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Synthesis of evidence yields high social cost of carbon due to structural model variation and uncertainties

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Estimating the cost to society from a ton of CO_2—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. A growing literature has examined the effect of fundamental structural elements of the models supporting SCC calculations. This work has accumulated in a piecemeal fashion, leaving their relative importance unclear. Here, we perform a comprehensive synthesis of the evidence on the SCC, combining 1,823 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). ANOVA reveals important roles for the inclusion of persistent damages, the representation of the Earth system, and distributional weighting. However, our survey reveals that experts believe the literature underestimates the SCC due to an undersampling of model structures, incomplete characterization of damages, and high discount rates. 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 $283 per ton CO_2 for a 2020 pulse year (5% to 95% range: $32 to $874), higher than most official government estimates, including a 2023 update from the U.S. EPA.

climate change | social cost of carbon | meta-analysis | environmental economics

Significance

Estimating the social cost of carbon (SCC)—the cost of one additional ton of CO_2 emitted—is crucial for the analysis of climate change policies. Despite numerous recent studies investigating how fundamental aspects of model structure affect SCC evaluation, findings are scattered, making the relative importance of different modeling elements hard to establish. This paper synthesizes results from the published literature over the last 20 y, revealing a wide range of SCC estimates. However, survey evidence reveals experts believe estimates in the literature are too low due to a range of limitations in published values. Reweighting the literature to partly address these omissions more than doubles the SCC to $283.

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 subnational 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 in the climate system (thresholds where reinforcing feedbacks can amplify initial small perturbations to Earth system components to produce much large changes in climate) and associated uncertainties in damages (16–19); addressing model uncertainty,

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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 (20, 28, 29); modeling the distribution of climate damages and incorporating inequality aversion or distributional weighting (30–32); and explicitly representing climate damages to nonmarket goods, such as natural systems or cultural heritage, which are imperfectly substitutable with market-traded goods (33–36). (*SI Appendix*, section S3 contains more detailed discussion of the different model structures discussed in this paper and examples of papers integrating them into SCC estimates.)

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 intercomparisons 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 2,800 abstracts, we identified 1,823 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 socioeconomic 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 or underrepresented in the literature. Furthermore, we elicit experts' views on the degree to which various model structures that have been explored in the literature improve SCC estimates relative to estimates that exclude them, 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 previous studies, and an expert survey. We combine these lines of evidence to produce a synthetic SCC distribution using a random forest model (a form of machine learning) trained on variation in the literature but sampled to more closely match experts' assessment of model structures and discounting parameters. The resulting SCC distribution essentially amounts to a structured reweighting of published SCC estimates to better match expert-elicited model structure and discounting. Additional details on the literature review, coding of values, data cleaning and processing, expert survey, and construction of the synthetic SCC are provided in *SI Appendix*, section S2.

1. The SCC Distribution

The systematic review of the literature yields 1,823 SCC estimates (or distributions) from 147 studies (full references given in *SI Appendix*, section S4). Many studies report multiple SCC estimates. For each of the 1,823 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 1,823 estimates). *SI Appendix*, 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 nonindependence between papers with shared authors, or for different quality of studies using a normalized citation-based weighting, give quantitatively similar distributions (*SI Appendix*, Table S4).

Fig. 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, under the uniform weighting of all papers and estimates. The figure gives the distribution of SCCs for pulse years between 2010 and 2030, which we use as the 2020-equivalent SCC 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 higher than the median ($39). Statistical tests show evidence for a heavy tail in the SCC distribution with finite mean but infinite variance, echoing (47) (see *SI Appendix*, Table S5 for relevant statistical tests). SCC estimates in the right tail (upper 10% of values) are more likely to include persistent or growth damages (odds ratio of 8.2), improved earth system modeling (2.3), or climate tipping points (2.1), as well as parametric uncertainties in adaptation rates (3.0), the damage function (2.9), equilibrium climate sensitivity (1.7), and the pure rate of time preference (1.4).

Fig. 1 also shows how the 2020 SCC distribution differs based on particular characteristics of the estimate. The second panel shows variation across nine different model structures, compared to a distribution of estimates that exclude all nine changes (the "Reference" distribution), a model structure similar to the original DICE model (up to the 2016 version) (48). 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 market and nonmarket goods in the utility function. The third panel shows the well-documented sensitivity to discounting assumptions, with estimates using less than a 2.5% discount rate producing

