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48 Abstract

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Not all carbon dioxide emission scenarios are equally likely: a subjective expert assessment

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Abstract
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1 Introduction

Scenarios of future greenhouse gas emissions are important tools for exploring possible future climatic changes and the associated impacts (IPCC 2008; Moss et al. 2010; Nordhaus 1994b; van Vuuren and Carter 2014; Wong and Keller 2017). Baseline emission scenarios are the thread connecting the three working groups composing the Intergovernmental Panel on Climate Change (IPCC) Reports: integrated assessment models produce such scenarios (Working Group III; WGIII), which are fed to climate models producing climate change projections (WGI) which, in turn, are used, together with the socio-economic implications underpinning baseline emissions, to assess the impacts of climate change (WGII).

Scenarios are beset with deep uncertainties that are inherent in assumptions about factors such as future technology developments, lifestyle changes, policy formulations, and economic and demographic trends (Arrow and Fisher 1974; Walker et al. 2013). Several methods are used to deal with this “deep” uncertainty (Schneider 2002). We group them in three overarching categories and lay out the main arguments of their proponents, as well as the counterarguments from detractors.

One approach emphasizes that assigning probabilities, or probabilistic statements, to scenarios is not meaningful at all as there is insufficient information to make such assessments and, instead, the scenarios should be considered as alternative plausible futures (Nakicenovic et al. 2014).

A second approach considers scenarios to be equally likely in the absence of sufficient information to decide otherwise consistent with the principle of insufficient reason (Sinn 1980) that was first enunciated by Bernoulli and Laplace (Bernoulli 1896; de Laplace 1814). This principle states that if one is ignorant of the process that leads to an event occurrence (and therefore has no reason to believe that one way is more likely to occur, compared to others), it is a good starting point to assume that all possible events are equally likely (see, for example, Sinn 1980). Wigley and Raper (2001) used this assumption in their interpretation of a set of baseline emission scenarios that did not have explicit probabilities attached.

A third approach emphasizes the importance of assigning explicit (subjective) probability statements to long-term emission projections. Schneider (2002) illustrated this view by pointing out that stating a meteorite can destroy the Earth is a useless statement for policymakers unless it is accompanied by information on the probability of such an event. Researchers with similar views have used more probabilistic scenario approaches, even though such approaches suffer from the need to assign probabilities to events that are inherently unknown (see, for example, Berger et al. 2017; Hall et al. 2012; Webster et al. 2003). A compelling reason in favor of providing probabilistic information is that, even in the absence of formal probabilities, scenario developers and scenario users will make implicit probability assessments: based on current knowledge, the scenarios reported or used are apparently considered to be plausible enough for policy making, if they are not already interpreted as all equally likely. In the specific case of the IPCC reports, for instance, scenario information is conveyed across working groups, i.e., across disciplinary fields. In such settings, ambiguity in the implicit probabilistic assumptions made by different groups can be even more problematic. The main critique to this approach, however, is that the deep uncertainty simply makes any assessment of probability meaningless and can in fact distract people from looking at the full range of options.

Integrated assessment models are tools used to generate future emission scenarios independent of the approach taken with respect to likelihood (see Weyant 2017 for a detailed discussion on the models). A recent, prominent example of model-based scenarios is shared socio-economic pathways (see Fig. 2), which figure prominently in the most recent assessment reports from the IPCC. These scenarios embrace the first approach: scenarios are not assigned probabilities and, instead, are considered to be possible, alternative futures (Riahi et al. 2017).

While we agree that assigning probabilities is hard, the simple idea motivating our research is that the lack of information on probability may force users to make implicit personal probability assessments that may be inaccurate, uninformed, increase the variance in the interpretation of the scenarios, and lead to poor decisions and outcomes. This may be true, for example, for users that belong to other disciplinary fields, e.g., researchers in climate science and climate impacts or for users who are outside academia such as government officials assessing national policies. For instance, people often interpret the set of scenarios as bounds for largest/smallest emission levels (e.g., Wigley and Raper 2001). Alternatively, users may interpret a scenario as being more likely than others (see, for example, the choice of scenarios in Fig. 3 of Burke et al. 2015). A final example demonstrating the need to account for the deep uncertainty surrounding emission scenarios is the challenge of designing coastal flood-risk management strategies (Bakker et al. 2017a, b; Wong and Keller 2017). Flood risk Q4 management strategies typically aim for low annual exceedance probabilities, for example, one in a hundred years (Jonkman et al. 2013). The performance of these strategies is highly sensitive to the upper tails of sea-level projections (Sriver et al. 2012). Because the upper tails of sea-level projections can hinge critically on the upper tail of emission projections, it is crucial to assign reasonable probability mass to this tail and to not cut it off (Fuller et al. 2017; Keller and Nicholas 2015; Sriver et al. 2012, 2018).

