

**Accelerated Article Preview****Comprehensive Evidence Implies a Higher Social Cost of CO<sub>2</sub>**

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1 **Comprehensive Evidence Implies a Higher Social Cost of CO<sub>2</sub>**

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3 Kevin Rennert<sup>1</sup>, Frank Errickson<sup>2\*</sup>, Brian C. Prest<sup>1\*</sup>, Lisa Rennels<sup>3\*</sup>, Richard G. Newell<sup>1</sup>, William Pizer<sup>1</sup>,  
4 Cora Kingdon<sup>3</sup>, Jordan Wingenroth<sup>1</sup>, Roger Cooke<sup>1</sup>, Bryan Parthum<sup>4</sup>, David Smith<sup>4</sup>, Kevin Cromar<sup>5,6</sup>,  
5 Delavane Diaz<sup>7</sup>, Frances C. Moore<sup>8</sup>, Ulrich K. Müller<sup>9</sup>, Richard J. Plevin, Adrian E. Raftery<sup>10</sup>, Hana  
6 Ševčíková<sup>11</sup>, Hannah Sheets<sup>12</sup>, James H. Stock<sup>13</sup>, Tammy Tan<sup>4</sup>, Mark Watson<sup>9</sup>, Tony E. Wong<sup>12</sup>, David  
7 Anthoff<sup>3†</sup>

8 <sup>1</sup>Resources for the Future, Washington, DC 20036, USA

9 <sup>2</sup>School of Public and International Affairs, Princeton University, Princeton, NJ 08540, USA

10 <sup>3</sup>Energy and Resources Group, University of California, Berkeley, CA 94720, USA

11 <sup>4</sup>Environmental Protection Agency, Washington, DC 20004, USA

12 <sup>5</sup>Marron Institute of Urban Management, New York University, Brooklyn, NY 11201, USA,

13 <sup>6</sup>NYU Grossman School of Medicine, New York, NY 10016, USA

14 <sup>7</sup>Electric Power Research Institute (EPRI), Palo Alto, CA 94304, USA

15 <sup>8</sup>Department of Environmental Science and Policy, University of California, Davis, CA 95616, USA

16 <sup>9</sup>Department of Economics, Princeton University, NJ 08540, USA

17 <sup>10</sup>Departments of Statistics and Sociology, University of Washington, Seattle, WA 98195, USA

18 <sup>11</sup>Center for Statistics and the Social Sciences, University of Washington, Seattle, WA 98195, USA

19 <sup>12</sup>School of Mathematical Sciences, Rochester Institute of Technology, Rochester, NY 14623, USA

20 <sup>13</sup>Department of Economics, Harvard University, Cambridge, MA 02138, USA

21 \* These authors contributed equally to this work

22 † e-mail: anthoff@berkeley.edu

23 **Abstract**

24 The social cost of carbon dioxide (SC-CO<sub>2</sub>) measures the monetized value of the damages to  
25 society caused by an incremental metric tonne of CO<sub>2</sub> emissions and is a key metric informing  
26 climate policy. Used by governments and other decision-makers in benefit-cost analysis for over  
27 a decade, SC-CO<sub>2</sub> estimates draw on climate science, economics, demography, and other  
28 disciplines. However, a 2017 report by the US National Academies of Sciences, Engineering, and  
29 Medicine<sup>1</sup> (NASEM) highlighted that current SC-CO<sub>2</sub> estimates no longer reflect the latest  
30 research. The report provided a series of recommendations for improving the scientific basis,  
31 transparency, and uncertainty characterization of SC-CO<sub>2</sub> estimates. Here we show that  
32 improved probabilistic socioeconomic projections, climate models, damage functions, and  
33 discounting methods that collectively reflect theoretically consistent valuation of risk,  
34 substantially increase estimates of the SC-CO<sub>2</sub>. Our preferred mean SC-CO<sub>2</sub> estimate is \$185 per

35 tonne of CO<sub>2</sub> (\$44-413/t-CO<sub>2</sub>: 5-95% range, 2020 US dollars) at a near-term risk-free discount rate  
36 of 2 percent, a value 3.6-times higher than the US government's current value of \$51/t-CO<sub>2</sub>. Our  
37 estimates incorporate updated scientific understanding throughout all components of SC-CO<sub>2</sub>  
38 estimation in the new open-source GIVE model, in a manner fully responsive to the near-term  
39 NASEM recommendations. Our higher SC-CO<sub>2</sub> values, compared to estimates currently used in  
40 policy evaluation, substantially increase the estimated benefits of greenhouse gas mitigation and  
41 thereby increase the expected net benefits of more stringent climate policies.

## 42 Main

43 Policies to mitigate greenhouse gas emissions are often evaluated in terms of their net benefits  
44 to society. The net benefit of a climate policy is the difference between the economic cost of the  
45 emission reduction (the mitigation costs), and the value of the damages that are prevented by  
46 that emission reduction (climate benefits, among others). In regulatory impact analysis the  
47 climate benefits of CO<sub>2</sub> emission reductions are typically computed by multiplying the change in  
48 CO<sub>2</sub> emissions caused by the policy with an estimate of the SC-CO<sub>2</sub>. This makes the SC-CO<sub>2</sub> a  
49 highly influential metric, informing analysis of a wide range of climate policies worldwide.

50 For more than a decade, the US government has used the SC-CO<sub>2</sub> to measure the benefits of  
51 reducing carbon dioxide emissions in its required regulatory analysis of more than 60 finalized,  
52 economically significant regulations, including standards for appliance energy efficiency and  
53 vehicle and power plant emissions<sup>2</sup>. In the United States, the SC-CO<sub>2</sub> has also been used as the  
54 basis for federal tax credits for carbon capture and storage; proposed federal carbon tax  
55 legislation; state-level zero emission credit payments for nuclear generators and power sector  
56 planning; among other applications<sup>3</sup>. The SC-CO<sub>2</sub> also supports decision making by government  
57 environmental agencies in other countries (e.g., Germany, Canada, and Mexico), and is used in  
58 standardized corporate environmental and sustainability accounting<sup>4</sup>.

59 The SC-CO<sub>2</sub> is estimated using integrated assessment models (IAMs) that couple together  
60 simplified representations of the climate system and global economy to estimate the economic  
61 effects of an incremental pulse of CO<sub>2</sub> emissions. These models generally follow a four-step  
62 process in which (1) projections of population and GDP inform a CO<sub>2</sub> emissions pathway; (2) the

63 CO<sub>2</sub> emissions path drives a climate model that projects atmospheric greenhouse gas  
64 concentrations, temperature changes, and other physical variables such as sea level rise; (3) the  
65 resulting climate change impacts are monetized and aggregated as economic damages; and (4)  
66 economic discounting combines all future damages into a single present value.

