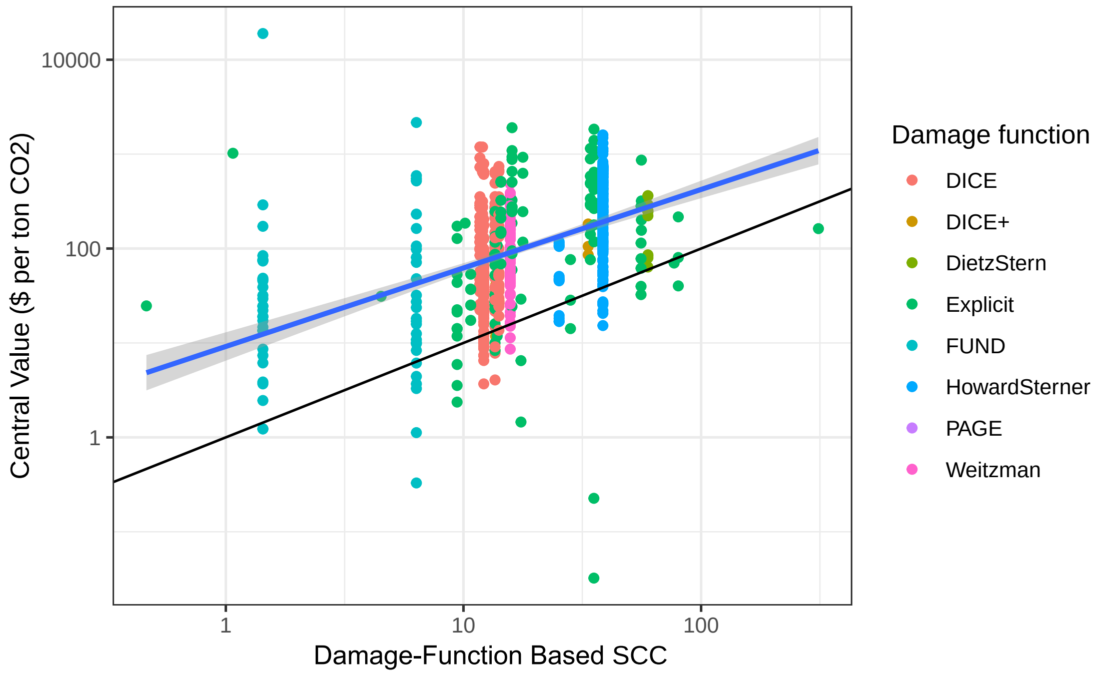

Figure S8: Calculated damage function based SCC values, compared to reported central values, for each estimate for which we can calculate a damage function based SCC. Dots are colored by the class of damage function used, where 'Explicit' refers to an explicitly described functional form rather than a standard damage function. The black line shows has unit slope, and a regression line is shown in blue.

S.2.1.9 Multi-Variate Regression

Figure 1 shows hows the 2020 SCC distribution changes with different univariate splits of the underlying estimates. This figure suggests that certain characteristics of SCC estimates contribute more significantly to variance in SCC values than others. However, multi-variate analysis that controls simultaneously for all variables with an influence on SCC values is required to credibly identify effects of particular structural and parametric model elements on SCC values. This section reports results from multivariate regression models using 3 sources of variation in the underlying dataset.

1. **Full Variation (No Fixed Effects)** The first model identifies the effects of different modeling decisions using the full variation across the whole SCC distribution. The estimating equation is (betas omitted for clarity):

   $\log(SCC_{idp}) = Year_d + Year_d^2 + DiscountRate_d + DiscountRate_d^2 + \mathbf{Struc_d} + \mathbf{Param_d} + \mathbf{Other_d} + \epsilon_{idp}$

   Where the dependent variable is the log of an SCC draw i, from distribution d, from paper p. (Using logs requires dropping the 2% of the distribution below \$0.) $\mathbf{Struc_d}$ is set of nine indicator variables describing the model structure of the estimate. $\mathbf{Param_d}$ is a set of indicator variables describing whether the estimate is drawn from a distribution containing parametric variation in one of 14 possible parameters. $\mathbf{Other_d}$ contains an additional six binary variables describing the estimate, such as whether it is a backstop price, and whether it is derived from versions of the DICE, PAGE or FUND models. Finally, the specification includes quadratic controls for the SCC year and discount rate. Residuals are clustered at the distribution level (i.e. allowing for correlation in the error term for draws from the same distribution of parametric uncertainty).

2. **Within-Paper Variation (Paper Fixed Effects)** The second approach adds fixed-effects by paper. The specification is the same as above, except for the addition of paper fixed-effects that control for all average differences between papers. Model parameters are then estimated off of variation reported *within* a single paper. For instance, a single paper might report the SCC

under alternate discount rates and under different model structures.

3. **Base SCC Comparison** The final multi-variate comparison uses variation between central SCC values and a standard model comparison point, which we term a "base SCC". (Results from this regresesion are also shown in Figure 2a.) Many papers run a standard version of an IAM, make some modification and report the effect of that modification on the SCC. Since the base SCC values are not original estimates, we record them specifically as comparison points, not separate observations of the SCC. The 'Base SCC Comparison' regression specifically uses variation between the base SCC values and other central SCC values that are comparable except for specific elements of model structure..

   The equation for this estimate is (betas omitted for clarity):

   $$log(SCC_{trs}) = \mathbf{Struc} + \mathbf{Other} + \theta_{trs} + \epsilon_{trs}$$

   Where the dependent variable is the log of the SCC for a ton emitted in year t, calculated using discount rate r, using scenario s, using both original and base SCC values. **Struc** and **Other** are defined as above. θ_{trs} is a fixed-effect for each unique combination of SCC year, discount rate, and scenarios. This means that parameters are only estimated off of variation coming from differences in model structure (or a limited set of other variables that might affect the SCC), conditioning on these other SCC determinants. Note that because we do not have data on parametric variation in the base SCC values from most papers, this regression uses only reported central values, not the full distribution including parametric uncertainty.

Note that the different variation used in these three approaches is distinct and, correspondingly, that the interpretation of the coefficients shown in Figure S9 is different for each model. For example, the effects of incorporating tipping points in the damage function are positive for the Base SCC comparison and the Paper Fixed Effects models, but are slightly negative in the Full Variation model. This can be rationalized if the set of papers that allow for tipping points in the damage function tend to, on average, incorporate them into a base model that produces an SCC on the low end of the full set in the data. This means that, on average, SCC from models with this structural model modification are lower than average (i.e. a negative coefficient in the Full Variation model), but the effect of this change, relative to a model that is the same except for this change, is an increase in the SCC (i.e. positive coefficients in the Paper Fixed Effects and Base SCC Comparison models).

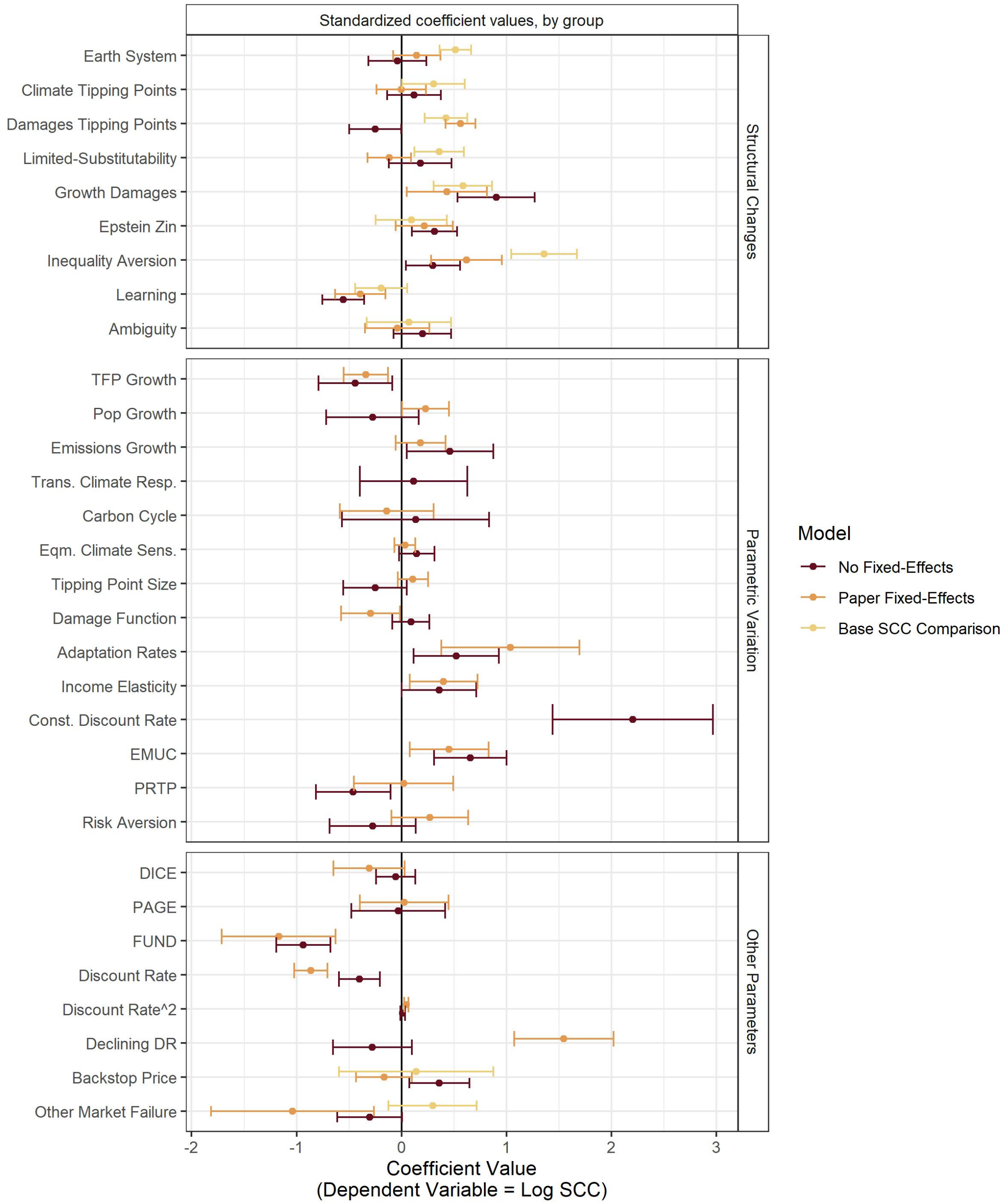

Figure S9: **Multivariate analysis of variation in published SCC estimates.** (a) Regression coefficients for three different multivariate regressions with 95% confidence intervals. The top panel is for our set of 9 structural model choices, the middle panel is for parametric variation, and the bottom panel is for other changes such as the base model. In all cases the dependent variable is logged SCC (in \$ per ton CO_2). Models also include non-linear controls for SCC year, except for the Base SCC model which controls for SCC year explicitly using fixed-effects. Reported coefficients may be missing if the variable is collinear with the fixed effects. Base SCC results are also shown in Figure 2a.

S.2.1.10 Analysis of variance

The analysis of variance determines the portion of the total variance attributable to each predictor. For this analysis, we use Paper Fixed-Effects regression discussed in Section S.2.1.9, except that we drop the SCC year quadratic and subset the data to just SCC years from 2010 to 2030 (inclusive). The estimates for each predictor are reported in Table S6.

Source of variation	Estimate	LOO Range		Bag Range	
Earth System	5.05	5.24	[5 - 7]	7.75	[0 - 41]
Climate Tipping Points	0.56	0.58	[0 - 1]	1.24	[0 - 4]
Tipping Point Size	0.06	0.07	[0 - 0]	1.42	[0 - 3]
Growth Damages	12.29	12.9	[12 - 17]	23.45	[5 - 80]
Epstein Zin	0.71	0.77	[1 - 1]	3.39	[0 - 24]
Ambiguity	0.01	0.02	[0 - 0]	0.53	[0 - 1]
Limited-Substitutability	4.53	4.66	[4 - 6]	4.95	[0 - 31]
Inequality Aversion	2.68	2.73	[2 - 4]	2.23	[0 - 9]
Learning	5.49	5.75	[5 - 7]	14.07	[6 - 84]
TFP Growth	2.57	2.74	[2 - 4]	9.76	[1 - 53]
Pop Growth	0.16	0.24	[0 - 1]	6.58	[0 - 36]
Emissions Growth	2.76	2.82	[2 - 4]	1.55	[0 - 5]
Trans. Climate Resp.	0.28	0.3	[0 - 0]	1.18	[0 - 4]
Carbon Cycle (Param)	0.2	0.23	[0 - 1]	0.55	[0 - 3]
Eqm. Climate Sens.	1.7	1.73	[1 - 3]	1.17	[0 - 4]
Damages Tipping Points	0.07	0.07	[0 - 0]	1.68	[0 - 9]
Damage Function	4.52	4.88	[4 - 7]	12.07	[1 - 49]
Adaptation Rates	0.91	1.03	[1 - 2]	7.61	[1 - 43]
Income Elasticity	0.42	0.47	[0 - 1]	4.59	[0 - 15]
Const. Discount Rate	0.59	0.75	[0 - 2]	7.49	[0 - 45]
EMUC	3.47	3.67	[3 - 5]	9.64	[2 - 45]
PRTP	0	0.06	[0 - 1]	5.26	[0 - 46]
Risk Aversion	0.16	0.15	[0 - 0]	0.99	[0 - 6]
Model group	23.59	23.87	[21 - 27]	27	[13 - 69]
Other Market Failure	1.45	1.52	[1 - 2]	1.72	[0 - 7]
Damage-based SCC	0.44	0.56	[0 - 2]	2.82	[0 - 16]
Discount Rate	25.32	25.77	[24 - 29]	37.78	[23 - 80]

Table S6: Analysis of variance (ANOVA) results corresponding to the paper fixed-effects regression in Figure S9. All entries are percentages of explained variance, excluding variance from paper fixed effects. The Estimate column reports the percent of explained variance across all included variables, as shown in the figure. The leave one out (LOO) Range reports the central estimate and range of variances calculated when each individual predictor is dropped, and the Bag Range reports central estimate and range of variances calculated when a random subset of these predictors is selected. Ranges are 95% ranges.