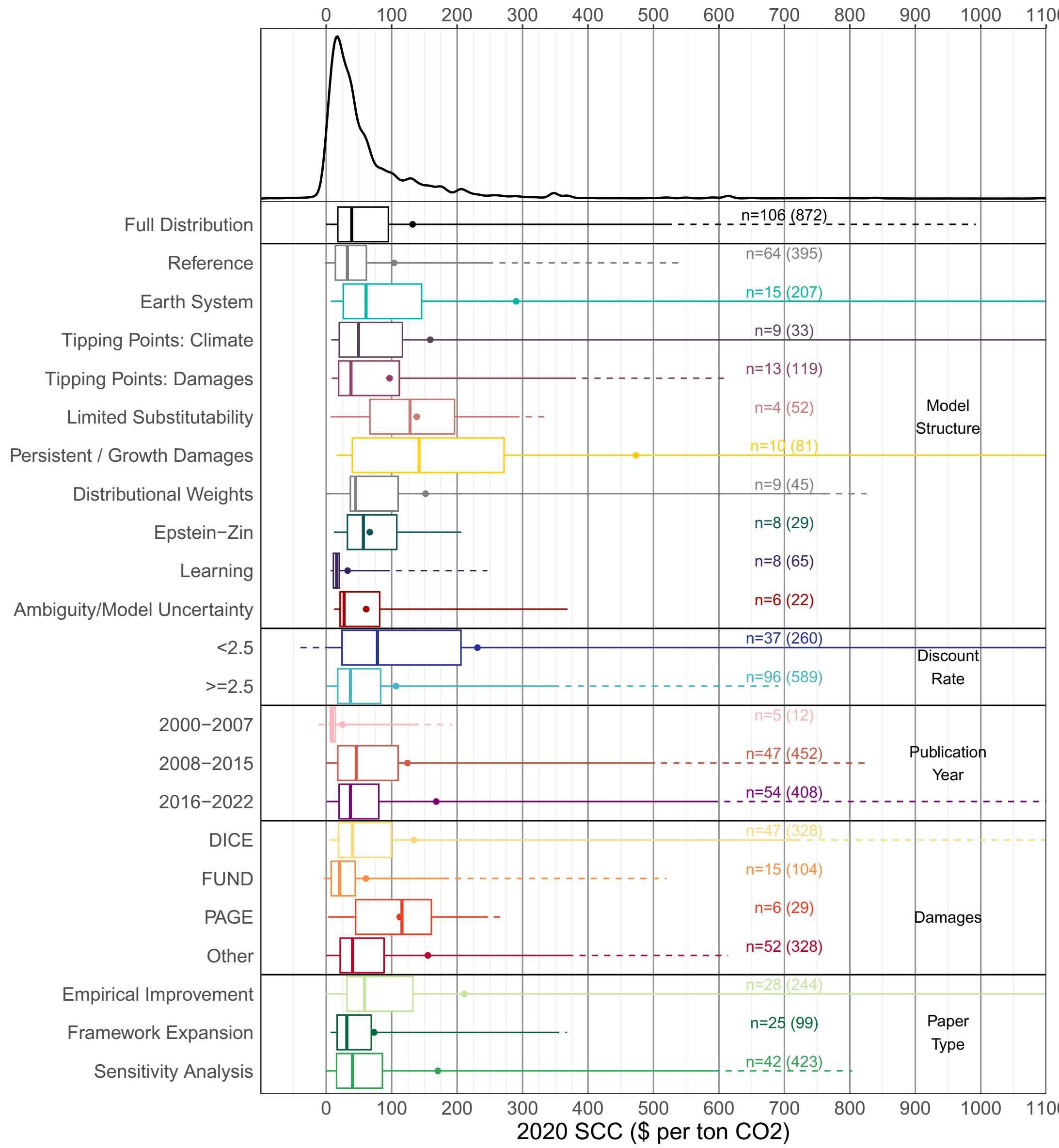

Fig. 1. Distribution of the 2020 SCC from the published literature (2020 $ per ton CO_2). Distribution and top boxplot show the distribution of all 2010 to 2030 SCC values (which we treat as the 2020-equivalent sample) from the published literature (equal weighting of all 147 papers). Other boxplots show subsets of the 2010 to 2030 distribution split by characteristics of published estimates, specifically model structure (see *SI Appendix*, section S3 for model structure descriptions and examples), 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), interquartile range (box), 5 to 95% range (solid line), and 2.5 to 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.

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 toward higher SCC values in papers published in the later part of our sample period, a finding similar to that reported previously (38). The limited set of early estimates (published prior to 2008) have a mean SCC ($25 per ton CO_2) five times lower than that of more recent estimates ($124 per ton for the 2008 to 2015 period and $168 for the post 2016 period). Note these univariate splits of the data are suggestive and should be interpreted with caution: other aspects of model structure or parameterization may vary systematically across these different subsets of the distribution and could be responsible for differences with the reference distribution, an issue addressed through a multivariate analysis below in Section 1.1.

The final panel in Fig. 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.