67 In 2017, a NASEM report assessing the SC-CO<sub>2</sub> estimation methodology used by the US federal  
68 government found that the leading IAMs used for estimating the SC-CO<sub>2</sub> have not kept pace with  
69 recent advances in climate, economic, and demographic science<sup>1</sup>. The NASEM report offered  
70 near-term recommendations for improving each step of the SC-CO<sub>2</sub> estimation process to  
71 improve the scientific basis, characterization of uncertainty, and transparency of the SC-CO<sub>2</sub>.  
72 Recently, Executive Order 13990 re-established the US *Interagency Working Group on the Social*  
73 *Cost of Greenhouse Gases* (IWG) to update the federal government's official SC-CO<sub>2</sub> estimates,  
74 and to consider these NASEM recommendations in the process. Others have also criticized the  
75 models supporting the past federal SC-CO<sub>2</sub> estimates for a number of problems including  
76 damages representations that do not reflect recent science, outdated climate system models,  
77 and imperfect characterization of the compounding uncertainties affecting SC-CO<sub>2</sub> estimates.<sup>5-7</sup>

78 Here, we provide probabilistic SC-CO<sub>2</sub> estimates from the Greenhouse Gas Impact Value  
79 Estimator (GIVE), a newly created integrated assessment model designed for quantifying the  
80 benefits of emission reductions. The model is built on the Mimi.jl platform, an open-source  
81 package for constructing modular integrated assessment models<sup>8</sup>. By using novel components  
82 for each step of the SC-CO<sub>2</sub> estimation process, GIVE incorporates recent scientific advances that  
83 are unaccounted for by the previous generation of IAMs used in regulatory analysis. Crucially,  
84 GIVE quantifies uncertainties in each component and propagates these compounding  
85 uncertainties through the entire computation, thus allowing for a theoretically consistent  
86 valuation of the risk associated with a marginal emission of CO<sub>2</sub>.

87 Each individual component in GIVE is based on recent peer-reviewed research on socioeconomic  
88 projections, climate modelling, climate impact assessments, and economic discounting. We  
89 implement GIVE with a set of internally consistent, probabilistic projections of population<sup>9</sup>, per-  
90 capita economic growth<sup>10</sup>, and CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O emissions<sup>3</sup> generated using a combination of  
91 statistical modelling and expert elicitation, collectively referred to as the Resources for the Future

92 Socioeconomic Projections<sup>3</sup> (RFF-SPs). Many existing IAMs use outdated climate models and have  
93 been shown to produce temperature dynamics inconsistent with more sophisticated Earth  
94 system models<sup>1,11</sup>. Further, damage functions supporting previous SC-CO<sub>2</sub> estimates are, to a  
95 large extent, based on studies from several decades ago<sup>1</sup>. A vast literature since then has  
96 expanded and improved our scientific understanding of how changes in climate will likely affect  
97 human wellbeing<sup>12</sup>. To address these shortcomings, we combine socioeconomic uncertainty with  
98 probabilistic models for the climate system and damage functions (defined as functions that  
99 relate changes in climate outcomes such as temperature to economic impacts in dollars). The  
100 GIVE model employs the FaIR v1.6.2 climate model<sup>13,14</sup>, the BRICK sea-level model<sup>15-17</sup>, and  
101 updated damage function components representing the latest empirical research for the impacts  
102 of climate on agriculture<sup>18</sup>, mortality<sup>19</sup>, energy consumption<sup>20</sup>, and sea-level rise<sup>21</sup>.

103 Recent important contributions to the SC-CO<sub>2</sub> literature have generated improvements to various  
104 components used by integrated assessment models<sup>22-27</sup> (see Supplemental Information section  
105 SI.3 for an overview of this literature). The GIVE model's key contribution to this literature is the  
106 holistic implementation of recent advances in probabilistic socioeconomics accounting for policy  
107 uncertainty, fully quantified scientific uncertainty including climate tail risk and sea-level rise,  
108 addition of non-market sectoral damages (i.e., costs not included in GDP accounting such as  
109 mortality risk), and economic discounting tied to uncertain economic growth. These advances  
110 allow for a full valuation of the risk resulting from those compounding uncertainties based on  
111 improved scientific, economic, and demographic evidence,<sup>3</sup> which have previously been  
112 unavailable. The GIVE model's implementation of this comprehensive set of scientific  
113 improvements affirms a key result from recent work on the SC-CO<sub>2</sub><sup>22-27</sup>, namely that improved  
114 scientific understanding of the components of SC-CO<sub>2</sub> calculation leads to a higher SC-CO<sub>2</sub> than  
115 has been previously used in US policymaking; moreover, our approach demonstrates this using a  
116 more robust methodology reflecting the current state of the literature. GIVE's inputs and outputs  
117 are spatially resolved at the level of 184 countries for population, income, and damages (except  
118 for agriculture damage outputs which are resolved at 16 regions). Climate change has the  
119 potential to exacerbate existing economic inequities<sup>6,28,29</sup>, and our work would allow future  
120 consideration of this issue through equity weighting<sup>30</sup>.

121 We calculate the SC-CO<sub>2</sub> as the discounted sum of additional damages per incremental tonne of  
122 CO<sub>2</sub> produced by an emissions pulse in 2020 along an uncertain emissions trajectory derived via  
123 formal expert elicitation that reflects continued technology and policy evolution. We use an  
124 empirically calibrated stochastic discounting framework consistent with the observed behaviour  
125 of interest rates and economic growth<sup>31</sup>. We provide 10,000 SC-CO<sub>2</sub> values using a Monte Carlo  
126 approach that samples interrelated socioeconomic, climate, and damage function uncertainties  
127 (Extended Data Table 2). The GIVE model can also be used to compute the social cost of other  
128 greenhouse gases (e.g., CH<sub>4</sub>, N<sub>2</sub>O, HFCs).

129 We illustrate the relative importance of our updated model components by comparing them to  
130 outputs from the well-known DICE model<sup>32</sup>. We also assess the sensitivity of our SC-CO<sub>2</sub> estimates  
131 to our choice of sectoral, regionally disaggregated damage functions by comparing them to two  
132 aggregate, global damage functions based on meta-analyses of the broader damages  
133 literature<sup>32,33</sup>.