When reporting variances in the bar chart in the main text (Figure 2b), parametric and structural predictors are combined. Specifically, Trans. Climate Resp., Carbon Cycle (Param), Eqm. Climate Sens., and Earth System are reported as "Earth System"; Damages Tipping Points and Tipping Point Size are reported as "Damages Tipping Points" (but not labeled in the figure); Epstein Zin and Risk Aversion are reported as "Epstein-Zin"; Model group (an indicator of DICE, FUND, PAGE, or other) and Ambiguity are reported as "Model & Model Uncertainty"; TFP Growth, Pop Growth, and Emissions Growth are reported as "Socioeconomic Uncertainty"; Const. Discount Rate and a quadratic in (effective) Discount Rate are reported as "Discounting"; and the Damage-based SCC, Damage Function, Adaptation Rates, and Income Elasticity are reported as "Damage Function Parameters".

Figure 2b does not show the residual variance or the variance attributable to paper-specific fixed-effects. These account for 30.8% and 37.3% of variance, respectively. The observations in the ANOVA regression are draws from the SCC distributions, so the residual variance is a combination of non-linearities and the uncertainty in the SCC estimates. When the ANOVA is performed on the SCC central values for each estimate, the residual variance is 23.8%, implying that cross-estimate uncertainty or non-linearities are more important than within-estimate uncertainty in explaining the residual variance.

S.2.2 Expert survey

We invited all authors of SCC estimates included in our meta-analysis, and for whom we could obtain a workable e-mail address, to participate in the expert survey. In the e-mail introduction (see text in annex to this supplement), we explained that the goal of the survey is to elicit experts' views on the SCC, uncertainty about its value, and how various structural model modifications affect the SCC. We communicated that results will be published without identifying any individual participant, and that we had obtained approval from the research ethics review board at UC Davis and approval from the social science research deanery and social science research laboratory at the University of Hamburg. We sent invitations to the effective population of 176 SCC authors on May 22, 2022, and closed the survey on July 07, 2022. 72 of the invited SCC authors participated, of which 68 provided quantitative responses and 48 responded non-anonymously, with response rates of 41%, 39% and 28%, respectively, which compares very well with similar expert surveys (*15–18*).

S.2.2.1 Survey design

The survey contains four questions with sub-questions and was conducted online via platform SoSci Survey (screenshots with all survey details are provided in Figures S10 to S18). The first question elicits estimates of the distribution of the SCC in the literature for the year 2020 (the central value and the 2.5 and 9.75 percentiles), akin to a prediction study as in the experimental literature (*19*), and the distribution of their best estimate of the 2020 SCC, "all things considered". In the second question, we elicit experts' estimates of how different model structures represented in the literature affect SCC estimates and whether and to what extent these model extension–as currently reflected in the literature–provide *improved* SCC estimates. In the third question, we elicit experts views on what drives any difference (or "wedge") between the two SCC estimates they provided in the first question. Finally, in the fourth question, we asked for expert's views on the most important steps for improving estimates of the SCC going forward with an open ended qualitative response option.

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Introduction and Purpose

This is an expert survey on the social cost of carbon (SCC); i.e., the marginal damage cost of emitting a metric ton of CO2. You have been invited to participate because you have authored a peer-reviewed study estimating the SCC published between 2000 and 2020. This short survey contains four questions and may be completed in around 15 to 20 minutes.

Our survey aims to elicit authors' views on the SCC and 'structural' changes to Integrated Assessment Models (IAMs) that affect the SCC. Such structural changes – including to the earth system module(s), climate damage function(s), and utility/welfare functions – may increase or decrease the SCC and are explored selectively in the literature, rather than systematically.

We expect experts' views on the importance of these structural changes to vary, just as we expect experts to differ in their assessment of the importance of other determinants of the SCC, such as parametric variation concerning discount rates. Consequently, the distribution of SCCs in the literature may not reflect experts' overall views about appropriate values for the SCC, *all things considered*.

If you agree to take part, you will first be asked to estimate the distribution of SCC values in the literature. You will also be asked to evaluate the effects on the SCC of key structural changes to IAMs. Finally, you will be asked for your assessment of the "true" distribution of the SCC, *all things considered*, as well as its drivers.

Taking part in this research study is completely voluntary.

You are free to decline to take part in this project. Please try to provide complete responses. However, you can decline to answer any question and you can stop taking part in the survey at any time, i.e., we also accept partial responses. Additionally, we encourage you to contextualize your quantitative responses with qualitative remarks.

You can also provide us with your name. Your name would allow us to check for non-response biases, to prevent multiple participations and to link responses to observable characteristics, such as relating to the SCC estimates from your published paper(s). If you choose not to, your answers will be anonymous. In any case, all results will be published in a way that no individual participant can be identified.

Questions

If you have any questions about this research, please feel free to contact the investigators, Moritz Drupp (Moritz.Drupp@uni-hamburg.de or +49-151-21221557) or Frances Moore (fmoore@ucdavis.edu or +1-617-233-3380).

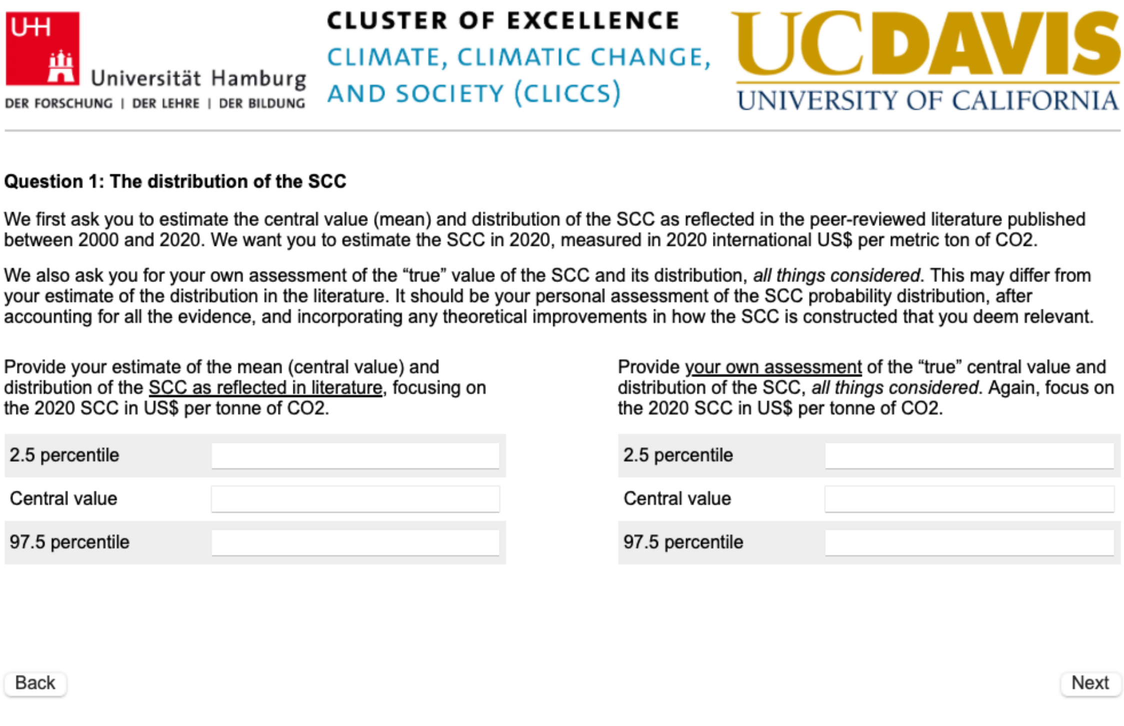
Start the Survey

Many thanks for lending your expertise to this research!

Please click on "Next" to start the survey.

Next

Figure S10: Screenshot of the Preamble.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Question 1: The distribution of the SCC

We first ask you to estimate the central value (mean) and distribution of the SCC as reflected in the peer-reviewed literature published between 2000 and 2020. We want you to estimate the SCC in 2020, measured in 2020 international US$ per metric ton of CO2.

We also ask you for your own assessment of the "true" value of the SCC and its distribution, *all things considered*. This may differ from your estimate of the distribution in the literature. It should be your personal assessment of the SCC probability distribution, after accounting for all the evidence, and incorporating any theoretical improvements in how the SCC is constructed that you deem relevant.

Provide your estimate of the mean (central value) and distribution of the SCC as reflected in literature, focusing on the 2020 SCC in US$ per tonne of CO2.

2.5 percentile	
Central value	
97.5 percentile	

Provide your own assessment of the "true" central value and distribution of the SCC, *all things considered*. Again, focus on the 2020 SCC in US$ per tonne of CO2.

2.5 percentile	
Central value	
97.5 percentile	

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Figure S11: Screenshot of Question 1.

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Question 2: Structural drivers of the SCC in the literature

We now ask you about the effect on the SCC of *structural changes*, which have been considered in the literature between 2000 and 2020. Note that the structural changes appear in random order, i.e., nothing is implied about their relative importance.

To fix ideas and ease comparability across respondents, we ask you to consider a mean SCC of around $40/tCO2 in 2020 international US$ as the baseline or reference case *without structural changes*, i.e. not including any of the model characteristics listed below, and formulate effect sizes relative to this reference. This SCC value is, for instance, close to the central 2020 SCC of $41.50/tCO2 in Bill Nordhaus' DICE2016R2 model (Nordhaus, 2018, *American Economic Journal: Economic Policy*).

We also invite you to comment on or further explain your answers.

Including tipping points in the climate system (e.g., Amazon forest dieback, ocean methane hydrate release)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it"?

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Allowing for persistent effects of temperature change on output (e.g., via effects on the capital stock or TFP growth rate)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it"?

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Figure S12: Screenshot of Question 2, Part 1.

Incorporating aversion to model uncertainty or ambiguity (e.g., by modelling second-order probabilities)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

○	○	○	○	○	○	○	○	○	○	○	○	○
< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it"?

○ Strongly Disagree ○ Disagree ○ Neither Agree nor Disagree ○ Agree ○ Strongly Agree

Using distributional or equity weighting

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

○	○	○	○	○	○	○	○	○	○	○	○	○
< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it"?

○ Strongly Disagree ○ Disagree ○ Neither Agree nor Disagree ○ Agree ○ Strongly Agree

Structural changes to the temperature response to emissions (i.e., to the earth system module(s))

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

○	○	○	○	○	○	○	○	○	○	○	○	○
< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it"?

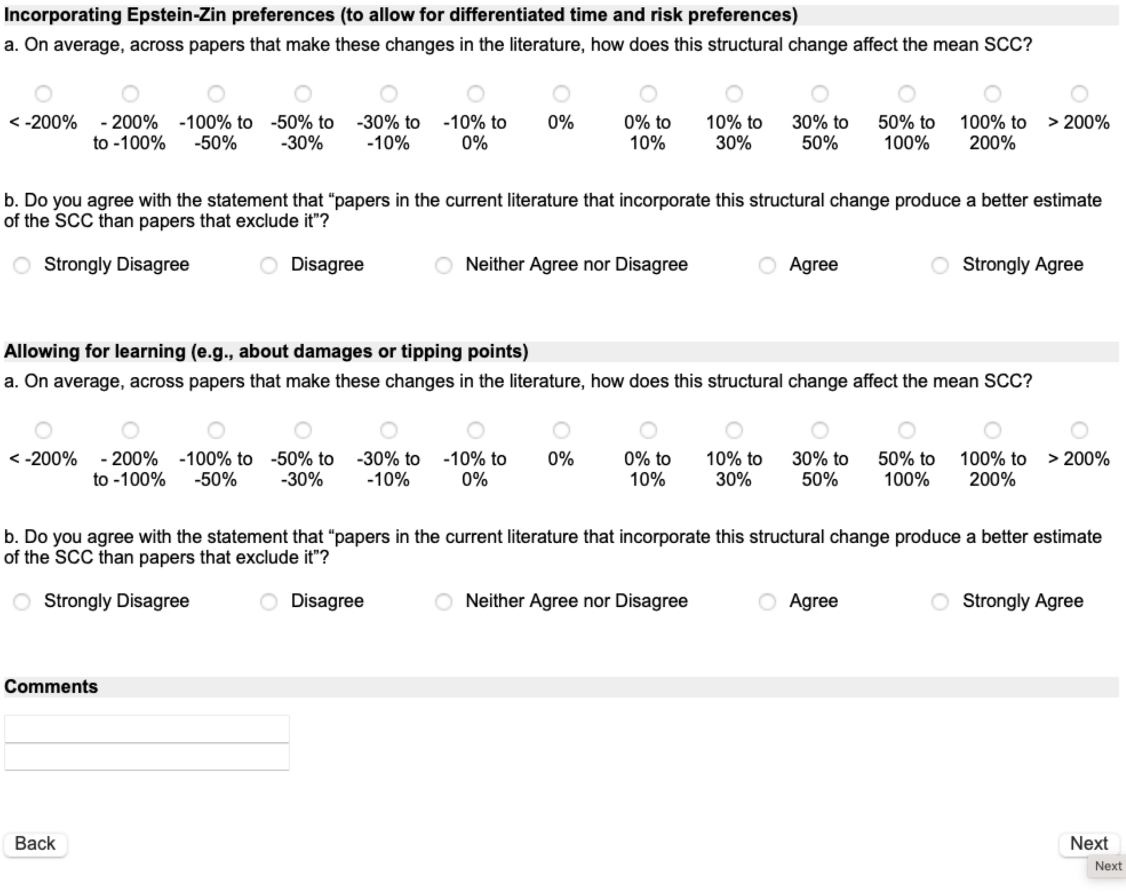
○ Strongly Disagree ○ Disagree ○ Neither Agree nor Disagree ○ Agree ○ Strongly Agree

Including tipping points in the damage function(s)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

○	○	○	○	○	○	○	○	○	○	○	○	○
< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

Figure S13: Screenshot of Question 2, Part 2.



Incorporating Epstein-Zin preferences (to allow for differentiated time and risk preferences)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that “papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it”?