1.1. Drivers of Variance in SCC Estimates. Fig. 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

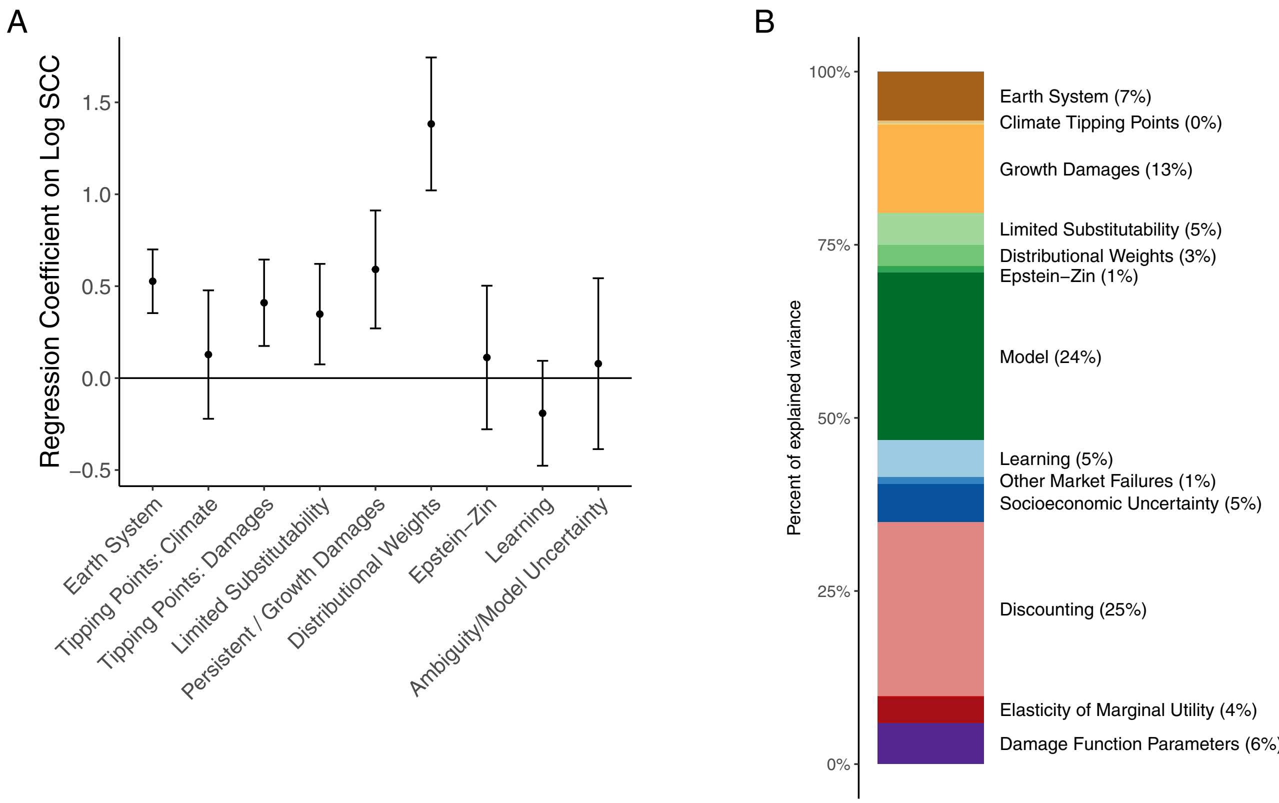

Fig. 2. Drivers of variance in published SCC estimates. (*A*) Effects of structural model characteristics on log SCC, controlling for other aspects of model structure, SCC year, emissions and socioeconomic scenarios, and discount rate (see *SI Appendix*, section S3 for model structure descriptions and examples). (*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.

uncertainty, and other model covariates—affect SCC values. While Fig. 1 shows distributions under different univariate splits of the data, multivariate analysis can better identify the effects of particular model structures and parameter values. Fig. 2*A* shows estimated effects of structural model characteristics on SCC values after controlling for other aspects of model structure, SCC year, emissions and socioeconomic scenarios, and discount rate. We plot relative changes in the SCC attributable to individual elements of model structure. Fig. 2*A* uses as identifying variation differences in results with and without model changes, which are reported in many individual studies. These are recorded explicitly in our data collection process. Additional regression models using other types of variation in the data are reported in *SI Appendix*, section S.2.1.9 and Fig. S9.

Fig. 2*A* 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, and elements of damages such as tipping points, limited substitutability between 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 (49, 50). 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 better future climate policy (24).

Fig. 2*B* 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. Fig. 2*B* shows that the single largest driver of 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 parameterization, 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.