134 Socioeconomic projections of economic growth, population, and greenhouse gas emissions  
135 represent important sources of uncertainty in the SC-CO<sub>2</sub>. In previous models, this uncertainty  
136 has been poorly characterized<sup>1,34,35</sup>. Population and growth scenarios based upon the Shared  
137 Socioeconomic Pathway (SSP)<sup>36</sup> narratives, which were prominently featured in the  
138 Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6)<sup>14</sup>, do not  
139 typically come with associated probabilities, though there have been efforts to assign such  
140 probabilities *a posteriori* based on expert surveys<sup>37</sup>. The small number of SSPs precludes sampling  
141 the large and continuous space of possibilities that characterizes future socioeconomics and  
142 emissions. A strength of scenario-based analysis is in the qualitative exploration of uncertainty,  
143 for example through the use of bounding scenarios, including scenarios accounting for outcomes  
144 well outside the range of historical experience that become increasingly possible over very long  
145 time horizons. Such an approach does not, however, facilitate the quantitative evaluation of  
146 uncertainty and the calculation of expected values, a common requirement for policy analysis. In  
147 some cases, a lack of quantification of relative probabilities can lead to disagreements over what  
148 scenarios constitute a plausible reference case<sup>38-40</sup>. A holistic, probabilistic approach to  
149 accounting for these uncertainties was recently introduced<sup>41,42</sup>. Building on this approach, we

150 sample the RFF-SPs, comprising multi-century probabilistic projections of population<sup>9</sup> and GDP  
151 per capita<sup>10</sup> at the country level as well as a distribution of projections of global CO<sub>2</sub>, CH<sub>4</sub>, and  
152 N<sub>2</sub>O emissions derived from a combination of statistical and expert-based approaches.

153 The RFF-SPs complement the scenario-based approach by providing an alternative approach that  
154 characterizes the joint uncertainty across annual GDP, population, and greenhouse gas emissions  
155 for the multi-century timespan required for climate damage estimation. They also leverage  
156 expert knowledge to account for potential future changes in policy and technology. They project  
157 that (Fig. 1): median world population peaks at 11 billion around 2130 and subsequently declines  
158 to 7.3 billion in 2300, (2.8 billion–21 billion: 5-95% range); median global per capita annualized  
159 economic growth declines slowly to reach a cumulative time-average rate of 0.88% between  
160 2020 and 2300 (0.17%–2.7%: 5-95% range); median net global CO<sub>2</sub> emissions decline to roughly  
161 40 percent of today's levels in 2100 (-20%-150%: 5-95% range), with slower declines thereafter  
162 (see Supplemental Information section SI.1 for more detail on the RFF-SPs).

163 Our mean SC-CO<sub>2</sub> estimate using the preferred discounting scheme is \$185/t-CO<sub>2</sub> (\$44-413/t-  
164 CO<sub>2</sub>: 5-95% range, in 2020 US dollars, as are all dollar results in this study) (Fig. 2). This is 3.6 times  
165 greater than the US government's current, most commonly cited mean value of \$51/t-CO<sub>2</sub> using  
166 a 3% constant discount rate<sup>43</sup>. We report mean SC-CO<sub>2</sub> values throughout this paper to align our  
167 results with the standard expected net benefit framework that is routinely used for policy  
168 analysis<sup>44</sup> and supported by standard economic theory<sup>45,46</sup>.

169 SC-CO<sub>2</sub> estimates are well-known to be highly sensitive to the discount rate<sup>32</sup> because the long  
170 residence time of CO<sub>2</sub> in the atmosphere means a CO<sub>2</sub> emissions pulse continues to cause  
171 damages long after it was emitted. Our preferred discounting scheme uses a 2% near-term risk-  
172 free discount rate, which reflects the recent literature on real interest rates<sup>47-49</sup>, which have  
173 declined substantially over recent decades<sup>50,51</sup>, as well as the central tendency from a survey of  
174 academic economists<sup>52</sup>. Our discount rate is related to stochastic consumption growth in a  
175 Ramsey-like equation, which is the commonly used approach to value marginal impacts amid  
176 uncertainty in future payoffs and consumption levels<sup>53,54</sup>. In this way, the parameterization of the  
177 discount rate captures risk preferences using the risk aversion parameters discussed in the  
178 *Methods*.

179 We also assess (Extended Data Fig. 1 and Table 1) the sensitivity of our SC-CO<sub>2</sub> estimates to  
180 discounting by also using near-term rates of 3% (\$80/t-CO<sub>2</sub> mean: \$12-197/t-CO<sub>2</sub> 5-95% range),  
181 to facilitate comparison with the US government's current, most commonly cited \$51/t-CO<sub>2</sub>  
182 figure, as well as 2.5% (\$118/t-CO<sub>2</sub> mean: \$23-280/t-CO<sub>2</sub> 5-95% range) and 1.5% (\$308/t-CO<sub>2</sub>  
183 mean: \$94-626/t-CO<sub>2</sub> 5-95% range). We additionally show (Extended Data Fig. 2) the temporal  
184 evolution of the discounted marginal damages by year based upon the preferred 2% near-term  
185 discount rate case.

186 Our SC-CO<sub>2</sub> estimates are based on regionally disaggregated damage functions for four sectors.  
187 As a sensitivity analysis, we replace the sectoral damage functions in GIVE with two distinct,  
188 globally aggregated damage functions that are based on meta-analyses of the climate impacts  
189 literature<sup>32,33</sup>. Under a 2% near-term discount rate, these sensitivity runs yield relatively similar  
190 SC-CO<sub>2</sub> distributions with mean values that differ by -18% to +11% (Extended Data Table 1) from  
191 our preferred SC-CO<sub>2</sub> estimate (Extended Data Fig. 1).

192 The single largest contributor to the overall increase in the SC-CO<sub>2</sub> relative to the widely used  
193 DICE model is the use of a lower near-term discount rate, with updated damage functions being  
194 the second largest contributor. We disaggregate impacts of the changes to the near-term  
195 discount rate, the sectoral damage functions, and the remaining GIVE components (the RFF-SPs  
196 and FaIR) in Table 1. We start by running DICE-2016R, which uses none of our updated  
197 components and uses DICE's default discounting approach, yielding an SC-CO<sub>2</sub> estimate of \$44/t-  
198 CO<sub>2</sub>. Updating the climate modelling, the socioeconomic scenarios, and the discounting approach  
199 reflecting a 3% near-term discount rate but retaining the DICE-2016R damage function increases  
200 the mean SC-CO<sub>2</sub> by 34% to \$59/t-CO<sub>2</sub>. Incorporating our sectoral damage functions in place of  
201 the DICE-2016R damage function further increases the estimate to \$80/t-CO<sub>2</sub>, or a total increase  
202 of 81%. Finally, using a lower 2% near-term discount rate has the largest effect, increasing the  
203 mean SC-CO<sub>2</sub> estimate to this study's value of \$185/t-CO<sub>2</sub>, a 321% increase relative to \$44/t-CO<sub>2</sub>,  
204 and a 3.6-fold increase relative to the widely cited US government value of \$51/t-CO<sub>2</sub>.