Strongly Disagree | Disagree | Neither Agree nor Disagree | Agree | Strongly Agree

Allowing for learning (e.g., about damages or tipping points)

a. On average, across papers that make these changes in the literature, how does this structural change affect the mean SCC?

< -200%	- 200% to -100%	-100% to -50%	-50% to -30%	-30% to -10%	-10% to 0%	0%	0% to 10%	10% to 30%	30% to 50%	50% to 100%	100% to 200%	> 200%

b. Do you agree with the statement that “papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it”?

Strongly Disagree | Disagree | Neither Agree nor Disagree | Agree | Strongly Agree

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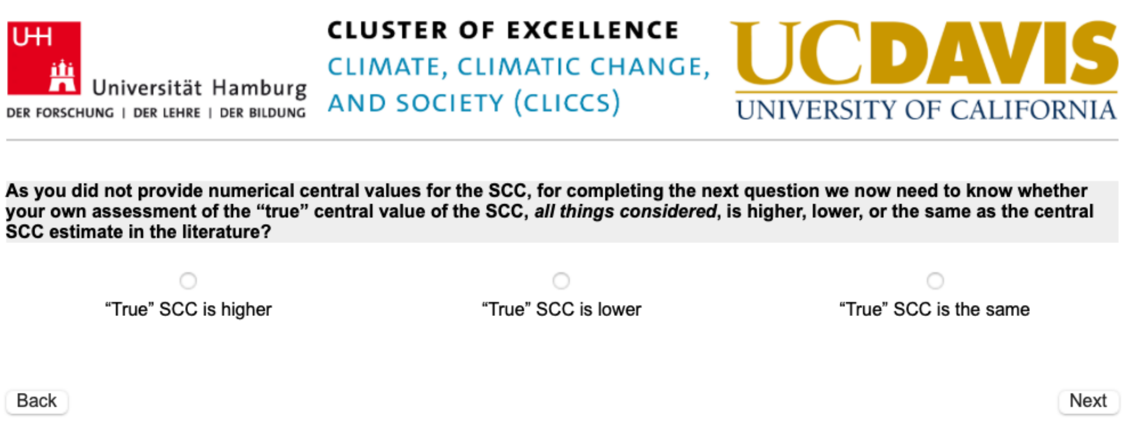
Figure S14: Screenshot of Question 2, Part 3.



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As you did not provide numerical central values for the SCC, for completing the next question we now need to know whether your own assessment of the “true” central value of the SCC, *all things considered*, is higher, lower, or the same as the central SCC estimate in the literature?

“True” SCC is higher | “True” SCC is lower | “True” SCC is the same

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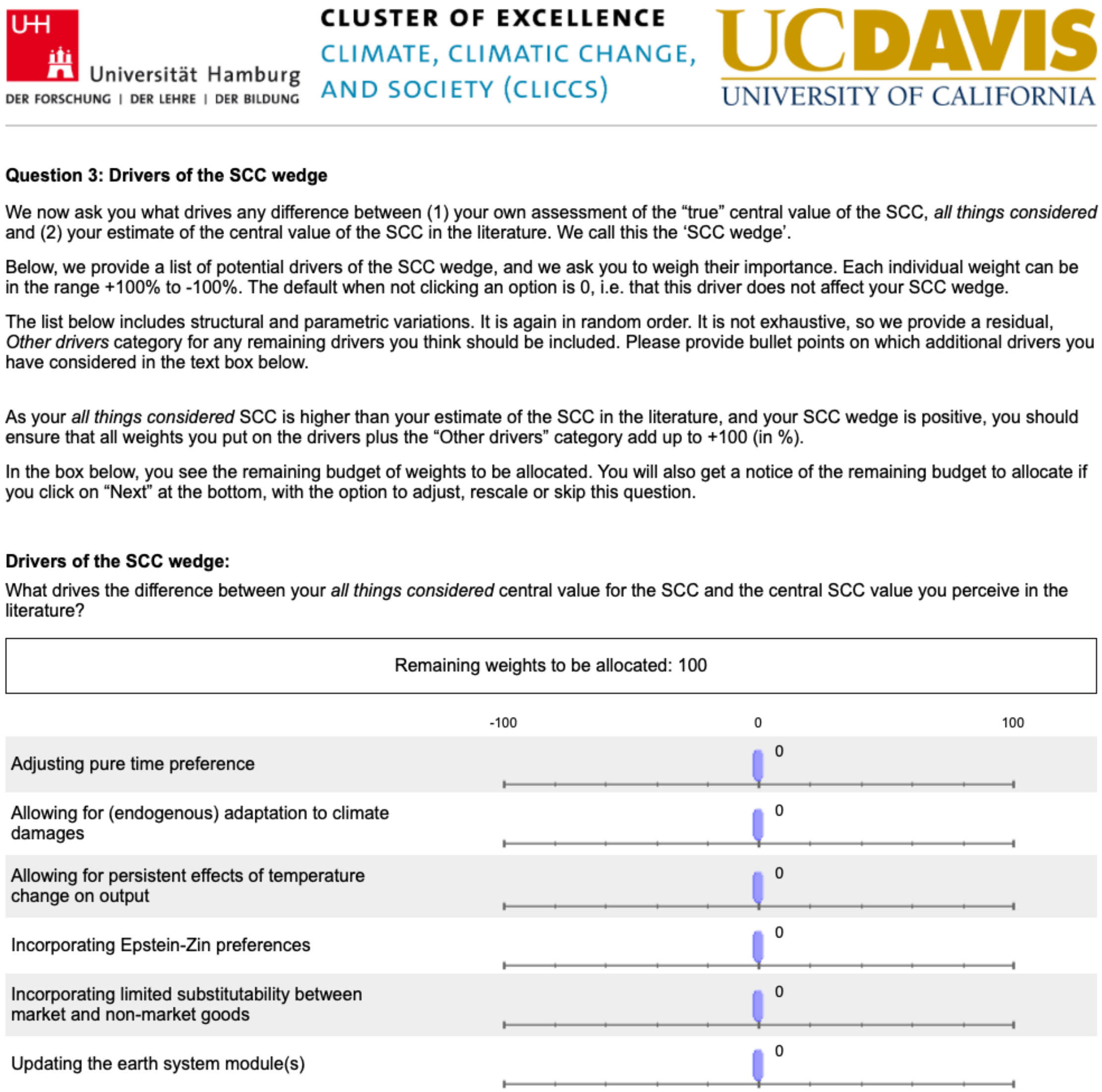
Figure S15: Screenshot of Interim Question in case the mean estimates for the SCC from Q1 were not answered (completely).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Question 3: Drivers of the SCC wedge

We now ask you what drives any difference between (1) your own assessment of the "true" central value of the SCC, *all things considered* and (2) your estimate of the central value of the SCC in the literature. We call this the 'SCC wedge'.

Below, we provide a list of potential drivers of the SCC wedge, and we ask you to weigh their importance. Each individual weight can be in the range +100% to -100%. The default when not clicking an option is 0, i.e. that this driver does not affect your SCC wedge.

The list below includes structural and parametric variations. It is again in random order. It is not exhaustive, so we provide a residual, *Other drivers* category for any remaining drivers you think should be included. Please provide bullet points on which additional drivers you have considered in the text box below.

As your *all things considered* SCC is higher than your estimate of the SCC in the literature, and your SCC wedge is positive, you should ensure that all weights you put on the drivers plus the "Other drivers" category add up to +100 (in %).

In the box below, you see the remaining budget of weights to be allocated. You will also get a notice of the remaining budget to allocate if you click on "Next" at the bottom, with the option to adjust, rescale or skip this question.

Drivers of the SCC wedge:

What drives the difference between your *all things considered* central value for the SCC and the central SCC value you perceive in the literature?

Remaining weights to be allocated: 100

	-100 … 0 … 100
Adjusting pure time preference	0
Allowing for (endogenous) adaptation to climate damages	0
Allowing for persistent effects of temperature change on output	0
Incorporating Epstein-Zin preferences	0
Incorporating limited substitutability between market and non-market goods	0
Updating the earth system module(s)	0

Figure S16: Screenshot of Question 3, Part 1.

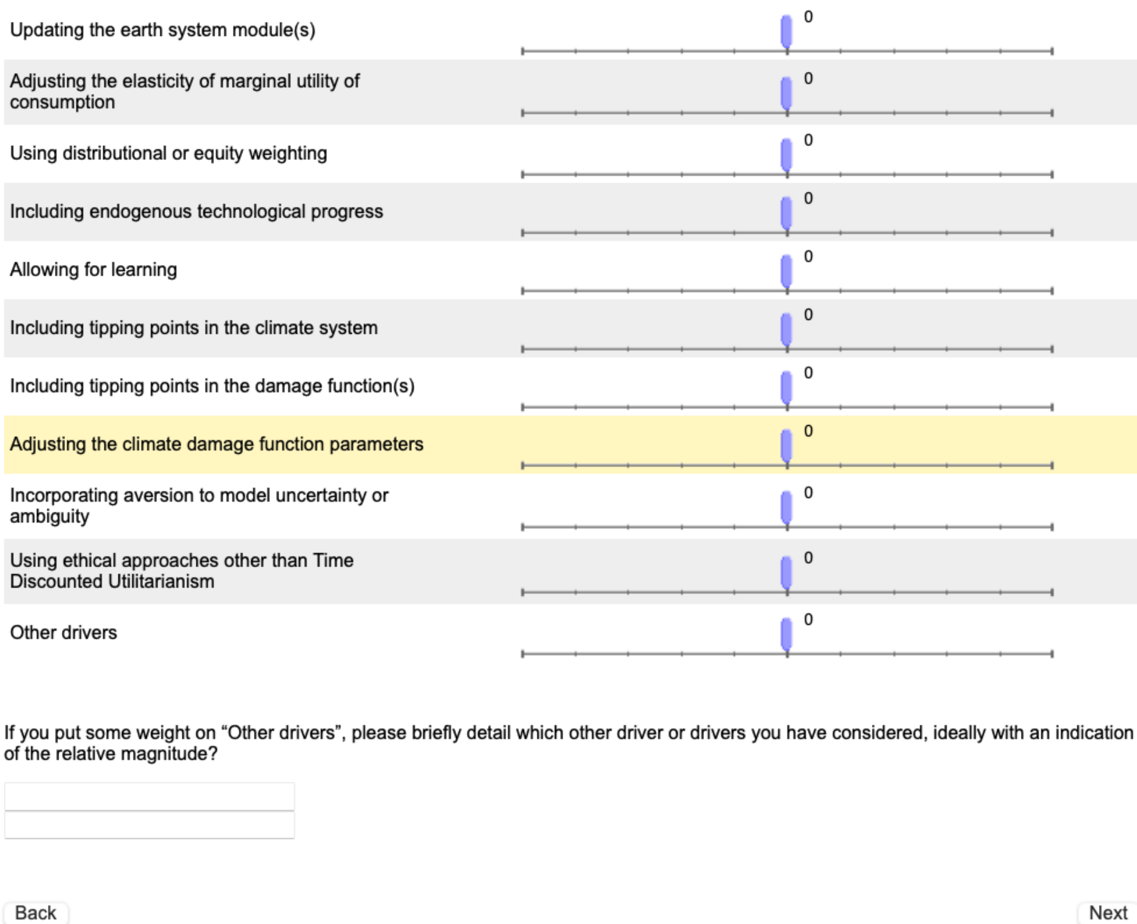

Figure S17: Screenshot of Question 3, Part 2.

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Question 4: Comments on next steps in improving the SCC

What do you think are the most important steps for improving estimates of the SCC going forward?

Your name

Finally, may we kindly ask you to provide your name? Your name would allow us to check for non-response biases, to prevent multiple participations and to link responses to observable characteristics, such as relating to the SCC estimates from your published papers.

We will hold your responses in the strictest confidence.

Upon closing the survey, we will create a separate password secured ID file that links identities to ID numbers and perform matching to meta-analysis data on this basis. The link of IDs to identities will be stored in password secured file to which only Moritz Drupp and Frances Moore have access. Also, the full dataset will be password secured. Results will only be published anonymously and such that no individual participant can be identified. Specifically, we will publish the meta-analysis data separately from the survey data, to ensure that no individual can be re-identified, and will only share data at an aggregated level with our co-authors on the project (Simon Dietz, James Rising, Ivan Rudik, Gernot Wagner).

Family name	
First name(s)	

We naturally also welcome anonymous responses if you do not want to reveal your identity.

Additional feedback

Feel free to provide us with any additional comments or feedback:

Many thanks for your valuable contribution!

Best regards,
Moritz Drupp (Hamburg) and Frances Moore (UC Davis)

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Figure S18: Screenshot of Question 4 and Ending.

S.2.2.2 Survey response cleaning

We took the following steps to clean the response data, indicated by row values #XXX, for final analysis. Row values of 1000 and beyond relate to response received via e-mail. Specifically, we

- removed one duplicate response, which was a subset (#698, retained #699)
- changed 2.5 and 9.75 percentiles for a single case in which they were entered reversely (#718)
- disregarded responses to Q3 of respondents who did not move any of the cursors.
- disregarded responses to Q3 in one case that only provided an all-things-considered SCC but no literature value and where the weights did not add up (#682)
- disregarded responses to Q3 in one case where weights did not add up and respondent ticked "Do not answer this question." (#626)
- disregarded responses to Q3 in one case where weights did not add up, appeared extremely strange and the respondent was anonymous so that it was not possible to follow-up.
- re-weighted weights in Q3 to add up for one respondent (#599) whose weights did not add up and who ticked "Rescale my weights such that they add up." in the survey
- added additional response categories, such as explained non-responses for authors who had retired in the meantime
- corrected SCC values of one expert (#576) based on e-mail communication following-up on a comment in the survey (see below) that the respondent had missed the option to go back within the survey to adjust the SCC estimates for equity weighting.
- de-anonymized one expert after the respondent had identified themselves and their response bilaterally (#750)
- added qualitative responses to Q4 from four experts who responded via e-mail, and a quantitative response to the SCC wedge for one respondent (#1000).