Given these motivations, we use a relatively new method (Fan 2018; Por and Budescu 2017) to assess the probability distributions of future emissions of carbon dioxide (CO_2) over the range implied by SSP scenarios. This method uses expert judgments—but instead of directly asking how likely a possible outcome is, it asks experts to judge the relative likelihood in multiple pairwise confrontations of two possible outcomes. We elicit the expert judgments about the emission scenarios without specifying the key drivers and without relying on any specific assumption. As is often the case in expert elicitation, we expect that the experts' judgments are based on, and reflect faithfully, their reading and interpretation of the relevant literature and various model simulations they have come across during their professional careers. We compare the resulting distributions with the emission ranges coming from the SSP implementation (Riahi et al. 2017) and the results of a recent multi-model uncertainty quantification analysis (Gillingham et al. 2018). Such multi-model quantification analyses can provide complementary insights to the expert elicitation method used here.

1.1 Subjective probabilities of emissions

Several problems stand in the way of estimating subjective probability distributions of future greenhouse gas emissions. Conceptually, assessing long-term global emissions is a complex and deeply uncertain problem with a very long time horizon (Lempert 2002; Revesz et al. 2014). Such projections depend on a multitude of interacting sources of uncertainty from various domains involving technical factors (e.g., the ability to capture and store carbon dioxide), social factors (e.g., rates of future population growth) and, of course, uncertainty about policy decisions affecting emissions in various countries, international agreements, and future technological innovations (e.g., Anadon et al. 2016; Arrow et al. 1995; Butler et al. 2014a, b; Thompson et al. 2016). Rogelj et al. (2011) document at least 193 published emission pathways alone in the time periods between 2010 and 2020. Standard estimation procedures can also be susceptible to various biases such as overconfidence (Bakker et al. 2017a, b; Draper 1995), anchoring (Ariely et al. 2003; Tversky and Kahneman 1974), and sensitivity to the partition of the range of the variable (Fox et al. 2005).

Furthermore, from a methodological point of view, estimating subjective probability distributions of future greenhouse gas emissions is nontrivial. When quantifying the distribution of continuous variables, it is often necessary to "discretize" them into a finite number of "bins" prior to estimating the probability associated with each bin. Fox et al. (2005) demonstrate that in many cases, the results are sensitive to the nature of the partition adopted, because people often anchor their judgment on an ignorance prior probability of 1/number of bins. Furthermore, when asked "what is the probability that the 2100 emissions will be between X_l and X_u CO_2", people tend to pay extra attention to this "focal" event and think of evidence supporting it and attend much less to the complementary outcomes (Tversky and Koehler 1994). One consequence of this pattern is that the sum of the judged probabilities over all the bins often exceeds one, violating the unitarity axiom. A powerful and compelling illustration is the recent study by Bosetti et al. (2017) who found extreme violations of the unitarity principle by delegates from multiple countries at the Paris COP21.

We adopt an approach designed to drastically reduce these problems. Instead of asking people to judge probabilities of various events, we ask them to compare pairs of events to each other and determine which of the two is more probable, and by how much. This approach relies on relative comparative judgments that are easier and more natural to judges than absolute judgments (Einhorn 1972; Morera and Budescu 1998) and can yield more accurate estimates (Fan 2018; Por and Budescu 2017). Since judges are not directly estimating the probabilities of specific events, they need not worry about the probability of their union adding up to one. Asking judges to compare pairs of events also reduces the tendency to focus on the target (focal) event, which is likely to encourage people to treat the two events in similar fashion, and seek to retrieve reasons in favor, or against, both events being compared.

Given an n-fold partition of the distribution, there are $n(n\text{-}1)/2$ distinct pairwise comparisons, so the procedure generates more data points than parameters being estimated. This allows us to (1) test for the internal (in)consistency of one's judgments and (2) estimate the single best fitting distribution according to well-defined statistical objective functions. In this spirit, we explicitly refer to this procedure as one that *estimates* (rather than elicits) a judge's subjective probability distribution. The Supplemental Materials (SM) have additional details on the technical implementation of this procedure.

1.2 The present research

We report results of three studies using this approach. For all three studies, we recruited climate change experts through Integrated Modeling Assessment Consortium (http://www.globalchange.umd.edu/iamc) online mailing lists. In addition to the straightforward goal of documenting the judges' perceptions, quantifying their beliefs, and documenting the points of agreement and the degree of inter-judge variability, the studies were designed to test two main methodological hypotheses about the new estimation procedure. Study 1 tests the hypothesis that the method is relatively insensitive to the partition (binning) of the target range; studies 2 and 3 use two different policy scenarios and test the hypothesis that the method is sufficiently sensitive to capture the impact of the (relatively subtle) differences between them. The latter two studies vary in terms of the displays that were presented to the judges and, as such, test the impact of the presentation mode and format on the final estimates. From a substantive perspective, the results allow us to (a) determine whether the experts, implicitly, assume all emission scenarios are equally likely, (b) document the degree of inter-judge (dis)agreements regarding future emissions, and (c) compare the various experts' judgments with the predictions of some of the key models.

2 Study 1

2.1 Methods

We recruited 44 participants from the 2016 CD-LINKS workshop in Venice. Of those who reported demographic information, 69% were male, 58% had PhDs, 66% were involved with SSP modeling, with an average of 11-year work experience in their primary field. The experts were either developers or users of the SSP scenarios, and hence familiar with long-term emission projection scenarios.