205 The four climate damage sectors represented in the model vary substantially in their respective  
206 contributions to the overall magnitude and uncertainty of the SC-CO<sub>2</sub> (Fig. 3). Temperature  
207 mortality impacts are the largest driver of the SC-CO<sub>2</sub>, contributing a mean partial SC-CO<sub>2</sub>



208 (defined as the SC-CO<sub>2</sub> estimated for an individual impact sector) of \$90/t-CO<sub>2</sub> (\$39-165/t-CO<sub>2</sub>,  
209 5-95% range) to the \$185/t-CO<sub>2</sub> total using a near-term 2% discount rate. Agricultural impacts  
210 have a similar mean contribution of \$84/t-CO<sub>2</sub>, but greater uncertainty, with a 5-95% partial SC-  
211 CO<sub>2</sub> range spanning -\$23 to \$263/t-CO<sub>2</sub>. This large range, which includes the potential for  
212 beneficial effects of higher temperatures and CO<sub>2</sub> concentrations on agriculture, arises due to  
213 compounding uncertainty in the relationship between CO<sub>2</sub>, temperature, and crop yields and  
214 how these factors interact with the economic system to affect human welfare<sup>18</sup>. We sample  
215 uncertain parameters for mortality and agriculture (see *Methods*), the damage sectors for which  
216 parameter uncertainty is quantified in the underlying studies.

217 The relatively small contribution of sea-level rise, which includes both coastal damages and  
218 adaptation costs, to the total SC-CO<sub>2</sub> (mean partial SC-CO<sub>2</sub> of \$2/t-CO<sub>2</sub>, \$0-4/t-CO<sub>2</sub>, 5-95% range)  
219 is attributable in part to the inertia in the physical system connecting CO<sub>2</sub> emissions and sea-level  
220 rise and in part to the optimal regional adaptation response allowed by the Coastal Impact and  
221 Adaptation Model (CIAM) that we incorporate into GIVE<sup>21</sup>. Such optimal, forward-looking  
222 adaptation responses can substantially reduce estimated coastal damages relative to a static  
223 scenario assuming no response to evolving coastal risks<sup>55,56</sup>. Future research could improve the  
224 characterization of plausible versus optimal coastal adaptation responses. The relatively slow  
225 pace of sea-level rise also causes the greatest damages to occur far in the future when  
226 discounting effects are strongest. Energy costs for residential and commercial buildings (based  
227 on Clarke et al. 2018<sup>20</sup>) also make a relatively small contribution to the overall SC-CO<sub>2</sub> (mean  
228 partial SC-CO<sub>2</sub> of \$9/t-CO<sub>2</sub>, \$4-15/t-CO<sub>2</sub>, 5-95% range), due to increased energy demand from  
229 cooling being offset by decreased heating demand and future technological progress; these  
230 results are broadly consistent with other recent empirical work<sup>57</sup>.

231 We quantify impacts on four critical, globally significant damage sectors that are often considered  
232 to contribute the most to the SC-CO<sub>2</sub><sup>1,58</sup> and for which studies exist that can be readily  
233 incorporated into SC-CO<sub>2</sub> estimation due to their global coverage, regional disaggregation, and  
234 monetization. A limitation of this study is that other categories of climate damages, including  
235 additional non-market damages other than human mortality, remain unaccounted for. The  
236 inclusion of additional damage sectors such as biodiversity<sup>59</sup>, labour productivity<sup>60,61</sup>, conflict<sup>62</sup>,

237 and migration<sup>63</sup> in future work would further improve our estimates. Current evidence strongly  
238 suggests that including these sectors would raise the estimates of the SC-CO<sub>2</sub>, although  
239 accounting for adaptation responses could potentially counteract some of that effect. Other  
240 costs of climate change including the loss of cultural heritage, particular ways of life, or valued  
241 ecosystems, may never be fully valued in economic terms but would also likely raise the SC-CO<sub>2</sub>  
242 beyond the estimates presented here. The addition of alternate studies covering the same  
243 sectors to incorporate additional independent lines of evidence is also a promising area for  
244 continued work to improve the SC-CO<sub>2</sub>. The modular structure of the Mimi.jl framework  
245 facilitates such addition of new damage sectors with ease, providing a flexible basis for future  
246 scientific improvement of the SC-CO<sub>2</sub>.

247 While we approximate the effects of a rapid Antarctic ice sheet disintegration tipping point within  
248 the BRICK sea-level component, incorporating additional potential discontinuities in the climate  
249 system would further improve our SC-CO<sub>2</sub> estimates<sup>64</sup>. We expect that, in total, the future  
250 inclusion of additional damage sectors and tipping elements is likely to raise the estimates of the  
251 SC-CO<sub>2</sub>, and therefore that the estimates from the present study are likely best viewed as  
252 conservative. Similarly, accounting for different climate model structures, as the recent IPCC AR6  
253 report does in chapter 7<sup>14</sup>, would further strengthen the robustness of our SC-CO<sub>2</sub> estimates and  
254 their associated uncertainty levels. For example, that chapter (see Cross-Chapter Box 7.1, Table  
255 2 therein) shows the MAGICC climate model projects slightly higher temperature increases than  
256 the FaIR model.

257 The methods employed in this study reflect the culmination of several important advances:  
258 development of fully probabilistic very long-run socioeconomic inputs that natively incorporate  
259 uncertainty over future climate policy; incorporation of state-of-the-science representations of  
260 the climate system and sectoral damage functions; and an empirically calibrated discounting  
261 approach that accounts for uncertainty in future economic growth. These advances collectively  
262 allow for the full characterization of uncertainties, and their compounding interactions,  
263 throughout all steps of SC-CO<sub>2</sub> estimation, including sectoral market and nonmarket damages to  
264 human health. Their implementation on Mimi.jl<sup>8</sup>, an open-source, modular computational  
265 platform for assembling IAMs, improves the scientific basis and transparency of the resulting

266 estimates and is responsive to the NASEM near-term recommendations. The methodology also  
267 provides a straightforward means to calculate SC-CO<sub>2</sub> results for other years and estimate the  
268 social cost of other greenhouse gases (e.g., CH<sub>4</sub>, N<sub>2</sub>O, HFCs). Our higher SC-CO<sub>2</sub> values, compared  
269 to estimates currently used in policy evaluation, substantially increase the estimated benefits of  
270 greenhouse gas mitigation, and thereby increase the expected net benefits of more stringent  
271 climate change policies.