S.2.2.3 Publication bias discussion

Figure 1 shows the distribution of SCCs published in peer-reviewed journals over the 2000-2020 period. It is important that this is not interpreted as a standard meta-analysis. In the classic meta-analysis, multiple studies have produced empirical measurements of the same quantity, which can be combined to give lower-variance estimates of the quantity of interest. The SCC estimates we bring together here are fundamentally distinct in that they are not observational measurements of an empirical quantity, but primarily results of model simulations. The variation in Figure 1 reflects not uncertainty related to statistical sampling (as in a classic meta-analysis), but epistemological uncertainty in model parameters and structure. The distribution should be thought of as an integration over this uncertainty as reflected in the published literature over the last 20 years.

This interpretation does raise the question of how different the distribution would be if it also included unpublished SCC estimates (or those published but not in peer-reviewed journals). The question of publication bias arises repeatedly in the context of standard meta-analyses, where it typically refers to missing evidence of small effect sizes due to a lack of incentives to publish null effects. It is not clear whether similar asymmetric publication incentives operate around SCC values and, if so, in what direction they would shift the distribution. On the one hand, there is some evidence of a conservatism in scientific publishing, such that one might expect an anchoring around previously published estimates and therefore a narrower distribution in the published literature compared to unpublished model results (*20, 21*). On the other hand, others might suggest that extreme SCC values (either very high or very low) might be more noteworthy and so be more likely to proceed to publication, implying a wider distribution in the published literature. Existing studies show evidence in both directions, with Havranek et al. (*22*) finding substantively lower average SCC values in peer-reviewed published journals than those published in other outlets while a review by Tol (*23*) finds the opposite.

Our expert survey was designed to fill key knowledge gaps on the SCC that the meta-analysis alone cannot answer: the role of publication bias and insights on key drivers of the SCC and next steps for improving its estimation. The standard concern regarding publication bias is that due to researcher and editorial incentives, leading to file drawer problems or questionable to fraudulent research practices (e.g. p-hacking, data fabrication), estimates of a true effect size is represented in a biased form in the literature. Standard approaches are to examine z-scores of irregularities in p-values for experimental studies that aim to investigate some true effect size. Yet, these are not directly applicable to our setting, as many individual SCC papers do not have the goal of producing the best estimate of the SCC. These papers are comparative in nature and explore the effect of some variation in plausible parameters or some extension of the IAM structure to investigate how this affects the SCC. Oftentimes, they do so starting from a well-established, conventional baseline, such as the latest DICE model, and consider only one or a few extensions. Thus, these studies will—by design—provide a 'biased' estimate of what the study authors may themselves consider an appropriate estimate of the "true" SCC.[1]

Previous work has investigated publication bias by comparing peer-reviewed and non peer-reviewed work on the SCC (*22*). Yet, for the reasons detailed above, comparing published and unpublished papers trying to estimate the SCC does not provide the most useful benchmark for detecting publication bias. We therefore investigate the role of publication bias by means of the expert survey. Specifically, any differences between an expert's literature and best-estimate SCC values serves as an indication of publication bias.

As illustrated in Figure 3a (for the subset of experts that also anwered the question on the SCC wedge breakdown), our data suggests that experts believe the peer-reviewed literature exhibits a substantial and significant downward bias (t-test, t=6.063, two-sided P<0.000). This is also apparent given the substantial rightward shift in the "true" distribution—one that asked experts to account for all things they deemed missing or imbalanced in the published literature—compared to the estimated literature distribution in Figure 1. Indeed, we find that 82.82% of experts think the central SCC in the literature to be biased downwards as compared to its true value, 9.09% think that it is represented correctly in the literature and 9.09% think the SCC to be biased upwards in the literature.

[1] There may be an incentive—akin to p-hacking in the empirical literature—for such comparative studies, as the chance that they get published well may increase if the paper reports a strong effect of introducing a certain structural model modifications. The magnitudes of structural model modifications may thus be overestimated in the literature.

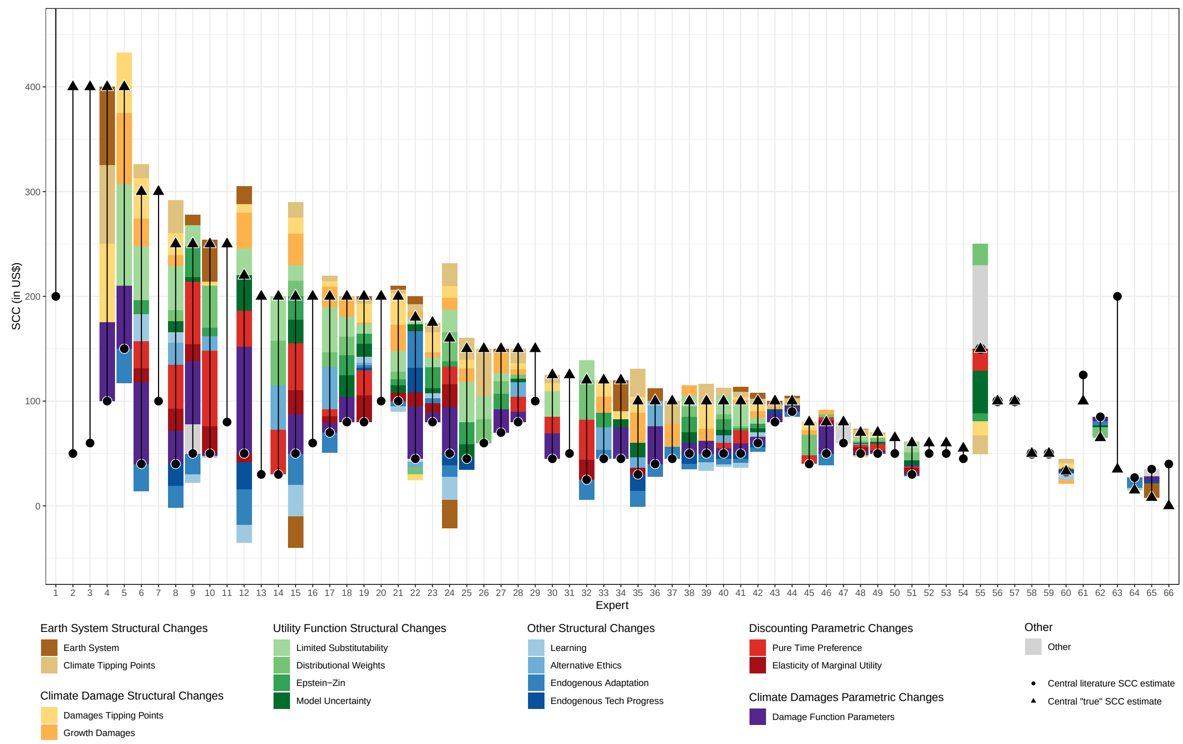

Figure S19: Individual estimates of the central 2020 SCC in the literature and the central "true" 2020 SCC value "all things considered".

S.2.2.4 Non-response and strategic response bias analysis

We conduct a number of non-response and strategic response bias checks (*15, 16*). To investigate non-response bias, we compare non-anonymous respondents with the rest of the population of authors along observable characteristics such as their continental location, gender and year of PhD, number of publications in SCOPUS and their h-index. We complement this with data from our meta-analysis on the median 2020 SCC in their published papers (using 2010-2030 pulse years as the effective 2020 sample), the median discount rate employed in their SCC papers, as well as the proportion of their SCC estimates that contain one of the major structural model modifications, and the proportion of their SCC estimates that we classified as 'framework expansion' or as 'empirical improvement'. Overall, we find that identified respondents ($n_{ir} = 48$) exhibit very similar characteristics as the anonymous part of the population sample ($n_{non-ir} = 128$), which contains the anonymous respondents ($n_{ar} = 27$). We find no significant differences across groups in terms of being located in North-America (t-test, t=0.970, two-sided P=0.334), Europe (t-test, t=-1.476, two-sided P=0.142), Asia (t-test, t=0.522, two-sided P=0.602) or Oceania (t-test, t=0.598, two-sided P=0.550), being classified as 'male' ($n_{ir} = 44$, $n_{non-ir} = 109$; $\chi^2(1)$=1.303; P=0.339), year of PhD award (t-test, t= -0.4799, two-sided P=0.632), number of publications (t-test, t=0.701, two-sided P=0.484) and h-index (t-test, t=0.570, two-sided P=0.0.569. We also find no significant differences in terms of their discount rates employed (t-test, t=-1.461, two-sided P=0.146) and their 2020 SCC estimates (t-test, t=-0.189, two-sided P=0.851). Ientified respondents have published more frequently on what we classified as 'empirical improvement' (t-test, t=-2.432, two-sided P=0.016), they do not exhibit a higher proportion of having published a 'framework expansion' (t-test, t=-0.384, two-sided P=0.702), nor on any of the sub-classifications, such as on climate or damage tipping points (t-test, t=0.615, two-sided P=0.975; t-test, t=-1.461, two-sided P=0.540), earth system model updates (t-test, t=-1.281, two-sided P=0.202), alternative utility function specifications, e.g. using Epstein-Zin (t-test, t=-1.281, two-sided P=0.885), or alternative ethical approaches (t-test, t=0.283, two-sided P=0.778). This null finding is noteworthy as having mentioned some of these in the initial e-mail invitation might have induced experts who have published more on these to be more likely to respond to the survey.

To investigate strategic response bias, we compare responses by anonymous and identified respondents.

We find no significant difference in views on the central "true" SCC all things considered (t-test, t=-0.991, two-sided P=0.325), and the upper and lower percentile ranges are almost identical (two-sided P=0.898 and P=0.949). While anonymous respondents estimate a much lower central 2020 SCC in the literature (t-test, t=-2.497, two-sided P=0.015), the upper and lower SCC literature range estimates do not differ (two-sided P=0.420 and P=0.241). Both groups also do not differ in whether their best-estimate SCC is higher than their literature estimate (n_{ar} = 25, n_{ir} = 41; $\chi^2(1)$=0.916; P=0.339), or in the magnitude of their SCC wedges (t-test; t=-0.486, two-sided P=0.628). Further, we do not find any differences in their views on whether any of the different model structures represent an improved estimate of the SCC (t-tests, lowest P=0.140, for persistent growth effects), and anonymous respondents are also not more likely to provide comments on any of the questions (lowest $\chi^2(1)$=0.012 is P=0.358 for Q3). Yet, anonymous respondents put considerably more weight on 'other drivers' in question 3 (t-test, t=-3.027, two-sided P=0.004), and less weight on pure time discounting (t-test, t=1.731, two-sided P=0.090). Whereas anonymous respondents are not more likely to provide comments on model structures in Q2 or on next steps for improving the SCC (n_{ar} = 27, n_{ir} = 48; $\chi^2(1)$=0.012; P=0.913). While responses of the anonymous sample are different along some dimensions, we do not detect a clear signal of efforts to strategically distort the survey results, particularly because the best-estimate, comprehensive SCC does not differ across samples. Differences appear to rather stem from different views on the SCC in the literature and on the role of pure time preference in driving the SCC wedge. To be inclusive of the whole range of reasonable views, we thus retain anonymous responses as part of our main analysis. We repeat the strategic response bias analysis by splitting the sample at the median into early and late respondents. The general hypothesis is that respondents who want to strategically affect the results may respond earlier. We find no significant differences along all those dimensions reported on above, except that early respondents are more likely to provide comments on next steps for improving the SCC (n_{early} = 33, n_{late} = 33; $\chi^2(1)$= 7.174; P=0.007).

S.2.2.5 Additional analyses of the merged dataset

Among the identified respondents, a higher 2020 SCC median in an expert's own publications is highly significantly associated with estimating a higher SCC in the literature (β=0.05, $t_3$3=4.50, P <0.000), and weakly significantly associated with a higher best-estimate SCC estimate (β=0.12, $t_3$3=1.75, P=0.089).

We do not find significant differences in literature or best SCC estimates across continents (but those by experts from Asia tend to be lower and those by experts from Europe tend to be higher).

We find a strongly significant gender effect: The few female experts estimate a significantly higher SCC value in the literature (t-test, t=4.269, two-sided P<0.001) and also a "true" SCC value that is more than twice as high as the corresponding estimate by male experts, with \$288 versus \$130 (t-test, t= 3.80, two-sided P<0.001), and a higher SCC-wedge (t-test, t= 2.74, two-sided P=0.009).

We next relate the proportion of an expert's included papers published on specific model structures and whether they are more likely to agree or strongly agree that "papers in the current literature that incorporate this structural change produce a better estimate of the SCC than papers that exclude it" (Q2). We do not find this to be the case for any of the extensions. However, we find that having published a higher share of papers on some specific extensions—persistent growth damages (β=14.01, t_{40}=2.13, P=0.040), Epstein-Zin preferences (β=22.73, t_{40}=6.63, P <0.000), and distributional weights (β=27.34, t_{40}=2.87, P=0.007)—is associated with assigning more weight to these model structures as drivers of the central SCC-wedge.

S.2.2.6 Survey Assessment of Alternate Model Structure

Experts were asked to rate their agreement with the statement "papers including X produce a better SCC than those excluding it?" on a five point scale (Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree) for 9 elements of model structure. Responses to these questions, for 53 experts that provided answers to this question are shown in Figure S20.