We partitioned the range of the 2100 greenhouse gas emissions based on the emission range of the SSPs (Riahi et al. 2017) into six mutually exclusive and exhaustive intervals (see Fig. 1). Fan (2018) has shown through simulations and experimental work that six-fold partitions do a good job in this context for a variety of distributions. We manipulated the widths of the segments and compared three conditions (see Fig. 1): (1) equally spaced bounds (*Equal*) and (2) wider segments in the central intervals (*Tail*) and narrower in the tails, or wider segments in the tails of the intervals (*Center*) and narrower in the center of the distributions. We randomly assigned participants to one of the three conditions and asked them to compare all 15 distinct pairs of intervals. We asked the participants to judge the relative likelihood of various possible ranges of 2100 CO_2 emissions: "When making your judgments, please consider the emission development on the basis of current trends, i.e., a baseline scenario. Do not assume that ambitious goals are automatically implemented, but focus, instead, on a situation where climate policies would be mild, at best" (see Figs. A1 and A2 in the SM for experimental stimuli). In the IPCC special report, a baseline scenario "refers to scenarios that are based on the assumption that no *mitigation* policies or measures will be implemented beyond those that are already in force and/or are legislated or planned to be adopted… The term baseline scenario is often used interchangeably with reference scenario and no policy scenario" (IPCC 2018). Additionally, a baseline scenario is generally understood to be the "middle of

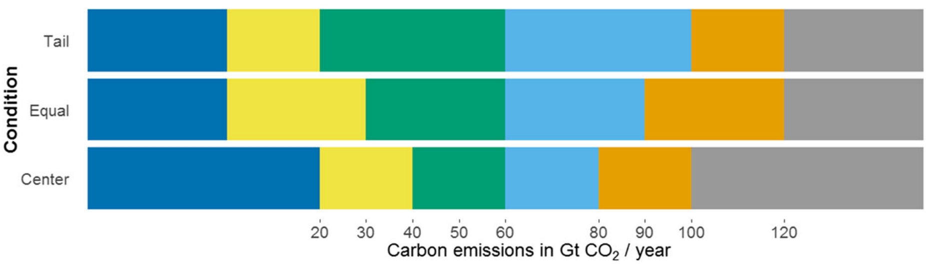

Fig. 1 Emission ranges (in 2100 emissions, Gt CO_2/year) participants were asked to evaluate by condition

the road pathway, where current trends propagate towards the future" (Mogollón et al. 2018, p. 3), or a "middle of the road SSP2 scenario" (Lucas et al. 2019, p. 489). Q6

More specifically, the participants judged how much more likely one interval was relative to the other (e.g., 2100 emissions between 60 and 90 Gt CO_2/year, compared with 2100 emissions greater than 120 Gt CO_2/year). We used the constant-sum method (Torgerson 1958) where judges respond by sliding a bar on a scale of fixed length and dividing it into two segments that are interpreted to reflect the ratio of interest (see Fig. A2 in the SM). These ratio judgments were used to derive a cumulative distribution function (cdf) that was presented to the respondents who were allowed to revise it, manually. To aid judgments, we showed, on each page, a figure that displayed the greenhouse gas emission ranges (in Gt CO_2/year) of the five SSPs from the years 2010 to 2100 and provided the minimum, maximum, and 10–90th percentile of the range in IPCC Assessment Report 5 (see Fig. 1). The study concluded with a set of questions about the respondents and seven post-experimental questions on the ease of use of the method. Two respondents were chosen by random draw to receive $50 Amazon gift cards.

2.2 Results

We quantify internal inconsistency of the judgments (Crawford and Williams 1985) by the (log-scaled) mean square error between the judged and the corresponding ratios predicted by the solution (geometric means). We dropped six respondents from the analysis because their measures of internal inconsistency were outliers by Tukey's rule. Let Q1 and Q3 denote the first and third quartiles of a distribution, respectively, and let the inter-quartile range IQR = (Q3–Q1). Participants with estimates greater than (Q3 + 1.5*IQR) are considered outliers (Tukey 1977). Thus, we analyze 38 valid experts.

We used the experts' judgments to estimate six points on their probability distributions of the emissions. Next, we used these six probabilities estimated by the procedure and interpolated linearly to obtain 38 individual cumulative probability density functions (cdfs) consisting of 101 points (from 0 to 1 in 0.01 increments over the − 30 to 150 Gt CO_2/year range). The emission ranges [− 30, 150] were induced by our interpolation procedure such that − 30 was assigned a probability of 0, and 150 was assigned a probability of 1 for all respondents.