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## 404 Tables

Row	Scenario	Mean SC-CO <sub>2</sub> (\$/t-CO <sub>2</sub> )	Incremental Change (\$/t-CO <sub>2</sub> )	Share of Total Change (%)
a	DICE-2016R	\$44		
b	GIVE w/ DICE damage function, 3% near-term discount rate	\$59	\$15	11%
c	GIVE, w/ sectoral damages, 3% near-term discount rate	\$80	\$21	15%
<b>This study:</b>				
d	GIVE, w/ sectoral damages, 2% near-term discount rate	\$185	\$105	74%

405 **Table 1 | Evolution of mean SC-CO<sub>2</sub> from DICE-2016R to this study.** All SC-CO<sub>2</sub> values are expressed in  
406 2020 US dollars per metric tonne of CO<sub>2</sub>. (a) represents the SC-CO<sub>2</sub> using base DICE-2016R deterministic.  
407 The mean SC-CO<sub>2</sub> of \$44/t-CO<sub>2</sub> is similar to the value previously estimated from IWG DICE-2010 of \$46/t-  
408 CO<sub>2</sub> at a 3% discount rate, after converting to 2020\$<sup>65</sup>, (b) then retains the DICE-2016R damage function  
409 but otherwise deploys GIVE under discounting parameters of  $\rho = 0.8\%$ ,  $\eta = 1.57$ , which are consistent  
410 with a 3% near-term discount rate, (c) then replaces the DICE-2016R damage function with our sectoral  
411 damage functions, (d) then uses our preferred discounting parameters from this study of  $\rho = 0.2\%$ ,  $\eta =$   
412 1.24, which are consistent with a 2% near-term discount rate. The final row represents the preferred  
413 mean value from this study.

414 Figure legends

415 **Fig. 1 | RFF-SP socioeconomic scenarios and the resulting climate system projections.** a-c, Probabilistic  
416 socioeconomic projections for global population (a), per capita GDP growth rates (b), and carbon dioxide  
417 emission levels (c) from the RFF-SP scenarios. d-f, corresponding climate system projections that account  
418 for parametric uncertainty in FaIR and BRICK for atmospheric carbon dioxide concentrations (d), global  
419 surface temperature changes relative to the 1850-1900 mean (e), and global mean sea-level changes  
420 relative to 1900 (f). In all panels, solid centre lines depict the median outcome, with darker shading  
421 spanning the 25-75% quantile range and lighter shading spanning the 5-95% quantile range.

422 **Fig. 2 | SC-CO<sub>2</sub> distributions vary with the choice of near-term discount rates.** Distributions of the SC-  
423 CO<sub>2</sub> based on RFF-SP scenario samples, a stochastic, growth-linked discounting framework, uncertainty in  
424 the FaIR climate and BRICK sea-level models, and uncertainty in climate damage parameters. Colours  
425 correspond to near-term average discount rates of 3.0% (blue), 2.5% (orange), 2.0% (red, our preferred  
426 specification), and 1.5% (teal). Dashed vertical lines highlight mean SC-CO<sub>2</sub> values. Box and whisker plots  
427 along the bottom of the figure depict each SC-CO<sub>2</sub> distribution's median (centre white line), 25-75%  
428 quantile range (box width), and 5-95% quantile range (coloured horizontal lines) values. All SC-CO<sub>2</sub> values  
429 are expressed in 2020 US dollars per metric tonne of CO<sub>2</sub>.

430 **Fig. 3 | Partial SC-CO<sub>2</sub> estimates and uncertainty levels strongly differ across the four climate damage**  
431 **sectors.** Box and whisker plots for the climate damage sectors included in the GIVE model, based on partial  
432 SC-CO<sub>2</sub> estimates for each sector. Figure depicts the median (centre white line), 25-75% quantile range  
433 (box width), and 5-95% quantile range (coloured horizontal lines) partial SC-CO<sub>2</sub> values. Black diamonds  
434 highlight each sector's mean partial SC-CO<sub>2</sub>, with the numeric value written directly above. All SC-CO<sub>2</sub>  
435 values are expressed in 2020 US dollars per metric tonne of CO<sub>2</sub>.

## 436 Methods

### 437 **Socioeconomic projections**

438 The RFF-SPs<sup>3</sup> used in this study were designed to address the requirements for socioeconomic  
439 projections posed by SC-CO<sub>2</sub> estimation: (1) The roughly 300-year time-horizon required to  
440 account for the vast majority of discounted future damages; (2) the need for geographically  
441 disaggregated estimates of GDP and population to support damages at a regional scale; (3)  
442 uncertainty accounting for expected future changes in both technology and policy (the SC-CO<sub>2</sub> is  
443 measured against the best estimate of future emissions, inclusive of future mitigation policies  
444 except the one under analysis); and (4) the interdependence of future population, GDP, and  
445 greenhouse gas emissions trajectories<sup>1</sup>.

446 The RFF-SPs address key shortcomings identified in the approach to socioeconomic projections  
447 originally developed by the US IWG in 2010<sup>66</sup> and used consistently through the current US  
448 interim estimates<sup>43</sup>. The IWG used five socioeconomic scenarios to 2100, drawn from the Energy  
449 Modeling Forum 22 modelling exercise<sup>67</sup>, one of which represented future climate policy. The  
450 IWG scenarios were critiqued for not spanning the true uncertainty in GDP, population and  
451 emissions, nor reflecting the broader scenario literature overall<sup>34,68</sup>. The RFF-SPs used here  
452 improve on those scenarios by explicitly characterizing uncertainty in the demographic, economic  
453 and emissions projections.

454 The multi-century time horizon required for the projections is long relative to the length of the  
455 historical record available to estimate country-level statistical models of population and  
456 economic growth. Accounting for uncertainty in future emissions over that time horizon requires  
457 assessing the potential for structural changes in technology and policies that are out of the range  
458 of historical experience. To address these challenges, the RFF-SPs were generated based upon a  
459 combination of statistical and expert-based approaches.

460 We generated probabilistic, country-level population projections through 2300<sup>9</sup> by extending the  
461 fully probabilistic statistical approach used by the United Nations (UN) for its official population  
462 forecasts to 2100. We further incorporated feedback and improvements suggested by a panel of  
463 nine leading demographic experts convened to review preliminary results.

464 Our trajectories of country-level GDP per capita from 2018 to 2300 come from a multifactor  
465 Bayesian dynamic model, in which each country's GDP per capita is based on a global frontier of  
466 developed economies and country-specific deviations from that frontier<sup>10</sup>. We reweight the  
467 probabilities of the Bayesian model trajectories using results from the RFF Economic Growth  
468 Survey, a formal expert elicitation focused on quantifying uncertainty in long-run economic  
469 growth<sup>3</sup>.