We apply a Bayesian hierarchical model to convert responses to this question into a multivariate probability distribution that can be used to sample the random forest model. The model makes the

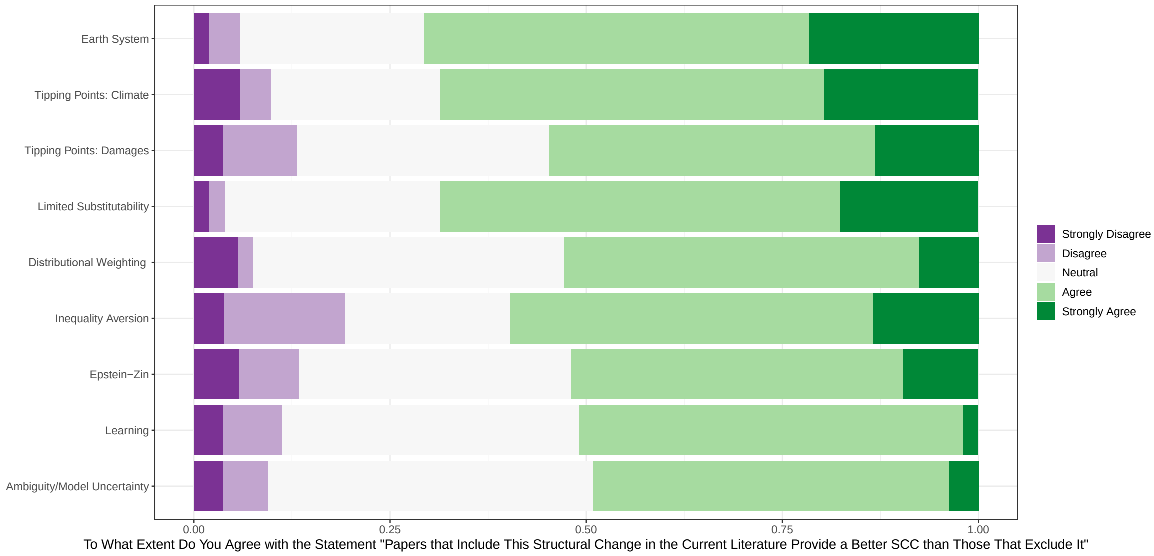

Figure S20: Distribution of views from the expert survey asking respondents for their assessments of the SCC papers with varying model structure.

following assumptions:

- Each expert has a belief about the likelihood that including a given structural model element is beneficial. This belief is uncertain, and represents a distribution over probabilities.
- The response categories– "Strongly Disagree", "Disagree", "Neither Agree nor Disagree", "Agree" and "Strongly Agree"– represent a discretization of this probability space. To choose one category, an expert will take a random draw from their belief distribution.
- Each expert has a consistent ordered scheme for mapping probability values to categories. Also, they accurately report their beliefs.
- We can usefully talk about the "common belief" across experts. This is a (hyper-)distribution, from which each expert's beliefs are drawn. It is possible to partially pool the beliefs across the experts to generate an estimate of this common belief.

This represents a kind of meta-analysis, which allows us to simultaneously generate an estimate of the common beliefs about structural model elements, and expert beliefs that are consistent with these. If the expert beliefs are estimated to be very uncertain, a high level of pooling will be used since all estimates will be consistent with a common value. If expert beliefs are certain and not alike, little pooling will be used and the estimate of the common belief will be uncertain.

We use the following Bayesian model to implement these ideas. Let the central logit value of the belief of expert j on question k be

$$\theta_{jk} \sim \mathcal{N}(\mu_k, \tau_k)$$

The actual reported level is a categorical variable drawn from an ordered logistic:

$$l_{jk} \sim \text{OrderedLogistic}(h\theta_{jk}, h\vec{c}_j)$$

where h is a global parameter that determines the spread around the central value (that is, how likely it is for an expert to report a category higher or lower than their central belief).

The categorical divisions are deviations from a naive partitioning of the probability space into 5 equal regions, represented by

$$c_j \sim \mathcal{N}([\text{logit}(0.2), \text{logit}(0.4), \text{logit}(0.6), \text{logit}(0.8), \text{logit}(1.0)], \sigma)$$

where σ determines the variation between expert understandings of the categories.

We further impose weakly informative priors that $h \sim \text{Exponential}(0.001)$ and $\tau_k \sim \text{Cauchy}(0, 1)$.

The result of this analysis is shown in Figure 3c. Some questions show a higher degree of agreement (e.g., ambiguity/model uncertainty) than others (e.g., distributional weighting). Summary statistics and parameter values are shown in Table S7.

	mean	se_mean	sd	2.5%	25%	50%	75%	97.5%	n_eff	Rhat
Ambiguity μ	0.35	0.00	0.10	0.15	0.28	0.35	0.42	0.56	5881.72	1.00
Earth System μ	0.79	0.00	0.12	0.56	0.71	0.79	0.87	1.05	4277.46	1.00
Epstein-Zin μ	0.40	0.00	0.12	0.16	0.32	0.40	0.48	0.63	4430.73	1.00
Inequality μ	0.48	0.00	0.14	0.21	0.39	0.49	0.58	0.76	3132.52	1.00
Learning μ	0.34	0.00	0.10	0.15	0.27	0.34	0.41	0.54	7069.27	1.00
Limited Sub. μ	0.77	0.00	0.11	0.56	0.70	0.77	0.85	1.00	5690.99	1.00
Persistence μ	0.42	0.00	0.10	0.22	0.34	0.41	0.49	0.62	5665.33	1.00
TPs: Climate μ	0.73	0.00	0.13	0.47	0.64	0.73	0.81	0.98	4692.44	1.00
TPs: Damages μ	0.49	0.00	0.12	0.25	0.41	0.49	0.58	0.74	4303.60	1.00
Ambiguity τ	0.19	0.01	0.14	0.01	0.08	0.17	0.28	0.51	609.14	1.00
Earth System τ	0.44	0.01	0.19	0.04	0.31	0.45	0.57	0.81	503.55	1.01
Epstein-Zin τ	0.39	0.01	0.19	0.03	0.25	0.39	0.52	0.76	443.44	1.01
Inequality τ	0.68	0.01	0.19	0.25	0.58	0.69	0.80	1.04	249.03	1.02
Learning τ	0.21	0.01	0.14	0.01	0.10	0.20	0.31	0.51	577.08	1.01
Limited Sub. τ	0.29	0.01	0.18	0.02	0.15	0.28	0.42	0.65	598.69	1.01
Persistence τ	0.22	0.01	0.16	0.01	0.09	0.20	0.33	0.56	506.57	1.00
TPs: Climate τ	0.48	0.01	0.22	0.04	0.33	0.49	0.64	0.90	364.83	1.01
TPs: Damages τ	0.49	0.01	0.20	0.07	0.36	0.51	0.63	0.86	430.27	1.01
h	3.22	0.05	0.54	2.57	2.89	3.12	3.40	4.60	130.10	1.03
σ	0.36	0.00	0.04	0.29	0.34	0.36	0.39	0.45	799.47	1.00

Table S7: Posterior distribution statistics for common parameters, computed by Stan, using 4 chains, each with iter=2000; warmup=1000. n_eff is a measure of the effective number of MCMC draws of the posterior distribution that were achieved. Rhat is a measure of convergence, where full convergence produces a value of 1.0.

S.2.2.7 Qualitative comments

Below we report qualitative comments received in the online survey or via e-mail, not edited except in cases where this is necessary to preserve anonymity. Numbers refer to individual experts by row values (#XXX). Row values of 1000 and beyond relate to response received via e-mail.

Comments on Question 2: Structural drivers of the SCC in the literature

#553 Persistent effects are still under debate about how to integrate them in IAM. Current implementations are not satisfying.

#558 My responses to b are all else equal - I would have preferred this to say the same model or paper with or without a specific feature.

#562 Uncertainty would not alter SCC that much. Exceptions would include uncertainty about the damage function related to tippiing points or uncertainty about how rapid the temperature increases I believe.

#569 For most of these I put "Neither agree or disagree" not because I don't think they are important to develop further, but because I don't think the evidence base is quite there yet or because I think there are a set of difficult ethical assumptions inherent in making these changes that I'm not sure are better than the current assumptions.

#572 most of my responses are very impressionistic based on recollections of a partial and idiosyncratic reading of the literature. would have to conduct a more systematic review to have any confidence in my answers. but i assume what you want here are impressions

#576 When producing my own distribution in the previous page, I really focused on damages and discount rate holding structure constant. However, I would note that some of these parameter changes do not impact the social cost of carbon as much in my opinion, but instead the optimal tax. This is particularly true for learning by doing, as learning by doing can substantially impact the optimal tax, though I think it will have a limited effect on the most likely climate scenario.

#598 In simple models, a lot depends on how the damage function is calibrated. A simple damage function could also include damage on capital, tipping points, non-market goods, etc. In models with learning on damages, I assume that the model without learning does monte-carlo, does not have the option to change the plan when information is discovered and has therefore a much larger risk premium.

#623 I don't think "tipping points" as advanced by Lenton, Schellnhuber, etc are physically justified by the available science. I think the main thing missing in terms of losses associated with CC is a reasonable representation of the on-going costs of extreme events. These have been mostly neglected in the development of DICE-like IAMs. I think lots of ideas around equity-weighting in SCC estimations start to lose contact with political reality quite fast. I'm not exactly sure how to bound "structural changes" so I down-weighted the potential effects. These could be higher, given some possible interpretations.

#628 it is hard to distangle the impacts of uncertainty and learning in the questions. Generallyu I would think that uncertainty (for example in ECS, tipping points etc) increases SCC, but with that uncerrtainty eventual learning of the issue at hand (eg ECS) reduces the SCCncreases

#633 Each of these questions merits a proper meta survey paper so my answers are highly noisy and should not be taken too serious at all

#645 Some of the statements were ambiguous, like 'Structural changes to the temperature response to emissions', 'tipping points in the damage function' or 'persistent effects of temperature change on output'. It was very hard to evaluate what these actually mean, what their inclusion means (i.e. how are they included in a model) and thus what impact they could have on the SCC. Model uncertainty and ambiguity are very important concepts in this context. But are they something that we can objectively judge and quantify in the SCC? Or are they rather points that we should recurrently remind ourselves and reflect upon. Yes, there are mathematical theories that allow one to incorporate second-order probabilities and the aversion to ambiguity. But does that really capture all the ambiguity there is, or do these theories just convey 'artificial crispness' (as Weitzman described this) that is not truly the thing we are after?

#659 Re some of the above topics I am aware of only one study, in others not even one. So difficult to come up with my guesstimate.

#660 Why did you leave out CO2 fertilization effects? That's one of the big differences among IAMs and SCC estimates. I took the "structural changes to temperature response" to mean the Equilibrium Climate Sensititivity parameter. This is one of the big uncertainties in climate modeling not only among models but between model-based and empirical estimates. The term "tipping points" is overly vague. The proper term is "bifurcations". If they exist they are properties of the climate system, they are not induced by forcings. The literature "incorporating tipping points" gives a sense of looking for ways to make a simulation model crash and generate a dramatically larger SCC, without explaining how such a bifurcation could have existed throughout the present and previous interglacials without causing similar crashes even during much warmer periods. This genre looks to me to lead to higher SCC's of lower scientific quality. Adding growth impacts from temperature and precip changes in principle should increase the quality of the empirical estimate but in practice the results are very uncertain and of indeterminate sign. So they look to me like better quality but no change to the mean or median estimate. I don't have any familiarity with the techniques for incorporating aversion to ambiguity, Epstein-Zin preferences or constrained substitutability.

#687 On inequality, it depends on what you mean by inequality. Current estimates show convergence of incomes so this would increase the discount rate and reduce SCC. If you add in the inequality of the impacts of climate change,, which are borne by the poor, then this could well increase the SCC. If you then introduce catastrophic effects to the poor, you will have dismal theorem type effects which could be really important welfare wise. None of this nuance can be captured by the questions. On the climate science questions: whether updating the energy balance model will increase or decreas the SCC, I am afraid that I have not read so many papers on this topic, so i do not have a good basis for giving answers here. On tipping points, this is a dificult question. We know so little about how likely they are to occur and how bad tipping points will be in terms of economic damages that it is a difficul tcall to say that an estimate of the SCC for policy purposes is better for their inclusion. What is required is a presentation of the range of what is known, coupled with some decision / welfare theoretical approach to assess what the welfare maximisng approach is when faced with such dramatic uncertainties (a la Barro, Weitzman etc.). recent work by Dietz et al (2021) tends to indicate that tipping points will be trivial in terms of impact on GDP due to physial factors (e.g. feedbacks) but also economic factors (discounting, damage function and the fact that an optimal path will reduce the risks considerably) . So, difficult to say whether I think they should inform THE SCC,but they should inform the range of possibilities that are presented to policy makers for sure. the above comments are written rather quickly. I think they make sense. Happy to clarify ex post if need be.

#738 I found it really hard to answer these questions. First of all because I do not think there is a true SCC. The SCC depends on valye laden assumptions such as the discount rate, how to value the loss of a statistical life in poor countries, how to value risk, and how to value nature... hence, there can be no true answer here. Furthermore - how a change in the model will affect the SCC depends of course on how the change was implemented and how that structural phenomena was implemented before... so for some of these questions I was uncertain about how to ask. ,

#749 The only truly realistic change is including uncertainty in the scc rather than speaking of a distirbution of scc, and that change will raise the scc

#752 I find this page of questions somewhat ambiguous as the answer usually depends on the details of what is considered "structural change". Depending on these details in many if not most cases the answer to "part a" can change the sign and the answer to "part b" can change from Agree to Disagree. I decided in each case what I guessed you might be after, and I did not represent the literature per se but that part of the literature corresponding to my guess of what you might be after. E.g. growth change: even the DICE model has a pass through of the damages on the capital stock (so yes, agree, important), but I assumed you are likely after assuming direct damages on the growth rate rather than output or capital stock (then answer is, no, disagree that it improves the estimates conditional on current knowledge). There are similar ambiguities in most questions.

Comments on Question 3: Drivers of the SCC wedge.
"If you put some weight on "Other drivers", please briefly detail which other driver or drivers you have considered, ideally with an indication of the relative magnitude?"

#576 I did not consider equity weights in my $200. If I considered equity, then I would have multipled my estimate by 2.5 coming to an estimate of $500. I put 5% on the elasticity of marginal utility of consumption and Epstein Zinn preferences each, as these are really a joint decision in my opinion. I think though that market rates have declines, which further supports these differing parameter values underlying an extended Ramsey equation.

#617 Difficult for me to answer. My main thinking and own contribution have concerned the tail probabilities.

#626 hard to grasp this question I am afraid

#641 Shares with sliders?

#650 Generally, nonconstant discounting and monetizing more sources of damages should lead to a higher SCC. Adaptation and more granular (geographically) treatment of damages should decrease the SCC.

#660 Other drivers: I include endogenous adaptation here (I wasn't sure if that's what you meant by allowing for learning). Updating the earth system module: I take this to mean updating the ECS parameter to empirically-constrained ranges Adjusting the climate damage function: I include incorporation of CO2 fertilization and global greening effects here.