The median of the 38 individual estimated medians across all judges was 54.36 Gt CO_2/year, and the median of the individual interpolated IQRs was 58.45 Gt CO_2/year (see Table 1 for median medians and IQR of medians). We compared the results across the three partitions of the range and found no statistically significant differences between the three partitions in terms of the median emissions ($\chi^2(2) = 1.36$; $p > 0.05$ using Van der Waerden normal scores), or the inconsistency indices ($\chi^2(2) = 0.46$; $p > 0.05$ using Van der

t1.1 **Table 1** Median of and IQR of the median estimates in all studies

	Study	Condition	*N*	Median of medians	IQR of medians
t1.2	Study	Condition	*N*	Median of medians	IQR of medians
t1.3	1	Baseline	38	54.4	37.0
t1.4	2	Baseline	10	71.4	37.2
t1.5	2	Paris	10	56.5	27.1
t1.6	3	Baseline	18	67.8	29.1
t1.7	3	Paris	18	45.60	31.0

All values are in Gt CO_2/year

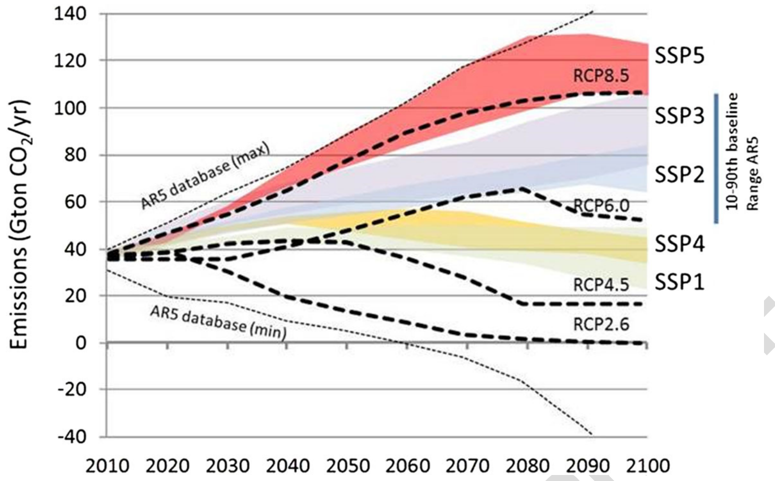

Fig. 2 Development of emissions following the shared socio-economic pathways (SSPs) (Riahi et al. 2017) and representative concentration pathways (RCPs) (van Vuuren et al. 2011). The shaded areas for the SSPs indicate the range of outcomes of different models as captured by Riahi et al. (2017); for the RCPs, the so-called marker scenario is shown (see van Vuuren et al. 2011). The figure also shows the literature range for baseline scenarios as reviewed in the Fifth Assessment Report of IPCC as well as the highest and lowest scenario in the database (Clarke et al. 2014). The range of baseline scenarios excludes the lowest and highest 10% of scenarios in the literature in order to exclude outliers as is also done in the IPCC Chapter; no probabilistic interpretation is meant

Waerden normal scores), so we conclude that *the proposed estimation procedure is insensitive to the partition of the domain* (Fig. 2).

There was a large degree of inter-individual variation in the estimated subjective probabilities, as shown in the first panel of Fig. 3. The results show that most experts were not assigning equal probabilities to the ranges (if they were, all distributions would lie on the diagonal). This is remarkable, since there is empirical evidence that human judges intuitively default to assuming equal probabilities across states (Fox et al. 2005; Seale et al. 1995). Clearly, this is not the case for most experts in our study. The second panel displays three convex hulls of the probability distributions (around the median estimate) corresponding to the full data set, as well as the central 90% and 50% of estimates, at each emission level. The figures present the region of estimates that is shared by 90% and 50%, respectively, of the experts and illustrate the level on inter-expert agreement. Clearly, one can identify a core consensus of the experts by trimming the more extreme judgments.

We examined the propensity of the judges to revise the cdfs extracted from their judgments. If the experts perceive the distribution as a faithful representation of their beliefs, we should expect to see only minor adjustments. Indeed, only 53% of the judges made adjustments, and the adjustments were minor, suggesting that the original distributions captured adequately the experts' beliefs. We compared in each case the original and the modified distributions and calculated the absolute distance between the two at every point. The mean |revision| across participants was 0.06, and the median |revision| was 0.01. Only a couple of judges made more serious adjustments.[1]

[1] Three participants (two in Study 1 and one in Study 3) produced estimates that resulted in negative median emissions. The Study 1 participants manually revised their estimates after seeing the cdf the ratio scaling method produced; the Study 3 participant did not revise the cdf.

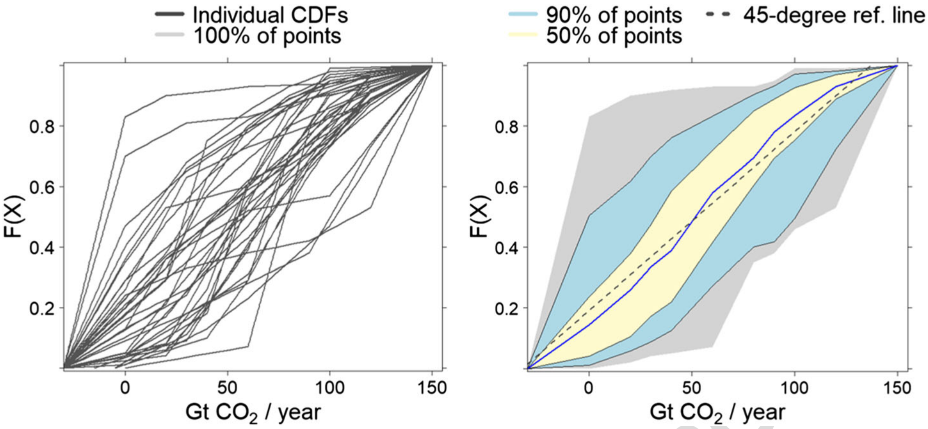

Fig. 3 Individual distributions of 2100 emissions in the baseline treatment of 38 expert judges and their 90% and 50% convex hulls (study 1). The solid blue line is the interpolated median emission at each probability