470 The resulting probabilistic socioeconomic trajectories represent an alternative to existing  
471 scenario-based approaches, such as those based on the Shared Socioeconomic Pathways  
472 narratives. Such scenarios do not typically come with associated probabilities, though there have  
473 been efforts to assign such probabilities to the SSPs *a posteriori* based on expert surveys<sup>37</sup>. The  
474 use of non-probabilistic scenarios have been criticized in the literature for being overconfident  
475 and failing to reflect uncertainty<sup>69</sup>. Indeed, multi-century socioeconomic projections are deeply  
476 uncertain, as illustrated by the wide 5-95% ranges that we consider (see Figure 1). The scenarios  
477 based on the SSP narratives and their commonly used extensions beyond 2100<sup>63,70-72</sup> fail to span  
478 that uncertainty.<sup>3</sup>

479 We also generate multi-century distributions of global CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O emissions through RFF's  
480 Future Emissions Survey, which elicited experts in socioeconomic projections and climate policy<sup>3</sup>.  
481 Experts provided uncertainty ranges for future fossil fuel and process-related CO<sub>2</sub> emissions as  
482 well as changes in natural CO<sub>2</sub> stocks and negative-emissions technologies, incorporating their  
483 own uncertainty around future mitigation policy. They also quantified the sensitivity of emissions  
484 projections to future economic growth, thereby allowing for the development of a joint set of  
485 projections of emissions and economic growth. The experts additionally provided uncertainty  
486 ranges for trajectories of CH<sub>4</sub> emissions, N<sub>2</sub>O emissions, and net CO<sub>2</sub> emissions from other  
487 sources of CO<sub>2</sub> emissions and sinks.

## 488 **Climate models**

### 489 (1) FAIR

490 We represent the global climate system and carbon cycle dynamics using version 1.6.2 of the  
491 Finite Amplitude Impulse Response (FaIR) model.<sup>73-75</sup> FaIR is an emissions-based simple climate  
492 model with a carbon cycle that depends on background warming levels and cumulative carbon

493 uptake by land and ocean sinks. This state-dependency enables FaIR to replicate the equilibrium  
494 and impulse-response behaviours found in more sophisticated Earth system models, which is  
495 important for producing scientifically grounded SC-CO<sub>2</sub> estimates. These features are not found  
496 in the previous climate models used for SC-CO<sub>2</sub> calculations, which lack carbon cycle feedbacks  
497 and have been shown to respond too slowly to changes in radiative forcing<sup>1,11</sup>. We run FaIR with  
498 randomly sampled CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O emissions time-series from the RFF-SPs and represent other  
499 greenhouse gases and short-lived climate forcers using the SSP2-4.5 scenario<sup>76</sup>, the scenario that  
500 most closely matches the median RFF-SP emissions trajectories. We account for climate model  
501 uncertainties by randomly sampling a calibrated 2,237-member ensemble of parameters that  
502 was produced using FaIR as part of the IPCC AR6<sup>74</sup>. See Supplemental Information section SI.2 for  
503 more detail on the FaIR model.

#### 504 (2) BRICK

505 We make probabilistic projections of regional changes in sea level using the Building blocks for  
506 Relevant Ice and Climate Knowledge (BRICK) model. BRICK represents individual contributions to  
507 sea level from the Greenland and Antarctic ice sheets, glaciers and small ice caps, thermal  
508 expansion, and land water storage and has been thoroughly described in prior studies<sup>15</sup>. BRICK  
509 downscales changes in global sea level to regional changes using maps of time-invariant scaling  
510 factors<sup>15,77</sup>. The Antarctic ice sheet model component also accounts for a potential tipping point  
511 where rapid ice sheet disintegration can occur when annual mean Antarctic surface temperatures  
512 cross an uncertain threshold<sup>16</sup>.

513 We closely follow past work and calibrate BRICK to the historic sea-level record over the period  
514 1850-2017 with a Bayesian framework<sup>15,17,78,79</sup>. This calibration process uses observational  
515 constraints on global mean sea-level changes<sup>80</sup> in addition to individual contributions from  
516 glaciers and small ice caps<sup>81</sup>, the Greenland ice sheet<sup>82,83</sup>, the Antarctic ice sheet<sup>84</sup>, and trends in  
517 thermal expansion<sup>85</sup>. It further statistically accounts for measurement error estimates provided  
518 with each observational time-series data set<sup>86</sup>. We select physically informed prior distributions  
519 for BRICK's uncertain parameters that are consistent with previous model calibration studies<sup>15,17</sup>.  
520 For the Antarctic ice sheet model component, we select prior distributions based on a  
521 paleoclimate calibration that uses independent sea-level data from 240,000 years before the

522 current era to the present<sup>16</sup>. We use our calibration framework to create a Markov chain of ten  
523 million representative samples from BRICK's joint posterior parameter distribution and assess  
524 convergence based on graphical diagnostics and Gelman-Rubin potential scale reduction factors  
525 that are less than 1.1<sup>87,88</sup>. We discard the first one million samples for the initial burn-in period  
526 and select a random subset of 10,000 samples from the remaining chain for our final sea-level  
527 parameter values. The distributions of the uncertain parameters in BRICK are shown in  
528 Supplemental Information Table 4.

## 529 **Damage functions**

### 530 (1) Sea-level rise

531 The sea-level rise damage calculations are based on the work of Diaz<sup>21</sup> which presents the Coastal  
532 Impacts and Adaptation Model (CIAM). CIAM is an optimization model that assesses the costs of  
533 various adaptation strategies against flooding damages and potential impacts from regional  
534 changes in sea level. It chooses the least-cost strategy for each of over 12,000 coastal segments  
535 across the globe in the Dynamic Interactive Vulnerability Assessment (DIVA) database<sup>89</sup> after  
536 taking into account local physical and socioeconomic characteristics. CIAM's potential adaptation  
537 strategies are specified as a combination of (1) a choice on retreating inland from the coastline,  
538 protecting coastal communities and infrastructure, or remaining in place without taking any  
539 adaptive actions and (2) a choice on the degree of investment in coastal defence against several  
540 different storm surge return periods conditional on protection being decided on. The DIVA  
541 database provides generalized extreme value distributions that define these return periods for  
542 each individual segment.

543 CIAM is a deterministic model. All uncertainty in coastal damages is therefore the result of  
544 uncertain sea-level projections that arise due to GIVE's probabilistic emission scenarios and  
545 climate and sea-level model parametric uncertainties that we sample.

### 546 (2) Building Energy Expenditures

547 The energy demand damage function is based on the results of Clarke et al. (2018)<sup>20</sup>, a study that  
548 used the Global Change Analysis Model (GCAM)<sup>90,91</sup> to project how climate change affects  
549 regional building energy demand through 2100. GIVE's damage functions relate each degree of  
550 global temperature rise to a change in regional energy expenditures, expressed as a proportion

551 of that region's GDP. We derive these damage functions using output data provided by the  
552 authors of Clarke et al.<sup>20</sup>. That output includes, for each of the 12 GCAM regions, the net change  
553 in regional energy expenditures as a proportion of regional GDP at various temperature levels  
554 (varying over both time and scenario). Clarke et al.<sup>20</sup> note that this relationship is approximately  
555 linear in temperature. For each of the 12 GCAM regions, we fit a linear function to these  
556 datapoints by regressing the net change in energy expenditures as a proportion of GDP on global  
557 temperature rise relative to the preindustrial period. We assume the intercept is zero to ensure  
558 the resulting function yields no change in energy expenditures at zero temperature rise. This  
559 yields a coefficient for each region, denoted  $\beta_j^E$  (see Supplemental Information Table 2 for these  
560 values). Energy damages for each country  $i$  located in region  $j$  are then calculated using the  
561 corresponding coefficient, as

562 *Change in Energy Expenditures as a Proportion of GDP* $_{i,t} = \beta_j^E \times (\text{Temperature Rise})_t.$  (1)

563 We multiply this energy expenditure share by country-level GDP to generate damages in dollars.

564 Clarke et al.<sup>20</sup> did not feature any explicit consideration of uncertainty, so we do not include  
565 uncertainty in this damage function. Uncertainty in energy-related damages remain, however,  
566 due to GIVE's uncertain temperature projections and GDP trajectories.