#679 Measurability problem in climate damage functions: SCC considers only measurable/marketable damages. F.e. costs of "wildlife extinction" not considered/not measurable in terms of GDP/welfare loss.

#687 I didn't say other but, my responses are based on the fact that one does not need too much in the way of other changes to get to the SCC that I would prefer. Many of the other points above are important, but not necessary to explain the difference. there may be some discrepancy between these responses and the previous responses, but i am explaining here the primary deerminants of the gap in terms of my original position on the SCC which rested on the above aspects.

#697 Impact on sentient animals

#738 Of course - this is tricky to answer... so please see my answers as rough estimates. For instance - changes in the damage function, could be done by change ion the parameters or by adding tipping points. It is not trivial to disentangle these.. the same with the discount rate and eta vs rho

#742 I will need to go back and do the first question. I think it would be better to have one think through the components first, no?

Question 4: Comments on next steps in improving the SCC.
"What do you think are the most important steps for improving estimates of the SCC going forward?"

#553 Understanding the impact of damage persistence and the interplay with adaptation.

#558 better incorporation of the latest science in the earth system modeling; ability to more adequately capture tipping points, including economic ones such as collapse of maritme food sources and massive migration better modeling of how economic systems and prices will adjust; better modeling of uncertainty

#562 SCC fully considering the effect of learning on multiple uncertain features at the same time

#567 Transparency about modelling choices and their effects on the SCC; improving climate damage estimations; explicity taking into account nature's values and relative price changes; societal discussions and refelctions about intergenerational equity and fairness

#569 Exploring tipping points, better characterizing damage functions, improving exploration of different ethical frameworks.

#572 improved evidence base for calibration of damage function parameters. i.e., more empirical studies of the influence of climate changes on economic performance and well-being.

#579 macro-economic modeling to understand pathways by which climate change might haver persistent effects on the economy

#598 Combine risk and non-marketed goods, a more dynamic damage function (warming speed matters and temperature may affect tfp growth) It is not widely known that in most models the risk premium is actually low (increasing the risk aversion parameter from 2 to 6 increases the SCC by a mere 5 to 10% even when there are tipping points in the model). I find that puzzling, but it might also simply be true. Requires further research though.

#608 Better representation of the natural cycles of heat, emissions, and ecological processes (e.g., tipping points, methane emissions from thawing permafrost, etc.) Identification of permanent asset damages by climate change

#620 Better damage estimates, especially better treatment of adaptation and extreme weather

#641 less theory, more empirics an end to climate determinism inclusion of the large literature on the links between vulnerability and development inclusion of the large literature on the valuation of health and nature young economists should learn how to use search engine and read the literature, including papers that are more than 5 years old

#644 Invistigate and incorporate individual's perference towards climate change, at present, we only consider the economists'/politicians' perferences.

#650 Quantifying and monetizing more sources of damages (e.g. impacts to marine resources). Ultimately, modeling the climate system with tipping points and feedback is likely to have a larger impact but my sense is that omitted damage sectors are the lower hanging fruit.

#659 Identifying the best studies and focusing mean statistics on these (i.e. removing clearly incomplete or biased studies, as they contaminate the statistics. The topic is too important to leave it to statistics. Informed judgement is important too.

#660 Spend less time dreaming up implausible "tipping point" catastrophes and more time quantifying aerial CO2 fertilization effects, agricultural adaptation strategies and global greening impacts. Also, the authors who look for growth/TFP impacts make glib associations with extreme weather, without citing any data or IPCC assessments on the subject. The links to changes in extreme weather are weak and of ambiguous sign. It doesn't provide a credible rationale for expecting TFP changes due to warming. The use of RCP8.5 and related SSP's should be stopped. It's a ridiculous storyline. Authors who use it are clearly putting their finger on the scale to get a dramatic result and a splashy headline but it is a waste of the reader's time. There's been very little attention paid to Tiebout sorting, but it seems to me it should result in people relocating themselves closer to their privately-optimal temperatures.

#669 Need better process-based models.

#673 Estimates of limited substitutability of non-marked goods Estimates of the persistence of damages on market and non-market sectors with adaptation Robustness analyses with regard to alternative approaches to intergenerational equity and efficiency

#679 Inclusion of additional "damage types" in climate damage functions

#683 Dissagregation. A single number is too abstract to be useful for policy making.

#687 Damages. value of environment/relative prices, One thing that is missing from all of this is the handling of catastrophic risk and risk in general. Issues related to the climate beta, the insurance properties of climate mitigation and so on.

#693 better understanding of climate damages, both the aggregate across time for different climate futures, but also the spatial and socio-economic distribution of damages

#697 Including climate impacts on sentient animals

#708 Better understanding and measuring the pathways through which changes in climate affect the economy (e.g. not just TFP level hits calibrated to reduced form estimates).

#710 ethics, uncertainties-, distribution- and related preferences

#718 Better and more comprehensive modeling of cliamte damages. Better assesment of risks and ambiguities associated with cliamte change.

#738 Damage function

#739 A better estimation of damages, as well as of possibilities and costs of adaptation

#749 I believe we should better try to model the limits of our knowledge

#750 distinguishing between growth and level effects, accounting for non-market damages, damages functions that reflect climate impacts adequately

#752 Getting the valuation of climate (and ecosystems) over an extended future right/or more right in our simplistic economic valuation functions.

Additional feedback

#562 Look forward to the result very much!

#569 This is a really interesting survey!

#570 Bottom line – huge uncertainty over the SCC.

#572 Good luck with your study! This was not an easy survey to complete. I've tried to give you responses that are at least better than just noise :)

#576 This is an interesting survey, though, in some ways, I would have liked a slightly different set up. I wonder if the structural questions should have been upfront to debias individuals. By considering a variety of factors first, you may have better prevented anchoring. If I were to factored in equity weights for example, I think that my response would be very different. In particular, I would have given a range of $50 to $10,000 with a central estimate of $500. Most of the other considerations were factoring into thinking about the appropriate damage function and discount rate, except for substitutability. If I factored this in completely, I would probably have increased by SCC estimates between 50% to 100% even more. In fact, seeing everything laid out in your table about structural assumptions, made me realized how downward biased that I really think that SCC may be despite frequently thinking about the topic.

#592 Good luck with the study. I hesitated to put my name for a moment because i was embarassed if i wrote something contradictory or stupid. But i felt there is a value to being transparent for you. I should say though that answering seriously i should have spent an hour or two. Many of the issues are complex and some questions perhaps could be interpreted in different ways. I am however - as is common every evening, rushed to get through emails and decided to do the questionnaire quickly in 10 minutes and without going back over questions or consulting any document - just straight from the top of my head. I look forward to seing what will come of it and maybe discussing at some point.

#608 It was rather a hard task. I couldn't provide confident numbers myself, but you may still find some patterns from the data when combined with the others' responses.

#620 This is quite possibly the best survey I have ever filled in.

#623 Interesting survey - I'd like to hear the results.

#644 Thanks for your invitation! I think this survey is really useful in terms of gathering ideas.

#687 Tough survey. I am not confident in some of the answers since my reading of the literature is partial and my personal views on the SCC are heavily influenced by my papers and the few papers that I have been influenced by.

#710 It feels VERY wrong to answer this "off the cuff" without thinking longer about it. But some answer is better than no answer (...?). I want to "object" against the framing, at least a little. There is no such thing as an SCC "estimate". We project future marginal damages, at best. And we cannot even do that without several value judgments. To call the SCC an "estimate" may increase its political influence but masks what it is. And makes it vulnerable - you can always critisize any projected value or distribution based on the welfare function parameter choices or structural- or heroic assumptions of any specific model. That's why I really do not like that we use the same terminology as for say a neat RCT estimate of the impact of policy X on behavior Y. Anyway, that was my little pet peeve there. Good luck with the project. PS: Now I'll try to google the actual distribution and bite myself if I am very off ;-)

#738 Good luck with this. Sometimes it was difficult to give a clear cut answer...

#749 One note: I answered your questions as if you were asking for the mean via "central value". Median would be quite different.

#752 I found parts 1 and 3 quite useful. I am afraid that I found part 2 too ambiguous to be meaningfully interpreted.

#1000 I believe the literature has overestimated the SCC. My reasons are the following. Economists are quick to dismiss the benefits of CO2 fertilization. Economists tend to also dismiss future adaptation. Many economists do not realize tipping points are already part of traditional damage estimates. Some economists are reaching for damages that are likely to be small in the labor market, with conflict, from migration, and ecosystem change. Finally, my colleagues are a little confused about the endogeneity of the SCC. If society adopts a high SCC, there will be a lot of mitigation. This will lower the SCC. They should not be calculating an SCC based on Business as Usual unless they believe the SCC will have and should have no effect on policy.

#1001 Thanks for sending me the survey. Honestly, I feel I cannot respond. Sorry for that. Actually, I am now more convinced that the SCC is not helping us and that the cost-benefit analysis of climate change has caused more confusion to the decision-makers that benefit. When Nordhaus obtained the Nobel prize in 2018 the committee included a figure with an "optimal" stabilization temperature of 3C..., something that any IPCC report would endorse. With all my respect, I think the economic methods have been pushed too far in relation to what our data, models and projections and knowledge can really say and not. I have personally worked with the DICE model in the past and I know how sensible it is to small variations to few parameters and on the damage function selected. For that reason, I cannot respond. It can be 10 or it can be 10.000. I don´t know. I am not trying to deviate you from your plans or to argue on this (I might be wrong), but as I have received the mail 4 times, I had the necessity to explain to you why I cannot respond. Of course, I think we need to devote more efforts on putting monetary values to the damage (present and future) of climate change where we have information and keep on with the carbon pricing/markets. Also, if we need a reference-value for guiding decision-makers, I think that the cost of abatement (for example to achieve the Paris Agreement targets) can be a good reference-point as we have less uncertainty on some key technologies. Of course, this is my point of view.

#1002 I looked at your survey, but I can't answer the questions because they are based on the flawed assumption that the current BAU allocation is efficient, which it is not due to the mispricing of Greenhouse Gas Emissions. At an inefficient allocation the Social Cost is not well-defined.

#1003 For building a more complex IAM, I think non-linear climate feedback effects and distributional effects are really important. In the literature on real world impacts of climate change and extremes, it's very clear that the majority of the actual impact comes from climate extremes - heat waves, coastal erosion/inundation and hydrological extremes - which tend to have a non-linear response to climate forcing and there are the huge uncertainties and potentially catastrophic scenarios of runaway feedback mechanisms. In proportional terms, climate change clearly affects the poor a lot more than the rich. That's unlikely to change. I know economists and philosophers go back and forth about the discount rate - what it is and what it should be...but the distributional effects of damages within generations really matter to real people. And if massive inequality of consequence is not adequately addressed, it may lead to an increase in political instability and conflict.

#1007 Thank you for writing. I hope it is ok if I pass on filling in the form. As you probably know, I am not enthusiastic about using IAMs as the basis for calculating social cost of carbon or indeed as a basis for public policy in general. A challenge is to change the structures of economies fundamentally and rapidly. As I have argued, I think we should approach shadow pricing for carbon in a way which helps directly with that question and thus asking what are the prices that, when combined with other structural polices, help make this transformation happen. I fear that the process you are embarking might keep IAMs at centre stage when they really don't capture the urgent and major policy questions.

S.2.3 Random Forest Model and Synthetic SCC Distribution

S.2.3.1 Distribution-Based Random Forest Model

We train a random forest model as the basis for our synthetic SCC distribution. The random forest model has advantages over other statistical modeling approaches such as the multivariate regression analysis discussed in Section S.2.1.9. In particular, random forests (a form of machine learning) select both variables and functional forms as part of the model training exercise, allowing them to flexibly handle non-linearities and variable interactions without them having to be specified ex-ante by the researcher. This is valuable in this setting where underlying IAMs produce SCC estimates known to have complex, non-linear relationships with underlying variables.

Our random forest model is trained on published SCC values using 31 predictor variables: 9 binary variables describing model structure; 14 binary variables representing contributions to any parametric variation in the distribution; 2 variables capturing the damage function based SCC estimates; and 6 other variables including discount rate, SCC pulse year etc). We use a bespoke random forest algorithm that respects the unusual structure of our underlying data in which each observation is a probability distribution over the SCC (with 63% being delta distribution point estimates when no probabilistic information was reported).

We estimate 500 regression trees, training each using random samples of the dataset and explanatory variables. Splits in the regression trees are determined by the Anderson-Darling k-Sample Test, with the goal of maximizing variance between two distributions at each split. We prune trees with fewer than 7 nodes or large leaves (those that represent > 50 row, and span 0 to $10,000 SCC values), leaving 403 trees. Each leaf (i.e. terminal node) in a tree produces a distribution over SCC values based on the component observations in that leaf. The random forest takes the mean for each computed quantile generated by each of the 403 trees to produce a predicted distribution.

Variable importance is calculated by identifying which variables are used in classifying each observation in the training dataset, translating this into a "probability" of each variable being used across the training dataset, and taking the average of these probabilities over the forest. The variable importance plot is shown in Figure S21.