2. Placing the SCC Literature in Context Through Expert Surveys

Fig. 1 shows the distribution of 2020 SCC values published in the scientific literature between 2000 and 2020 (under a uniform weighting of papers and estimates). 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 *SI Appendix*, section S.2.2.3. Therefore, we complement the literature survey described in Section 1 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 responses of which 48 were complete. *SI Appendix*, section S.2.2 provides further details on survey design, distribution, and analysis.

Fig. 3*A* 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 overestimating 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 (Fig. 1). A number of reasons could account for why experts underestimate the mean SCC in the literature compared to our analysis, 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 (52), from 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 *SI Appendix*, section S.2.1.6 for further discussion), or experts applying a different weighting across papers and estimates than the uniform weighting we use to construct our literature distribution.

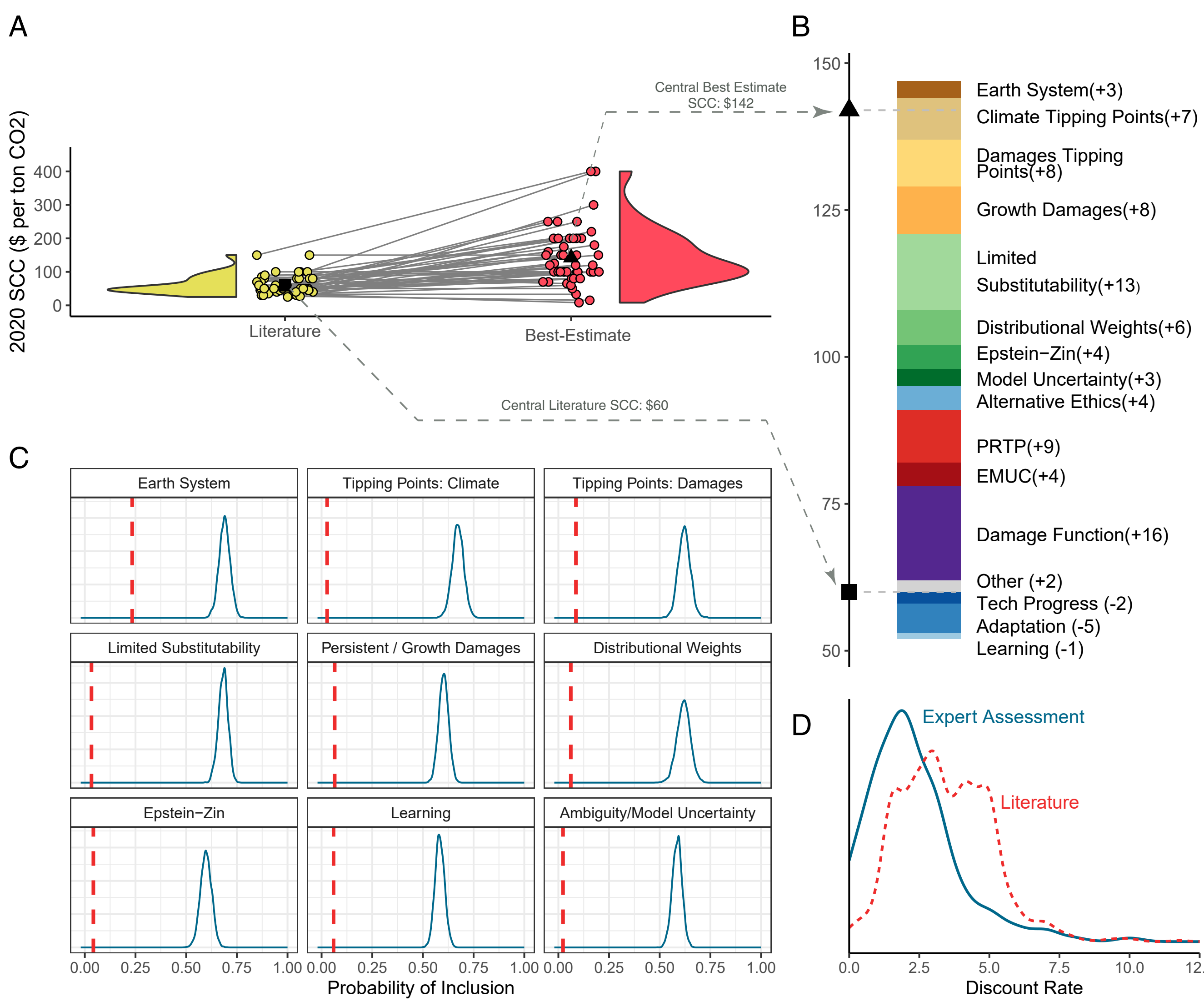

Fig. 3. Expert survey on SCC values, model structure, and discounting. (*A*) Expert assessment of the mean SCC value in the literature and best estimate of the mean of the SCC distribution, accounting for any systematic biases or over- or underrepresentation of different model elements in the published literature. Gray 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'?" (*SI Appendix*, Fig. S20) are converted into model inclusion probabilities using Bayesian hierarchical modeling of expert responses (described in *SI Appendix*, section S.2.2.6). (*D*) Distribution of discount rates in an expert assessment by Drupp et al. (51) (blue solid line) compared to the distribution in the published literature for 2020 SCC values (red dashed line).