567 (3) Temperature-related mortality

568 The mortality damage functions are based on the results of Cromar et al. (2022)<sup>19</sup>, who convened  
569 a panel of health experts to conduct a meta-analysis of peer-reviewed research studying the  
570 impacts of temperature on all-cause mortality risk, which includes human health risks related to  
571 a broad set of health outcomes including cardiovascular, respiratory, and infectious disease  
572 categories. The meta-analysis combined studies to produce regionally disaggregated estimates  
573 of the effects on all-cause mortality of each degree of warming across a broad range of baseline  
574 temperatures, including both increased mortality risk at high temperatures and reduced risk at  
575 cooler temperatures. This produced, for each of 10 regions, a point estimate (and its standard  
576 error) representing the net change in all-cause mortality risk per degree Celsius of globally  
577 averaged surface temperatures (see Supplemental Information Table 1).

578 To reflect uncertainty in these estimates, we sample these parameters  $\beta_j^M$  for region  $j$  from a  
 579 normal distribution centred on the point estimate and set the standard deviation equal to the  
 580 reported standard error. We then compute temperature-induced excess deaths in country  $i$  in  
 581 region  $j$  as

$$582 \quad \begin{aligned} & (\text{Temperature Induced Excess Deaths})_{i,t} \\ & = \beta_j^M \times (\text{Temperature Rise})_t \times (\text{Baseline Mortality})_{i,t}, \end{aligned} \quad (2)$$

583 where we calculate baseline mortality as the regional population level times its baseline mortality  
 584 rate from the RFF-SPs,

$$585 \quad (\text{Baseline Mortality})_{i,t} = \text{Population}_{i,t} \times (\text{Baseline Mortality Rate})_{i,t}. \quad (3)$$

586 We monetize these excess deaths using the value of a statistical life (VSL) as follows:

$$587 \quad \text{Monetized Excess Mortality}_{i,t} = \text{VSL}_{i,t} \times (\text{Temperature Induced Excess Deaths})_{i,t}. \quad (4)$$

588 The baseline VSL value for 2020 for the United States (denoted  $\text{VSL}_{US,2020}^{base}$ ) is derived using EPA's  
 589 1990 Guidance value of \$4.8 million and adjusted for income growth and inflation, resulting in a  
 590 2020 U.S. VSL of \$10.05 million in 2020\$ (U.S. EPA, 2010) (see data explainer notebook in  
 591 replication code for the full derivation). We then base the VSL for country  $i$  in year  $t$  on the EPA's  
 592 baseline VSL for 2020, adjusted for country  $i$ 's GDP per capita in year  $t$ , as

$$593 \quad \text{VSL}_{i,t} = \text{VSL}_{US,2020}^{base} \times \left( \frac{\text{GDP per capita}_{i,t}}{\text{GDP per capita}_{US,2020}} \right)^\varepsilon, \quad (5)$$

594 where  $\varepsilon = 1$  represents the income elasticity of the VSL. The primary function of  $\varepsilon$  is to adjust  
 595 the US VSL to other countries and at uncertain future income levels. We use a unit elasticity which  
 596 is in line with the central tendency of values recommended in the literature for such cases<sup>92-95</sup>.

#### 597 (4) Agriculture

598 The agricultural damage function is based on Moore et al. (2017)<sup>18</sup>, which estimated damages in  
 599 two steps using: (1) a meta-analysis of published studies of the effects of temperature, rainfall,  
 600 and CO<sub>2</sub> on crop yields that builds on previous work by Challinor et al. (2014)<sup>96</sup> and Porter et al.  
 601 (2014)<sup>97</sup>; and (2) a computable general equilibrium model to estimate the economic welfare



602 consequences of these yield shocks while accounting for trade patterns and supply and demand  
603 adjustments in agricultural markets across 16 regions.

604 Moore et al. (2017) present their results in the form of damage functions that directly relate  
605 global mean surface temperature increase to welfare change in economic terms. Their study  
606 presents three different parameterizations of these damage functions to characterize  
607 uncertainty: a central, low, and high estimate.

608 They estimated each of these three parameterizations for 1, 2, and 3 degrees Celsius of  
609 temperature increase, resulting in three piecewise linear damage functions for each region (see  
610 Supplemental Information Figure 1). To address uncertainty as part of our Monte Carlo sampling  
611 framework, we sampled a value from a triangular distribution with lower bound 0, mode 0.5, and  
612 upper bound 1 for each draw. Assigning the low, central, and high damage functions to each of  
613 these values respectively, the two nearest functions were linearly interpolated to produce the  
614 damage function for that draw, also interpolating linearly between the resultant 1-degree Celsius  
615 value and the origin since damages at zero temperature increase can be assumed to be zero.  
616 Importantly, this uncertainty sampling scheme preserves the covariance between regions arising  
617 through connections in the global trade network.

618 Lastly, we incorporated their results into our model via the equation,

619 
$$AgPctCost_{i,t} = \sigma_i \underbrace{\left( \frac{ypc_{it}}{ypc_{i1990}} \right)^{-\epsilon}}_{\text{ag share}} f_i(T_t),$$

620 where  $AgPctCost_{i,t}$  is the damage in the agricultural sector as a proportion of GDP in region  $i$  at  
621 time  $t$ ;  $\sigma_i$  is the share of agriculture in GDP in 1990 in region  $i$ ;  $\epsilon = 0.31$  is the income elasticity  
622 of the agriculture share in GDP<sup>98</sup>; and  $f_i$  is the piecewise linear function for region  $i$  resulting from  
623 the steps described above.