S.2.3.2 Sampling the Synthetic SCC Distribution

The synthetic SCC distribution is generated using a Monte Carlo sampling approach, drawing a vector of input variables from the expert distribution over model structure (Figure 3c) and discount rates (Figure 3d based on Drupp and Hansel (*15*)), as well as a set of constant predictor variables shown in Table S8. We generate a predicted SCC distribution from the random forest model for each of the 1 million draws from the input variable space. The final SCC distribution is.....The final result is a distribution that reflects expert assessments of discount rates and structural model characteristics,

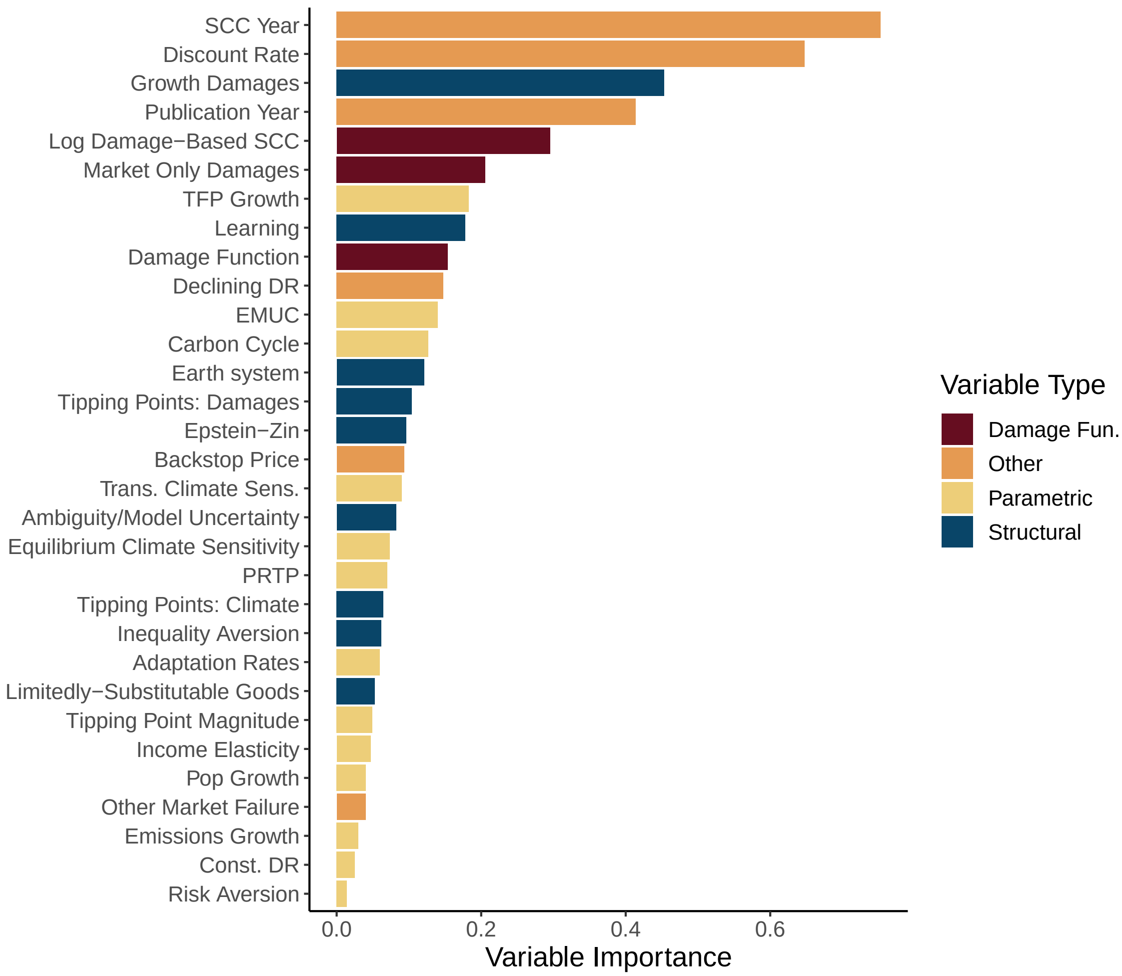

Figure S21: Variable importance for the random forest model. Variable importance is calculated based on the expected probability of conditioning on each predictor variable across all 403 retained regression trees. Variables that are chosen earlier in the regression tree have a higher importance since all subsequent predictions further down the regression tree are conditioned on them. PRTP = pure rate of time preference; EMUC = elasticity of marginal utility of consumption.

variation in the SCC due to structural and parametric uncertainty as reflected in the literature, and residual parametric variation.

Predictor Variable	**Value**	**Reasoning**
SCC Year	2020	2020 prediction year for comparison to other distributions in the paper
Publication Year	2020	More recent papers are most likely to represent current scientific knowledge
All Parametric Variation	1	Allow for any difference in mean SCC due to parametric uncertainty
Backstop	0	True SCC not backstop technology price
Other Market Failure	0	Capture climate externality and not other market failures

Table S8: Random forest prediction variables. Parametric uncertainty is over 14 variables (namely TFP growth, population growth, emissions growth, transient climate response, carbon cycle parameters, equilibrium climate sensitivity, tipping point magnitudes, damage function parameters, adaptation rate, income elasticity, discounting parameters (constant discount rate, PRTP, EMUC and Risk Aversion for some Epstein Zin papers).

To generate the waterfall plot in Figure 5b, we start with a prediction dataset with no structural modifications, no parametric uncertainty, no backstop price, non-declining discounting at 4.6%, market and non-market damages, no other market failures, and damages resampled from the different versions of the DICE damage function appearing in our literature survey. Then we sequentially adjust to this prediction dataset with each of the following modifications: (1) discount rates drawn from (*15*) and addition of declining discounting; (2) damages resampled from the whole training dataset; (3) each structural change; and (4) each form of parametric uncertainty. Because of interactions between these model elements, the order of operations matters for interpreting the decomposition. To ensure that each bar is independently interpretable, Figure 5b shows results averaging over 30 random orderings, while ensuring that parametric uncertainty is only applied after any necessary structural changes.

S.2.3.3 Synthetic SCC Sensitivity Analysis

Figure S22 shows sensitivity of the synthetic SCC distribution on various dimensions. Each plot shows the full snythetic SCC distribution (leftmost bar) and alternatve distributions varying a single dimensions, namely discount rate, model structure, publication year, and damage function. Additional quantiles and means for the synthetic SCC distribution and all sensitivity analyses is given in S9.

	2.5th	5th	10th	25th	50th	75th	90th	95th	97.5th	Mean
Synthetic SCC	14	32	52	97	185	369	636	874	1155	284
No Structural Changes	5	21	35	65	124	243	423	596	731	186
All Structural Changes	13	39	66	128	245	486	820	1138	1469	367
1% Discount Rate	24	49	73	123	223	420	705	937	1197	322
2% Discount Rate	29	47	66	106	188	353	587	789	1045	273
5% Discount Rate	5	18	30	63	135	302	575	828	1170	241
Publication in 2000	10	25	44	90	164	331	582	843	1125	260
Publication in 2010	8	26	46	93	171	347	608	889	1171	272
Publication in 2020	14	32	52	97	185	369	634	874	1153	284
DICE Damages	10	27	43	83	161	340	631	898	1195	269
FUND Damages	9	26	42	80	159	348	667	937	1256	276
Howard & Sterner Damages	19	41	66	120	218	403	652	877	1150	308
PAGE Damages	11	29	46	86	164	337	600	849	1125	263

Table S9: Percentile information and means of the synthetic SCC distribution and sensitivity analyses shown in S22. All in 2020 US dollars per ton CO_2.

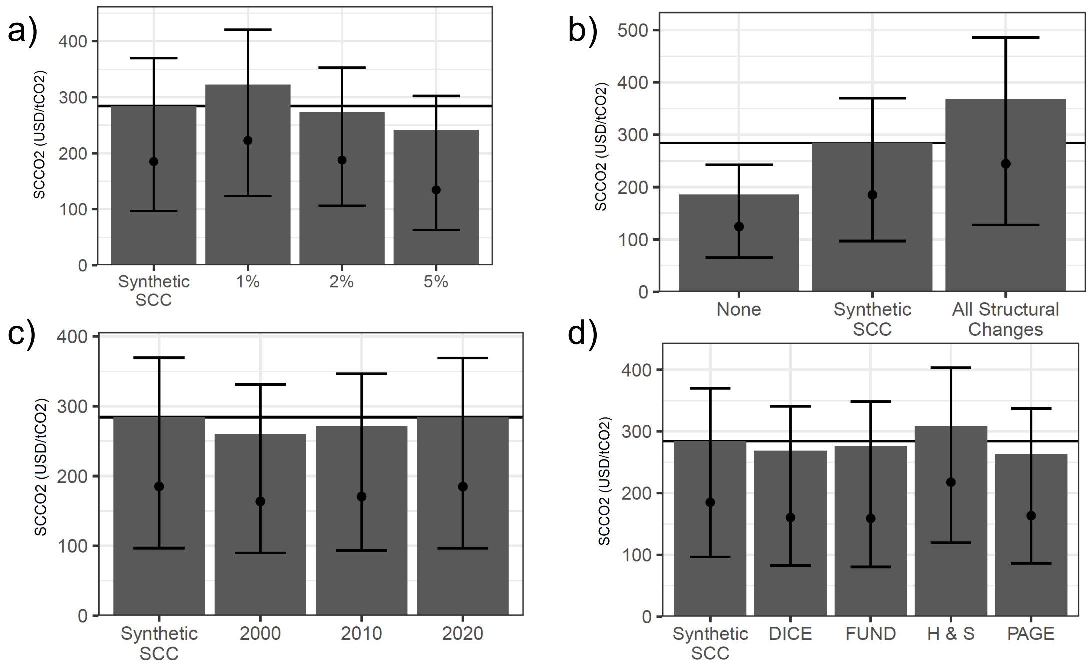

Figure S22: **Sensitivity of the synthetic SCC to alternate input assumptions.** Output distributions from the random forest based on input distributions used in the synthetic SCC (Figure 5, leftmost column in each plot) and alternate distributions that systematically vary one component. a) Discount rate parameter; b) Model structure, c) Publication year; and d) Damage function (H&S corresponds to Howard and Sterner (*24*)). Bars show distribution means, points the median, and error bars the inter-quartile range.

S3 Description of structural model modifications

In this section we describe each of the nine structural moedling elements discussed in the paper, their relevance to the SCC, and provide example references.

S.3.1 Ambiguity / Model Uncertainty

Climate policy grapples with many kinds and sources of uncertainty, and in many cases there is no agreed-upon quantitative distribution to describe that uncertainty. When multiple possible distributions are available, this problem is referred to as model ambiguity, and solutions typically assume that agents make pessimistic assumptions across the range of possibilities. A standard implementation of model ambiguity would follow a minimax approach, minimizing the welfare loss under the worst set of assumptions.

Higher values of the SCC represent larger losses in welfare for any emissions scenario, so model ambiguity selects higher values of the SCC across any range of possible values. Model ambiguity can also be included when selecting the optimal emission pathway. In this case, model ambiguity results in more cautionary decision-making, lower emissions, and a resulting lower SCC. In this context, the particular role of model ambiguity and the definition of the scenario (exogenous or optimal) is central.

Example Citations: (*25, 26*)

S.3.2 Earth System

Studies in this class make changes to the structure of the carbon cycle or warming modules relative to the simple 2-3 box carbon-cycle model and simple radiative-balance model used in versions of DICE, FUND and PAGE up to 2016. These modules map carbon dioxide emissions into atmospheric concentrations and atmospheric concentrations into climatic changes (principally temperature increases), respectively. Some models might add carbon-cycle feedbacks or might collapse the process into a single functional relationship between cumulative emissions and temperature, following evidence in more recent climate science (*27*).

The Earth system representation matters for the SCC because it determines how much temperatures, and where relevant other climatic variables, respond to CO2 emissions.

Example Citations: (*28, 29*)

S.3.3 Epstein-Zin Preferences

Epstein-Zin utility functions disentangle risk across time and states of nature, introducing both a richer set of preferences and the need to solve models recursively. While these types of utility functions have become standard in financial economics over the past 2-3 decades, they are relatively new in climate-economy models. Models that incorporate Epstein-Zin preferences are either computationally involved empirical calibration exercises or highly stylized, attempting to tease out the importance of individual parameters in a set of sensitivity analyses.

Epstein-Zin preferences matter for the SCC, as they ensure that higher risk aversion does not lead to higher discount rates, which in turn lead to lower SCCs. The greater the uncertainties and risk aversion, the greater is the impact of switching to Epstein-Zin preferences on the SCC.

Example Citations: (*30, 31*)

S.3.4 Distributional Weighting

The same monetary loss results in a greater welfare loss in poorer regions than it does in richer regions under commonly-assumed concave utility functions. Climate change is also projected to affect income groups differently. For instance, poorer regions are often in warmer areas and are expected to have some of the greatest climate impacts.

Distributional weighting, namely applying weights to dollar-valued impacts to different income groups, is typically used to operationalize inequality aversion. This can capture the higher welfare effect of income losses to poorer people and / or policy preferences that prioritize the well-being of the worst off. If poorer regions are exposed to greater climate impacts, then accounting for inequality aversion can produce large increases in the SCC.

Example Citations: (*32, 33*)

S.3.5 Learning

Models that incorporate learning allow the distribution over one or more unknown parameters to evolve over time, typically through a Bayesian update, as data generated by the relationship governed by the unknown parameter are observed over time. Some of the learning models are myopic in that the social planner in the model does not anticipate future learning. Other learning models are forward-looking where the social planner anticipates future learning and adjusts policy accounting for how it affects learning and subsequent welfare. A plurality of the papers in the literature have focused on learning about the equilibrium climate sensitivity – which can be learned from observations of temperature and levels of greenhouse gases – while other papers have included learning about damages, climatic and damage tipping points, and other aspects of the climate economy.

Learning matters for the SCC because as policymakers refine distributions over unknown parameters, they are better able to match climate policy to the true state of the system which will affect the SCC. Learning typically reduces the SCC because of active learning motives where additional carbon emissions magnify the signal of the unknown parameter relative to background noise, allowing for faster learning. Theoretically, learning's effect is a priori ambiguous and depends on nonlinearities and stock effects in the climate-economy.

Example Citations: (*34, 35*)

S.3.6 Limited Substitutability

These models explicitly allow for limited substitutability by disaggregating a comprehensive consumption good or a comprehensive capital stock into more detailed component parts. For instance, these model changes feature non-market environmental goods as a direct source of utility and allow for various degrees of substitutability with standard produced consumption goods. These models also typically disaggregate the effects of climate damages on both market and non-market goods.

As standard IAMs, like the DICE model, implicitly feature some degree of limited substitutability (Drupp and Hänsel 2021), the effect of explicitly introducing limited substitutability on the SCC is ambiguous. When the degree of substitutability between consumption and environmental goods is lower than in standard models, these model structures can substantially increase the SCC.

Example Citations: (*36, 37*)

S.3.7 Persistent / Growth Damages

Models that allow for persistent or growth damages introduce pathways for transient changes in temperature to have permanent effects on output. This is usually modeled as temperature affecting the growth rate of factor productivity or increasing the depreciation rate of capital stocks.