3 Study 2

3.1 Methods

To test the method's sensitivity to different scenarios, we asked a new group of experts to repeat the judgments under distinct climate change policies. We recruited 14 participants at the 2016 EMF meeting in June 2016 and retained only participants who completed both scenarios ($N = 11$). Of the nine participants who provided complete demographic information, eight were male; all had PhDs, with an average of 14 years of experience. We asked the respondents to judge the relative likelihood for all 15 pairs of emissions under no changes to current policies (duplicating the phrasing of the first study) and under a new scenario assuming implementation of the policies agreed on in the 2015 Paris Agreement. In the new scenario, participants were asked "when making your judgments, please consider what would be a realistic trajectory for future greenhouse gas emissions given the current status of international and national climate policies" (Fig. A4 in SM). The order of the two scenarios was counterbalanced across judges. To aid judgments, we included on each page the same graph presented in study 1 and the judges were given an opportunity to revise the estimated cdf after each scenario. The study concluded with the same set of demographic and post-experimental questions used in study 1. Two respondents were chosen by random draws to receive $50 Amazon gift cards.

3.2 Results

As expected, the interpolated median anticipated emissions under the Paris Agreement scenario (56.57 Gt CO_2/year) were considerably lower than the estimate under the baseline scenario (71.38 Gt CO_2/year) and, although the sample was too small for reliable statistical tests, a majority (7/10) of the judges confirmed this pattern. Superimposing the convex hulls of the central 50% and 90% estimates for the individual estimates under the two policies illustrates the apparent respondents' beliefs that the Paris Agreement would lower emissions (Fig. 4). *This demonstrates that our method is sensitive enough to reveal the* *different expectations of the judges under these different circumstances*. The judges revised, slightly, only five of the 20 cdfs (mean |revision| = 0.02, median |revision| = 0.02). In other words, the judges accepted the distributions we inferred as faithful representations of their opinions.

4 Study 3

Is it possible that the experts' judgments are anchored and affected by the graphical displays seen in the previous two studies? We replicated study 2 without presenting the SSP emission ranges shown in Fig. 1 to test this artifactual interpretation. This study was conducted a year after the signing of the Paris Agreement and, equally important, a few months after the US announced that it will leave the Paris Agreement.

4.1 Methods

We recruited 20 participants during the December 2017 IAMCs conference in Recife, Brazil. Of those who provided demographic information, 83% were male, 28% hold PhDs, 78% were involved in SSP modeling, with an average of 17.19 years of work experience in their primary field.

In addition to the timing and its possible implications about the perceptions of the Paris Agreement, this study differed from the second study in two respects: (1) no graphical representation of SSP emission ranges over the century was given to the participants while they made their judgments (see Fig. A10 and A12 in the SM) and (2) participants were shown only the emission ranges in the *Equal* condition (vs. the three binning conditions shown in the prior two studies). The experimental stimuli were otherwise identical, concluding with the same set of demographic and post-experimental questions used in the previous studies. Two participants were chosen by random draws to receive \$50 Amazon gift cards.

4.2 Results

We eliminated the judgments of two participants because of high inconsistency Tukey's rule and analyzed results of 18 participants. The median anticipated emissions under the Paris Agreement scenario (47.56 Gt CO_2/year) were considerably lower than the estimate under the baseline scenario (62.96 Gt CO_2/year), $\chi^2(1) = 3.39$, $p > 0.05$ using Van der Waerden normal scores. Moreover, 16/18 (88.89%) judges predicted lower medians under the Paris scenario. The bottom panel of Fig. 4 presents the superimposed central 50% and 90% convex hulls of the estimates under the two policies illustrates the shift in the respondents' beliefs that the Paris Agreement would lower emissions. Confirming the pattern observed in the previous studies, only 24 out of 40 (60) cdfs estimated were revised, with a mean |revision| = median |revision| = 0.01.

It is reassuring that the individual cdfs for the baseline condition are statistically indistinguishable from the judgments procured from the other two studies in the baseline condition, $\chi^2(2) = 5.67$, $p > 0.05$ using Van der Waerden normal scores (also see Fig. 6). Similarly, the median for the Paris judgments is not significantly different from the median judgments for this scenario in study 2, $\chi^2(1) = 1.97$, $p > 0.05$. This is consistent with the hypothesis that *the estimated cdfs do not depend on the presence of, nor are they anchored on, the display of the SSPs*.