Fig. 3*B* shows how experts decompose the perceived underestimate in the literature into constituent elements (individual responses documenting significant heterogeneity in both the wedge magnitude and decomposition are shown in *SI Appendix*, Fig. S19). Around two thirds of the $82 wedge between the experts' estimates is driven by structural model choices, particularly limited substitutability of nonmarket goods (13%), persistent/growth damages (9%), tipping points in the climate system (8%) and in damages (8%), and distributional weights (6%). Damage-function and discounting parameters make up around a third of the SCC wedge. Experts also estimate that underrepresentation of technical progress, adaptation, and learning leads to a small overestimate of the SCC in the literature.

Fig. 3 *C* and *D* 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 nine 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 (53) with a 2020 SCC of around $40 per tCO_2) for all elements except aversion to model uncertainty or ambiguity (*SI Appendix*, Fig. 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 nonmarket goods in the utility function, with some polarization over the issue of whether distributional weighting, as applied in the literature, improves SCC estimates. Note that there may be a number of reasons why experts do not believe particular modeling changes improve the SCC estimate. Experts may not agree with the premise of the modeling change (for instance, they may disagree that damages are best represented with the inclusion of tipping points), they may agree with the premise but believe implementation in the literature is inaccurate (for instance, they may agree climate change could affect growth rates but believe existing estimates of this effect are poorly parameterized), or they may disagree with the normative elements related to some changes (for instance, the reasoning behind the use of distributional weighting in SCC calculations). Our survey does not distinguish between these lines of reasoning.

Fig. 3*C* 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 *SI Appendix*, 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. Variance is highest for distributional weighting which had the largest fraction of respondents (19%) disagreeing or strongly disagreeing that this addition improved the SCC estimate. For all elements of model structure, however, representation in the published literature is far lower than expert assessment, with values ranging from 0.23 (Earth system modeling) to 0.02 for climate tipping points and model ambiguity.

Fig. 3*D* depicts a similar gap between expert assessment of discount rates [based on a prior expert survey reported by Drupp et al. (51)] 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 (54)], more than a percentage point lower than the literature mean of 3.4%. Figs. 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 there being an underestimate in the literature (Fig. 3*A*), and its attribution (Fig. 3*B*).

3. The Synthetic SCC Distribution

3.1. Motivation and Approach. In order to address the potential omissions from the published literature documented in Fig. 3 *C* and *D*, we combine information from both the literature analysis and expert survey to generate a synthetic SCC distribution that more closely matches experts' assessment of discounting and model structure choices. This process involves first using the variance across the 1,823 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 Fig. 3 *C* and *D*. This amounts to a reweighting 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 nonmarket 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 reweighting.

The random forest model estimates a set of 500 regression trees, each based on the 31 explanatory variables and a random bootstrap of the 1,823 SCC estimates. At each branch in the tree, the algorithm chooses the variable from a random sample of 10 of the 31 possible variables that divides the sample into two groups with the largest variance between them. Our data structure is unusual in that each of the 1,823 observations is 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 seven nodes or very large leaves are pruned, leaving a final 403 regression trees.

SI Appendix, Fig. 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 by Gillingham et al. (41) and Rennert et al. (3)]. Additional information on the random forest model is detailed in *SI Appendix*, section S.2.3.

We query the random forest model with just over 1,800 draws from the space of model structures and discount rates obtained from expert surveys (Fig. 3 *C* and *D*), also including other desirable SCC characteristics such as inclusion of parametric uncertainty, accounting for nonmarket damages, and recent publication year (detailed in *SI Appendix*, section S.2.3). Fig. 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 retained regression trees (the "leaves" in Fig. 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. An example of this can be seen in Fig. 4, where the draw from the input space includes growth rate damages, but the path