Accounting for persistent impacts of temperature generally increases the SCC. If temperature has persistent effects, then a temperature shock today affects output today and in future years. Conditional on a particular instantaneous damage function, this will increase total damages and the SCC.

Example Citations: (*4, 38*)

S.3.8 Tipping Points: Climate

Climate tipping points/elements have been defined as "subsystems of the Earth system that are at least subcontinental in scale and can be switched – under certain circumstances – into a qualitatively different state by small perturbations" (Lenton et al., 2008). Examples include the permafrost carbon feedback, melting of the Antarctic and Greenland Ice Sheets, and a slowdown of the Atlantic Meridional Overturning Circulation (AMOC). Some models include a representation of the key underlying geophysical relationships that govern the tipping point, while others simulate climate tipping points in a stylized way.

Climate tipping points are diverse in nature and affect the SCC in different ways. Some are positive feedbacks in the climate system that increase the temperature response to CO2 emissions, for example the permafrost carbon feedback. Ice sheet melting increases sea levels and thereby increases coastal adaptation costs and residual costs/damages. Large-scale circulation changes such as AMOC slowdown may primarily change the distribution of impacts across countries and this may affect the overall SCC depending on the incomes of the countries most affected.

Example Citations: (*2, 34*)

S.3.9 Tipping Points: Damages

Models that incorporate damage tipping points allow for economic output to be irreversibly reduced, potentially stochastically, if a particular climate threshold is crossed. Damage tipping points are stylized ways of capturing sudden non-linarities in impacts that could be associated either with abrupt climate system changes (the climate tipping points described above) or thresholds in socio-economic impacts from those changes (e.g. large-scale dislocations such as war or mass migrations). These models incorporate a new state variable that captures the extent of tipping and the probability of this state variable progressing (capturing further advances in tipping and greater damage) depends on the state of the climate system and random shocks.

Damage tipping points matter for the SCC because crossing a tipping threshold irreversibly moves us into a higher-damage world. This tends to increase the SCC because the value of the next ton of carbon must now account for the probability that the tipping threshold is crossed and the subsequent permanent increase in damages (though the SCC then drops once the tipping point is crossed).

Example Citations: (*31, 36*)

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SCC Meta-Analysis Code Book

Overarching study / value inclusion criteria:

1. Study calculates an “original” SCC (i.e. does not only report values calculated in other studies)
2. Excludes previous meta-analysis estimates
3. Excludes reporting SCC estimates calculated using a model presented in a previous paper. For example, if standard DICE 2007 is run and then modified in some way, the SCC from the modified model should be reported as a new central value, but the value from the standard run should not. (Instead it can be recorded as a “Base Model” value) - this avoids over-counting estimates from models that are re-used by multiple papers
4. Excludes estimates of an “optimal carbon tax” where the primary focus of the paper is modeling market failures other than climate change damages. Optimal carbon tax values that account for market failures other than climate change can be included, but should be flagged in Column M.
5. Excludes estimates of the social cost of methane, N2O or other greenhouse gases / radiatively active species
6. Includes values reported as supplementary analysis in appendix tables

Note that not all values in a paper will necessarily be explicitly coded in the spreadsheet. In some cases, reported variation in the SCC due to parametric variation will be “collapsed” into min-max values and reported as a range in the “SCC Distribution” section. Variation other than that due to SCC year, emissions scenario, discounting scheme, damage function, base / calibration model, or model structure should mostly be reported within a single row.

Bibliographic and Base Model Info

Column A: Unique ID number from full abstract list in “Paper Tracking” spreadsheet

Column B: Add Bibtex reference to this document and record Bibtex name here

Columns C-F: Self-Explanatory

Columns G-H: Report any prior model used for calibration purposes or for comparison. Use Column G (“Base IAM”) if study reports using a prior model and then adding modifications. Use Column H (“IAM Calibrated To”) if study reports calibrating an original IAM using a prior model.

Column I: Categorize the type of SCC study into one of four types:

1. Empirical Improvement: These are studies where the clear goal of the analysis is to improve representation of the climate system, climate damages, or otherwise better align IAM model results with pre-existing scientific or economic findings. Examples might

include improved representation of climate change (e.g. SLR dynamics) or incorporation of econometric damage estimates.

2. Framework Expansion: These are studies where they are adding to or extending the analytical IAM framework, with a view to better representing relevant factors driving climate change costs, but without as strong a tie to a particular empirical literature. Examples could include EZ utility papers, inequality aversion, learning, new discounting frameworks, multi-good utility papers.
3. Sensitivity Analysis: These are studies with a stated intention of only examining the sensitivity of SCC to modeling choices. Often these studies deliberately present a wide range of parameter values and do not take a strong position on which are or are not empirically preferred.
4. Other: Other types of papers can be coded as "Other". Most notably this includes papers reporting "standard" models (e.g. paper reporting the DICE 2013 update and results)

NOTE: This is a categorization of the *paper*, not a particular value from the paper. All rows from the same study should have the same value in this column. If a paper has multiple rows that could be coded differently (i.e. some framework expansion and some empirical improvement) then code the whole paper using the "highest" value, i.e. empirical improvement > framework expansion > sensitivity analysis.

Central SCC Value

Column J: Year of SCC.

- For papers reporting only discrete years, record all SCC years in separate rows.
- For papers reporting continuous SCC values (e.g. graphically), report 2020, 2050 and 2100 if possible. If post-2100 values are reported, also record latest SCC year reported.
- If these specific dates are not available, report earliest available, a mid-century value, and latest available

Column K: Report Central SCC value in $ per ton CO2. If central value is a median, then *also* record it in Column AR (50th percentile).

- Convert values reported in $ per ton C into $ per ton CO2 by dividing by 3.666667
- For values reported in other currencies, convert into $ per ton CO2 using exchange rate from the reported currency year, or the publication year if there is no currency year reported. Report exchange rate in the notes Column (BQ)
- If there is no clear central SCC value (e.g. just high and low values are reported) then this can be left blank and only the range or distribution reported in the "SCC Distribution" section of the sheet.

Column L: Backstop Price? - Enter a 1 if the value recorded in Column K is a backstop price

Column M: Other Market Failure? - Enter a short description of other market failures included in the value in Column K, if that value is an optimal carbon tax that includes market failures other than climate change damages. Examples could include “R&DExternality” or “LimitedRedistribution”.

Column N: Dollar year of SCC - record SCC dollar year if reported.

Column O: Emissions Scenario - record emissions or radiative forcing scenario used for SCC estimate in the row. Examples include:

- Optimal - SCC along the optimal emissions path
- BAU - SCC along the BAU emissions path
- Some radiative forcing scenario (e.g. RCP 7) or socio-economic scenario with associated emissions (e.g. A1B) - assumption is that reported SCC is a BAU SCC along this emissions trajectory (i.e. no mitigation)
- Some temperature or CO2 concentration threshold (e.g. 1.5 degree, 450 ppm) or other implicit emissions constraint (e.g. some risk level). For these cases, enter using the formulation “Constraint - <SPECIFIC CONSTRAINT>” e.g. “Constraint - 2degrees” or “Constraint - 400ppm”. This will help us identify these cases later on in the coding.

-> Only record variation in *emissions* scenario in this column, not variation across other model parameters

Column P: Socio-Economic Scenario - record socio-economic scenario used for SCC estimates in this row. This will particularly be used for determining the consumption growth rate for calculating the Ramsey discount rate. Possible entries include:

- If population and GDP or TFP growth rates are unchanged from the underlying base or calibration model, record the model name here, e.g. “DICE 2007”
- Record standard socio-economic scenarios e.g. SSP2 or A2
- If per-capita consumption growth rate is specified in the paper, record that here (e.g. 2% per year)

Column Q: Reported Base Model SCC - if available, record a Base Model SCC value that is “comparable” to the Central SCC value in the sense of sharing the same 1) discounting assumptions and 2) emissions scenario and 3) SCC year.

Discounting Parameters and Damage Function

Column R: If a constant discount rate (i.e. rather than the Ramsey formula) is used, record the % value here (i.e. 1.5 instead of 0.015 or 1.5%). If a declining discount rate is used, record the initial value here.

Column S: Record Pure Rate of Time Preference. If a declining PRTP is used, record the initial value here.

Column T: If central estimate uses a declining discount rate, add a 1 here. Otherwise leave blank.

Column U: Record EMUC used in Ramsey formula of Central Estimate

Column V-W: Record parameters of Epstein-Zin preferences, if applicable. Note most papers report IES = 1 / EMUC. If necessary convert from EMUC to IES.

Column X: Market Only Damages - Enter a 1 if the Central SCC Value is based on damages that explicitly include only market damages (e.g. calibrated to studies examining variation in GDP)

Column Y: Damage Function Info - Use this column to record the functional form of the damage function for models with only one damage function that depends only on temperature and falls on production (i.e. single region, single sector models). Leave blank if the model is not of this type (e.g. multi-region models). Information can be recorded in one of three ways:

1. If the damage function is left unchanged from the base or calibration model, re-enter that model name in here (eg. DICE 2007)
2. If the damage function is a variation commonly referred to by the original authors, enter the corresponding name here. Possible entries are:
    a. Weitzman - corresponding to damage function used in Weitzman (2012, Journal of Public Economics Theory)
    b. HowardSterner - corresponding to base damage function reported in Howard and Sterner (2017, Environmental and Resource Economics). (Note - some HowardSterner damage function specifications also include calibration to growth rate impacts, which can be indicated using "Calibrated" in Column AD)
    c. DietzStern - corresponding to damage function in Dietz and Stern (2015, The Economic Journal)
3. If neither 1 nor 2 apply, directly enter the damage function into the column, using T as the GMST change from the baseline used in the paper (e.g. 0.0004 * T^3). Any R expression is permitted. T is assumed to be contemporaneous temperature (i.e. warming in the same time period as damages occur) unless otherwise indicated, using syntax T_{t-k}.

Structural Changes

Column Z: Carbon Cycle - Enter a 1 if the values in this row include a structural change in the Carbon Cycle model, compared to the baseline or calibration model, or compared to DICE if no baseline or calibration model is reported.

Column AA: Climate Model - Enter a 1 if the values in this row include a structural change in the Climate Model (i.e. effects on the physical climate system, conditional on greenhouse gas concentration, including temperature and sea-level rise), compared to the baseline or calibration model, or compared to DICE if no baseline or calibration model is reported.

Column AB: Climate Tipping Points - Enter a 1 if the values in this row include climate tipping points. This means a representation of specific changes in the earth system such as ice-sheet processes, Amazon dieback, changes to the thermo-haline circulation.

Column AC: Damage Tipping Points - Enter a 1 if the values in this row include a stylized or abstract representation of tipping points as a change in damages without modeling the underlying drivers from the climate system (e.g. Cai, Lonztek JPE).

Column AD: Persistent / Growth Damages - Enter a 1 here if the values in this row include persistent damages, for instance via damages to the capital depreciation rate, TFP growth, or capital stock. Enter "Calibrated" if the damage function is calibrated to partially account for persistent damages but they are not represented structurally in the model.

- Note that standard DICE, because of endogenous capital formation, includes some small persistence in damages. Do NOT enter a 1 here for standard versions of DICE.

Column AE: Epstein Zin Utility - Enter a 1 if the values in this row come from a model using Epstein-Zin preferences

Column AF: Ambiguity / Model Uncertainty - Enter a 1 if the values in this row explicitly account for ambiguity or model uncertainty

Column AG: Non-Substitutable Goods - Enter a 1 if the values in this row come from a model with more than one good in the utility function that are imperfectly substitutable with each other

Column AH: Inequality Aversion - Enter a 1 if the values in this row include inequality aversion. Enter "Calibrated" if the damage function is calibrated to account for inequality aversion but it is not represented structurally in the model.

Column AI: Learning - Enter a 1 if the values in this row are from a model explicitly representing a learning process.

Column AJ: Alternative Ethical Approaches - Enter a 1 if the values in this row are based on a different ethical approach than discounted utilitarianism.

SCC Distribution

Columns AK to BA

Use these columns to record any reported variation around the Central Value recorded in Column K of this row. Values recorded in these columns should share the same SCC year, emissions scenario, and structural changes as the recorded central value. Unless damage function parameters and / or discounting parameters are being varied, they should also share the same damage function and discount rate.

Use “Min” (Column AK) and “Max” (Column BA) to report ranges with the two most extreme SCC values at the upper and lower end resulting from parameter changes not associated with probabilities

Use quantile columns to enter any reported quantiles of the distribution. This could come either from quantiles reported from a Monte Carlo sampling, from reported confidence intervals around values (e.t. 95% confidence intervals), or from one at a time sensitivity analysis, where the varying parameters have quantiles associated with them (e.g. varying the climate sensitivity to +1 or -1 standard deviation).

Note that the recorded distribution must be “well behaved” - i.e. values must be strictly increasing with quantiles. Otherwise the distribution sampling algorithm will not be able to interpret the entries.

All units in $ per ton CO2. If necessary, convert from $ per ton C or from values reported in other currencies, consistent with recording central value.

If central value is a median, *also* record value in the 50th percentile column (column AS)

Parametric Uncertainty

Use these columns to record parametric variation giving rise to either:

1) Variation recorded in the SCC distribution block. Enter a 1 if variation in this parameter contributes to the range reported in Columns AJ to BA

   OR

2) If no distribution is reported, but the central value recorded in Column K is a central value from a distribution (without the distribution being reported), then add 1s in the relevant columns in this section. For example, most PAGE09 values come from Monte Carlo runs of PAGE that include variation in:
   a) Transient climate response
   b) Carbon cycle
   c) Tipping Point Magnitude
   d) Damage Function
   e) Adaptation Rates
   f) Damage Income Elasticity

Additional Information

Column BP: Paper Location - Record where in the paper values in the row come from (e.g page number, figure, table). Could be multiple locations if central value and parametric variation ranges come from different places

Column BQ: Flag - Use this to add other informational flags to aid interpretation of values in this row

Column BR: Notes - Add any other notes here aiding interpretation of the values in this row

- Any additional notes on decisions made in coding a paper or information required to interpret values can be added in this Google Doc.