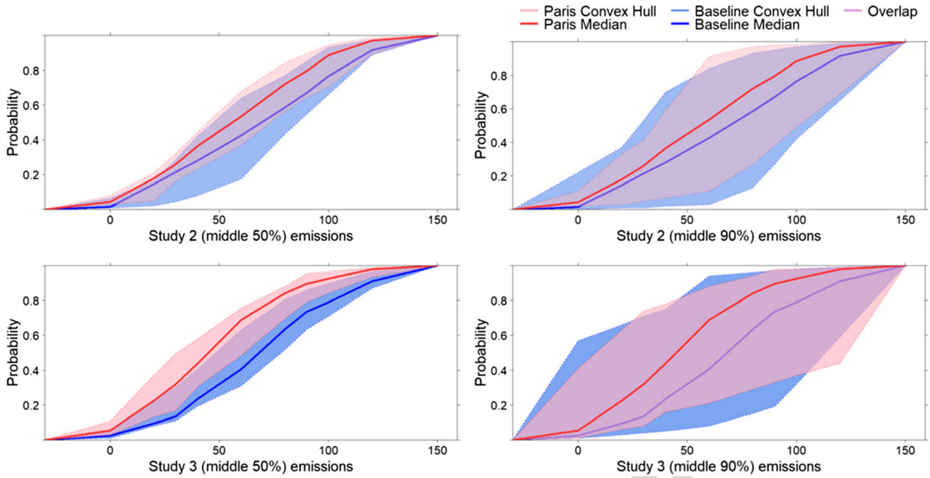

Fig. 4 Convex hulls for the baseline and the Paris Agreement policy judgments in study 2 (top left): 50%; top right: 90%) and study 3 (bottom left: 50%; bottom right: 90%). All carbon emission units in Gt CO_2/year

5 Analyses across the three studies

5.1 Perceptions of the new procedure

We start with an observation that, in line with the division among scholars concerning probabilistic information associated to long-term scenarios, some experts did not fill in the survey because they felt that assigning probabilities to scenarios was problematic. This is an important caveat to any statement concerning the acceptability of our method within the wider integrated assessment modeling community. The distribution of responses to the post-experimental questions is displayed in Fig. 5. The first four rows summarize responses to questions about the procedure itself and the last three rows refer to questions pertaining to the confidence in the estimated distributions. A strong majority

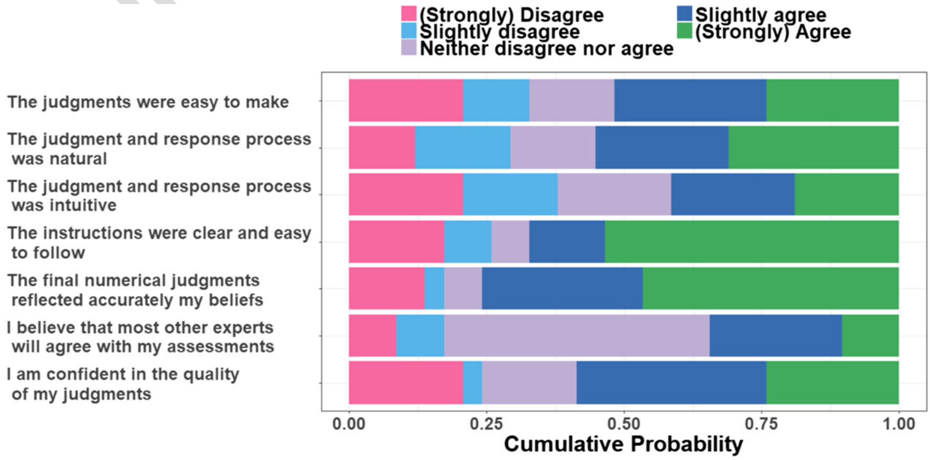

Fig. 5 Distribution of respondents' reactions to the task across the three studies ($N = 66$)

of respondents rated the procedure favorably in terms of ease of use and expressed a high level of confidence in their judgments. The noticeable exception is the fact that respondents exhibited surprisingly low expectations of agreement between their projections and those of other experts!

5.2 Comparison with other emission ranges for the year 2100 in the literature

How do expert judgments compare to the emission ranges generated by the modeling work aiming at projecting the storylines embedded in the SSPs? In Fig. 6, we include data from each of 66 experts in the two studies (for the baseline scenario only), as well as medians of all the experts in each of the studies, against the background of the ranges of the five SSPs that were shown to the experts (Riahi et al. 2017, and Figs. A1 and A2 in the SM). Each line in this figure displays the median projection as well as the central 50% of the distribution (IQR) and the central 90% of the distribution. We also include the 2100 emission distributions generated by the six models compared in the multi-model exercise aiming at exploring key drivers of emissions (Gillingham et al. 2018). Specifically, we present the central 50% (solid lines) and the 90% (dotted lines) of the distributions, which are plotted in ascending order (sorted by their median projections).[2] Most experts' medians and IQRs seem to adhere to the SSP ranges. This may be because SSPs are the main source of knowledge in the field and because we provided them in the judgment task. The experts' distributions are also comparable to the six distributions generated by the uncertainty analysis in Gillingham et al. (2018), but there are interesting differences. On average, the models' predictions are significantly higher using a Wilcoxon test (median of models = 87.27 and median of experts = 57.64; $W = 46.00$, $p = .002$).