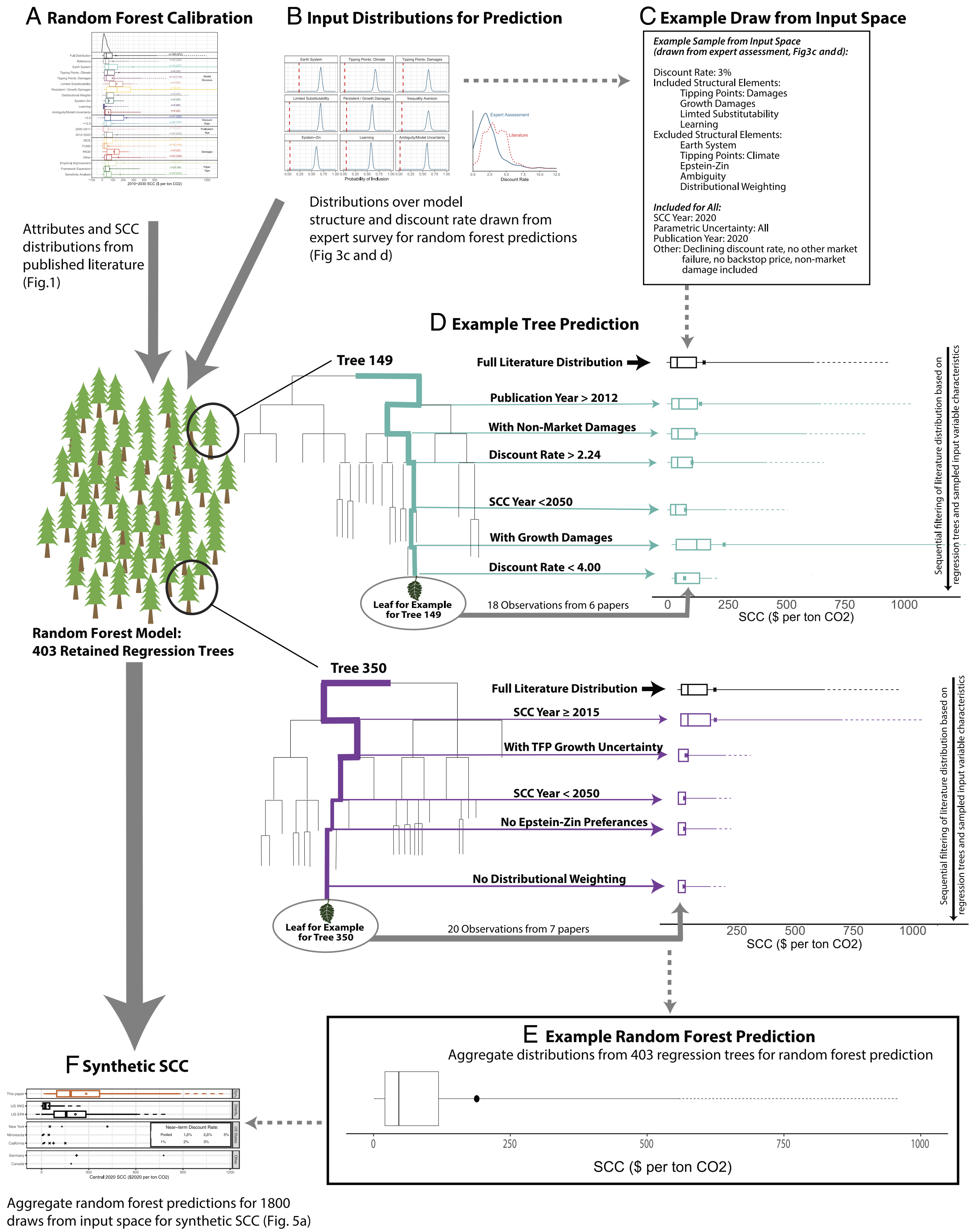

Fig. 4. Illustration of process for generating synthetic SCC distribution. The random forest is estimated using published SCC estimates (*A*) then queried using draws from model structure and discount rate distributions based on expert assessments (*B*). Each draw (*C*) has a single path through each 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 1,800 draws from the input distribution space (*F*). Boxplots show the median (line), interquartile range (box), 5 to 95% range (solid line), and 2.5 to 97.5% range (dashed lines). Dots show the mean after trimming upper and lower 0.1%.

for Tree 350 does not condition on growth damages, meaning the observations contributing to that tree's estimate will likely include SCC estimates with and without growth damages. Some model structures combining multiple elements are either very sparse in the literature or are not represented at all (*SI Appendix*, Fig. 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 (i.e., those with high variable importance, shown in *SI Appendix*, Fig. S21).

3.2. The 2020 Synthetic SCC Distribution. Fig. 5*A* gives the 2020 synthetic SCC. The distribution has a median value of \$185 per ton CO_2, an interquartile range of \$97 to 369, and a mean of \$283, after truncating the upper and lower 0.1% of the distribution. For comparison, Fig. 5*A* also shows two distributions of SCC estimates from the US government—values from the interim 2021 Interagency Working Group on the Social Cost of Greenhouse Gases (IWG) (52) and a 2023 analysis by the Environmental Protection Agency (EPA) (55) as well as official SCC estimates used by three US states, Germany, and Canada. The near-complete separation between the interim 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. This estimate is based on three older models (specifically DICE 2010, FUND 3.8, and PAGE 2009) using a methodology largely unchanged since the original 2010 IWG report (56).