In fact, one of the models' distributions from the Gillingham et al. (2018) uncertainty analyses predicts higher median emissions than each of the 66 experts in our study, and all of the Gillingham et al. (2018) models are in the highest quartile of the distributions in our samples. The distribution inferred from the models also has higher IQRs (median IQR of models = 85.79 and median IQR of experts = 52.26), but the difference is not statistically significant (Levene's test, $W = 105.00$, $p = .059$). The variability between the experts' median predictions is similar between the six models (SDs = 28.5 and 17.42, respectively; $F(70, 1) = 1.77$, $p > 0.05$. Figure A13 also presents similar results for the alternative scenario (under the Paris Agreement) based on the estimates from studies 2 and 3 and the same models. This particular pattern is consistent with, at least, two hypotheses. One possibility is that the experts' judgments reflect some degree of "group-think" as they are affected by commonly shared perceptions that permeate the field (see Broomell and Budescu 2009 for a model of inter-expert agreement). This effect may be stronger for the experts than for the models because the model-based estimates are derived independently using distinct assumptions and parameter estimates and are less susceptible to this group-think phenomenon. This can also explain the higher between-model variability. A second possible explanation relies on the nature of the uncertainty experiment performed in Gillingham et al. (2018). The analyses in Gillingham et al. (2018) assume uncorrelated

[2] Three participants (two in Study 1 and one in Study 3) produced estimates that resulted in negative median emissions. The Study 1 participants manually revised their estimates after seeing the cdf the ratio scaling method produced; the Study 3 participant did not revise the cdf.

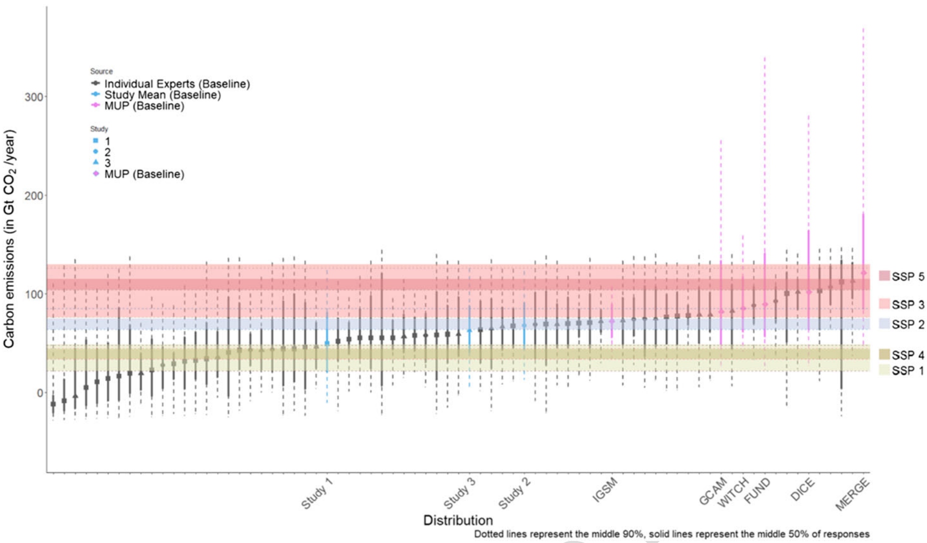

Fig. 6 Carbon emissions in 2100: the central 50% (solid lines) and 90% (dotted lines) distributions across all experts for study 1–3 ('baseline scenario', markers distinguishing across the three studies); in pink, results from the 6 MUP models (Gillingham et al. 2018), and ranges for the 5 SSPs (van Vuuren and Carter 2014)

probability distributions of two key drivers (i.e., population growth and economic growth). Failing to account for potential correlations among the two key drivers (population and economic growth) may have led to the wider ranges of estimates in Gillingham et al. (2018). Of course, the two explanations are not mutually exclusive.

We also look at the proportion of participants whose estimated medians fell in each of five SSP ranges (Table 2), across both scenarios. The medians are not distributed equally across the SSPs. For the baseline scenario, 24% of the medians fell within the SSP1 range, 21% within the SSP2 range, and 14% within the SSP3 range. For the Paris scenario, 46% of estimated medians fell within SSP1, 18% of responses fell within the SSP2 ranges, and 11% within the SSP3 range. Interestingly, only 5% of respondents fell within the range of SSP5 for baseline and none for the Paris scenario. No medians fell above this range.

Table 2 Distribution of participants whose medians fall within SSP ranges across all studies

SSP	Range	Baseline (*N*)	Paris (*N*)
	< 22	9 (14%)	2 (7%)
1	[22, 49]	16 (24%)	13 (46%)
4	[34, 44]	7 (11%)	4 (14%)
2	[64, 75]	14 (21%)	5 (18%)
3	[76, 130]	14 (21%)	3 (11%)
5	[104, 115]	3 (5%)	0
	> 115	0	0

All values are in Gt CO_2/year. In baseline condition, 22 of the responses did not fall within any SSP range and 10 responses fell within two of the SSP ranges

In the Paris condition, seven of the responses did not fall within any SSP range and four responses fell within two SSP ranges

6 General discussion

The three studies presented in this paper have both methodological and substantive implications. Methodologically, they represent, to our knowledge, the first attempt to establish the feasibility of the ratio judgment method for subjective probability estimation with substantive experts in their field of expertise. One could argue that the ultimate test of any procedure is its ability to predict accurately the target event being forecasted. Although we may never be able to perform this test (e.g., if the governments decide to move away from baseline scenarios towards decarbonization), results are very encouraging in many other respects. The procedure was (a) shown to be invariant under different partitions of the random variable (study 1), (b) sufficiently sensitive to reflect minor manipulations of descriptions in the scenario underlying the target variable (studies 2 and 3), (c) relative insensitive to the presentation format of the stimuli (study 2 compared to study 3), (d) judged positively by most users, and (e) perceived to lead to faithful representations of their views, as demonstrated by the fact that most of the experts did not revise their estimates (and mean revisions were minimal). The last finding is particularly important as experts often do not feel at ease with other methods (e.g., the use of open-ended questions or direct probability elicitation).

The results also add to our understanding of experts' perceptions of, and expectations about, future emissions at one point in time (the year 2100). There is a tradition of excellent papers involving direct elicitation of climate change experts' subjective probability distributions on a number of climatic indicators (e.g., Bamber and Aspinall 2013; Morgan et al. 2006; Morgan and Keith 1995; Nordhaus 1994a). These studies vividly illustrate the divergence of opinions in the field. The same applies to the assessments in this study as estimated from their ratio judgments (see Figs. 1 and 4) and is also echoed by the respondents' own perceptions (see Fig. 5). Perhaps surprisingly, for a small minority of experts, negative emissions are possible under the baseline condition (three experts had interpolated medians below 0), which may be due to optimism bias, or the phenomenon of perceiving bad outcomes as less likely than reality might suggest. But it could also derive from the inability of models to foresee disruptive changes in the availability and use of new technologies. Consider, as a hypothetical example, a rapid diffusion of a technology that relies on carbon dioxide that would be most cost effectively captured from the atmosphere. This could lead to negative emissions even in the absence of strong climate policies.

Despite the disagreements documented, the convex hulls of these distributions (especially to 50%) illustrate that there is a relatively narrow and homogeneous range of distribution that could be used to represent the experts' consensus, given current state of knowledge. This information complements other existing studies (e.g., Gillingham et al. 2018) and provides a useful aid to the users of scenario's projections.

Interestingly, the median emission levels projected by the experts under the Paris Agreement scenario (57 Gt CO_2/year) were much higher than those required to reach the target of global mean temperature "well below 2°C". The 2100 emissions of the SSP-based scenarios leading to 2.6 W/m_2 (corresponding to a likely chance of staying below 2 °C), for instance, show an average value of − 10.4 Gt CO_2, with a full range from − 27.5 to 0 (Gasser et al. 2015; Schleussner et al. 2016). The implication is that the respondents believe that the Paris Agreement will lead to lower emissions, but it is ultimately insufficient for reaching its overall goal. The median emission levels for the Paris Agreement scenario were consistent with the range reported by models projecting that climate action continues after 2030 at a level of ambition that is similar to that of the Intended Nationally Determined Contributions (INDCs) (see Fig. 2, Rogelj et al. 2015).

Most importantly, experts in our studies do not believe the distribution of expected emissions to be uniform over the range covered by the SSP scenarios. This observation suggests that developers and users of scenarios have a responsibility to use them without assuming equiprobability. In addition, they should warn planners and policy makers and think of ways to steer them away from this convenient, and easy to endorse, default assumption. Although the method seems to work well and generate sensible estimates, they are still embedded in deep uncertainty. The validity of any emission outcomes estimated by our method will be necessarily dependent on factors such as time and changes in circumstances and policy. This, of course, also applies to the alternative methods discussed in this paper.

Our method provides useful inputs for further analyses. The results could be used, for example, with probabilistic inversion techniques that can derive complex and potentially correlated model parameters from expert assessments (e.g., Cooke et al. 2006; Fuller et al. 2017). The results from this step can then be used to test the effects of parameter correlations discussed above. As a second example, the correlated model parameter estimates can be used to unveil key drivers of emissions and the uncertainties surrounding them (e.g., Butler et al. 2014a, b). This step can then inform the design of new mission-oriented research projects (cf. Christensen et al. 2018; Lutz et al. 2014; Wong and Keller 2017).

Projections of climate changes and the design of climate risk-management strategies hinge critically on baseline scenarios of greenhouse gas emissions. These studies are often silent on the deep uncertainty surrounding the emission scenarios or use ad hoc assumptions. These methodological choices can lead to poor outcomes. We demonstrate one possible way to help to mitigate this problem by obtaining probabilistic information from the experts who developed these scenarios in the first place.

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Q8 /Q9

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