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 includes substantial modeling improvements based on recommendations from a 2017 report from the National Academies of Sciences (57). Many of these, such as improved representation of the Earth system, discount rates closer to the expert assessment by Drupp et al. (51), and a fuller inclusion of parametric uncertainties in economic growth, climate damages, and Earth system dynamics, make the EPA estimate more similar to the set of inputs into the synthetic SCC. 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, particularly allowing for persistent climate damages, the inclusion of tipping points, distributional weights, and limited substitutability between market and nonmarket goods (Fig. 1). The German Umweltbundesamt (Environmental Agency; EA) (58) 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%, and a higher estimate of \$777 using a pure rate of time preference of 0%, to be used in sensitivity analyses. In general, the mean of our synthetic SCC distribution is higher than the large majority of SCC values used by governments in policy analysis, with the exception of those using very low discount rates (i.e., 1% in New York State or a 0% pure rate of time preference in Germany).

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. Fig. 5*B* 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 (53). 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 (53) compared to an interquartile range of \$25 to \$71 in Fig. 5*B*). As expected, the decomposition shows large effects of the discount rate, as well as important roles for certain elements of model structure 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.

SI Appendix, Fig. 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 *SI Appendix*, Fig. S22*B*: 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. *SI Appendix*, section S.2.3.4 also presents an alternate, regression-based synthetic SCC distribution, constructed using weights based on the expert survey combined with coefficients on structural model elements given in Fig. 2*A*. This approach is limited in its ability to capture the contribution of parametric uncertainties to the SCC distribution and interaction effects. It produces a substantially higher 2020 SCC distribution than the random-forest approach, with a truncated mean of \$633 per ton CO_2 and a median of \$463 (*SI Appendix*, Table S10).

4. Discussion and Conclusion

We present the most comprehensive synthesis to date of SCC estimates, as well as their parametric and structural drivers. Based on 1,823 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). ANOVA 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 believe the distribution of published SCC values to be too low due to an underrepresentation of different model structures, as well as discounting and damage parameter settings. Comparison of experts' views with the published literature validates this assessment; published SCC estimates both use higher discount rates and undersample alternate model structures compared to expert responses.

Our synthetic SCC distribution partially addresses this concern by effectively reweighting published SCC estimates to more

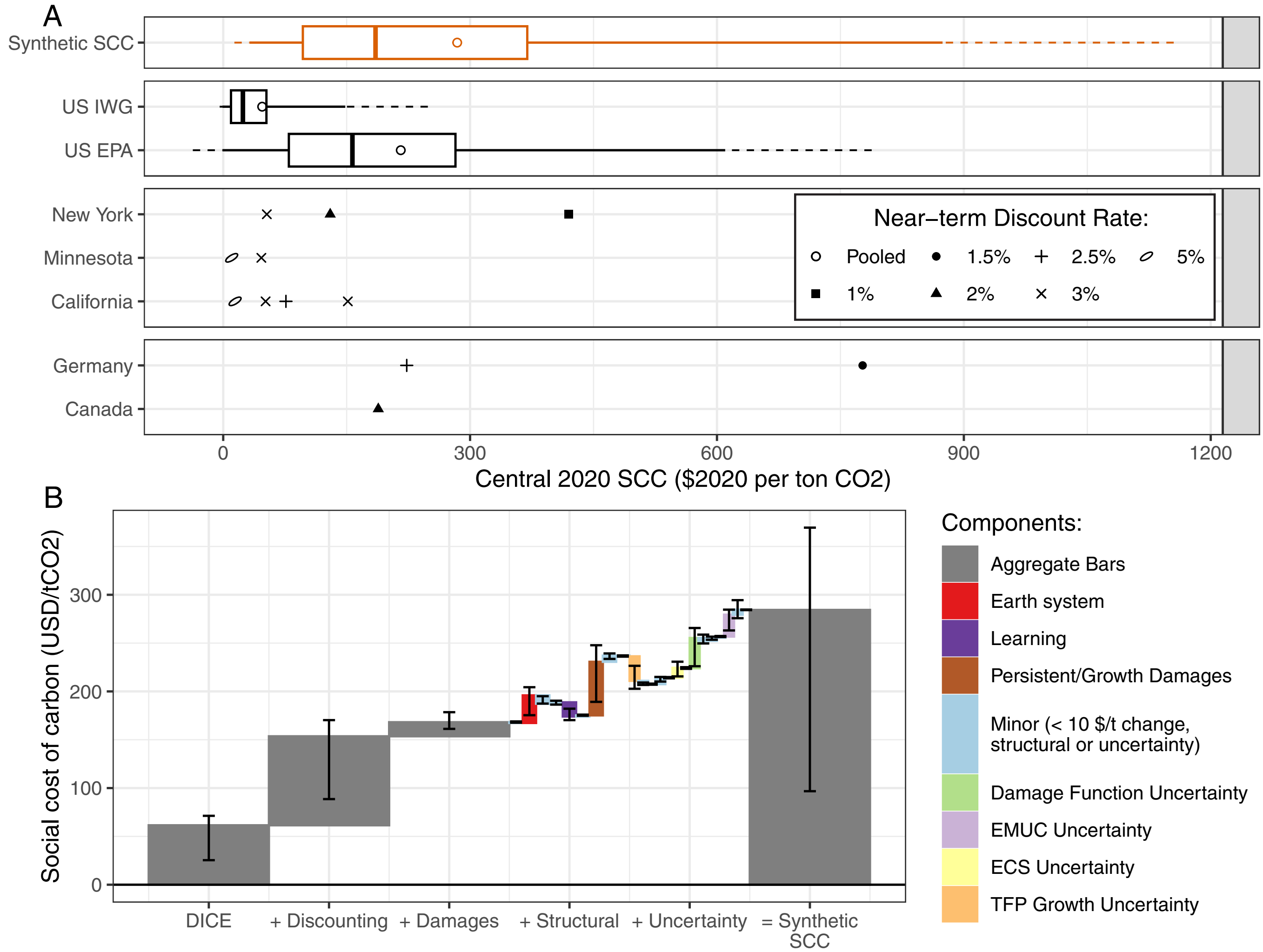

Fig. 5. Synthetic 2020 SCC distribution and decomposition. (*A*) Synthetic SCC distribution generated from the random forest model forced by input distributions over model structure and discounting shown in Fig. 3 *C* and *D*. 2020 SCC distributions from two US government SCC assessments, a 2023 EPA analysis (55) and the 2021 update from the Interagency Working Group (52). Boxplots show the median (line), interquartile range (box), 5 to 95% range (solid line), and 2.5 to 97.5% range (dashed lines). Dots show the mean after trimming the upper and lower 0.1% of each distribution. Other panels show the SCCs adopted by New York, Minnesota, California, and Canada (59), The German EA (58) is shown under two pure rates of time preference, 0% and 1%, shown at discount rates of 1.5% and 2.5% following near-term discounting assumptions (60). (*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 to the DICE model (53). 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.

closely match expert assessments of model structure and discount rates (as well as integrating other desirable qualities such as more recent publication years and inclusion of nonmarket damages and 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. While more modeling and empirical studies can help to fill those gaps, some fundamental uncertainties surrounding climate change and humankind's response to it will remain, and are additional to the structural uncertainties we quantify here. Nonetheless, our synthetic SCC analysis 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 2), 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 omissions in published SCC estimates increases 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

(55). 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" (61). Our findings strongly suggest that the 2021 interim 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.

5. Materials and Methods

5.1. Literature Review and Data Processing. Potentially relevant papers were identified through a keyword search of EconLit, Web of Science, and Scopus databases, returning 2,839 abstracts. Abstracts were reviewed by a team of research assistants for papers likely to report an original global SCC estimate. The 295 papers retained at this stage were reviewed by members of the author team, producing 147 papers reporting original SCC values (*SI Appendix*, section S.2.1.1). Coding rules for standardized data collection were developed in an iterative process with all papers recoded consistently once the code book was finalized (code book for data collection given in *SI Appendix*).

Data were standardized by converting monetary values to 2020 US dollars. Equivalent constant discount rates for papers using the Ramsey formula were calculated by merging in consumption growth rates from relevant socioeconomic scenarios (*SI Appendix*, section S.2.1.3).

5.2. Expert Survey. Expert population was the set of 176 authors in the papers included in the meta-analysis with working email addresses. All were invited to respond to an online survey, from which we received 68 responses of which 48 were complete. Complete survey instrument and data cleaning steps are described in *SI Appendix*, sections S.2.2.1 and S.2.2.2. While the survey could be answered anonymously, 48 respondents provided their identities, allowing the characteristics of nonanonymous respondents to be compared to nonrespondents plus anonymous respondents. This analysis shows no evidence of nonresponse or strategic response bias (*SI Appendix*, section S.2.2.4).

Expert survey data is available in an anonymized format; this allows reproduction of all main figures and results with the sole exception of supporting analyses that draw on data merged with expert characteristics in *SI Appendix*, sections S.2.2.4 and S.2.2.5.

Data, Materials, and Software Availability. All data and code to reproduce the analysis in this paper are available at zenodo.org (62).

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