#### 624 **Discounting**

625 Our discounting approach directly follows from NASEM recommendations as developed by  
626 Newell, Pizer, and Prest<sup>1,31</sup>. Given the long residence time of CO<sub>2</sub> in the atmosphere, the damages  
627 from CO<sub>2</sub> emitted today persist for centuries. These future damages must be converted to

628 present dollar equivalents using an appropriate discount rate. The climate economics literature  
 629 typically uses Ramsey-style discounting that links the discount rate to future economic growth<sup>99</sup>.  
 630 This linkage leads to the Ramsey-like equation for the discount rate over time, denoted  $r_t$ :  $r_t =$   
 631  $\rho + \eta \times g_t$ , where  $\rho$  is the rate of pure time preference,  $g_t$  is the average rate of consumption  
 632 growth from the year of the emissions pulse (described in the next section) to year  $t$ , and  $\eta \times g_t$   
 633 reflects the extent to which society discounts damages because future individuals are relatively  
 634 wealthier. More specifically,  $\eta$  reflects how much the marginal value of consumption declines as  
 635 consumption increases (a 1% increase in consumption corresponds with a  $\eta\%$  decline in the  
 636 marginal value of a dollar).

637 We evaluate the stochastic discount rate for each realized path of uncertain consumption growth  
 638 ( $r_t = \rho + \eta g_t$ ), explicitly and structurally modelling the uncertainty in discount rates that is often  
 639 summarized by a declining term structure<sup>100</sup>. This uncertainty in the discount rate leads to a  
 640 stochastic discount factor ( $SDF_t$ ) used to discount future marginal climate damages. The  $SDF_t$   
 641 can also be written equivalently in terms of relative consumption levels<sup>54,101</sup> as

$$642 \quad SDF_t = \frac{1}{(1 + \rho)^t} \left( \frac{c_t}{c_{2020}} \right)^{-\eta} . \quad (6)$$

643 We use this  $SDF_t$  to discount marginal climate damages ( $MD_t$ ) to a present value.

644 While the climate economics literature routinely uses a Ramsey-like approach to  
 645 discounting<sup>32,54,101–105</sup>, prior estimates by the US IWG disconnected discounting and future  
 646 economic growth by using a constant, deterministic discount rate. That approach implicitly  
 647 assumes that  $\eta = 0$ , corresponding to no linkage between consumption growth and discounting  
 648 as well as zero aversion to risk. Our approach re-establishes the Ramsey-like link between growth  
 649 and discount rates. We use  $\rho$  and  $\eta$  values that were empirically calibrated<sup>3</sup> to be consistent with  
 650 the RFF-SPs and evidence on the observed behaviour of interest rates<sup>48</sup>. This procedure also  
 651 produces near-term risk-free discount rates (defined as the average risk-free discount rate over  
 652 the first decade of the time horizon) consistent with the desired values, such as those reported  
 653 in Fig. 1. Our preferred SC-CO<sub>2</sub> estimate corresponds to a near-term 2% rate, which is consistent  
 654 with real risk-free interest rates over the last 30 years, and uses  $\rho = 0.2\%$  and  $\eta = 1.24$ <sup>3,31</sup>. The

655  $(\rho, \eta)$  values corresponding to the alternative near-term rates of 1.5%, 2.5%, and 3% are  
656 (0.01%, 1.02), (0.5%, 1.42), and (0.8%, 1.57), respectively.

657 The Ramsey-like form for the discount rate is a standard approach to value marginal impacts and  
658 account for their risk amid uncertainty in future payoffs and consumption levels in the discounted  
659 expected utility framework<sup>53,54</sup>. In that framework, the value of the  $\eta$  parameter reflects the  
660 degree of risk aversion as well as the inverse of the intertemporal elasticity of substitution. That  
661 framework is also used for benefit-cost analysis of policy and regulatory analysis under  
662 uncertainty, as it quantifies the risk premium associated with uncertainty and risk aversion in the  
663 valuation of a marginal emission of CO<sub>2</sub>. While the Ramsey framework is widely used, other  
664 considerations for decision-making under uncertainty in context of climate change, such as the  
665 role of epistemic uncertainty and alternative preference structures including ambiguity aversion,  
666 have also been proposed<sup>106</sup>. We use the discounted expected utility framework because it is the  
667 most established and widely used framework for regulatory and policy analysis<sup>107,108</sup>.

#### 668 **Estimating the SC-CO<sub>2</sub>**

669 We estimate the SC-CO<sub>2</sub> in a three-step calculation process. In the first step, we run the GIVE  
670 model out to the year 2300 for two separate cases: a “baseline” case and a “perturbed” case that  
671 adds an extra 0.1 MtC pulse of CO<sub>2</sub> emissions in the year 2020 and is otherwise identical. In the  
672 second step, we calculate marginal climate damages in year  $t$  as the difference in modeled  
673 damages per tonne between the pulse and baseline runs as

$$674 \quad MD_t = \sum_{d=1}^4 \sum_{r=1}^{R_d} (\text{Damages with Pulse}_{t dr} - \text{Baseline Damages}_{t dr}), \quad (7)$$

675 where we aggregate over each of the four damage sectors  $d$  at their respective geographic  
676 resolutions (i.e., countries or regions)  $r$ .

677 In the third and final step, we calculate the SC-CO<sub>2</sub> by discounting these marginal damages using  
678 the stochastic discount factors  $SDF_t$  from equation (5) above and then aggregate them over time  
679 into a single present value

680 
$$SC-CO2 = \sum_{t=2020}^{2300} SDF_t \times MD_t. \quad (8)$$

681 For our preferred results, we calculate 10,000 unique SC-CO<sub>2</sub> estimates. For each estimate, we  
682 sample the RFF-SP scenarios to account for uncertainties in global CO<sub>2</sub>, CH<sub>4</sub>, and N<sub>2</sub>O emission  
683 trajectories in addition to country-level population and GDP growth levels. We also sample  
684 parametric uncertainties in the FaIR and BRICK models as well as the agricultural and  
685 temperature-related mortality damage functions (Extended Data Table 2). As described above,  
686 our preferred SC-CO<sub>2</sub> estimate uses discounting parameters of  $\rho = 0.2\%$  and  $\eta = 1.24$  for a  
687 near-term rate of 2%.

688 When we report partial SC-CO<sub>2</sub> estimates for a given damage sector, we follow the estimation  
689 procedure outlined above, but only include the impacts from that individual sector when  
690 calculating marginal damages in equations (7) and (8). We normalize our estimates based on the  
691 emission pulse size and report all results throughout the paper in units of 2020 US dollars per  
692 metric tonne of CO<sub>2</sub>. We use the implicit GDP price deflator from the U.S. Bureau of Economic  
693 Analysis to convert values to 2020 dollars.

694 We typically summarize the distribution of our 10,000 SC-CO<sub>2</sub> estimates by its mean, i.e.,  
695  $E[SC-CO2]$ , where the expectation operator is taken jointly over all uncertain parameters  
696 determining marginal damages ( $MD_t$ ) and the stochastic discount factor ( $SDF_t$ ). This calculation  
697 is consistent with economic theory for pricing investments and other actions with uncertain  
698 payoffs, and therefore properly accounts for the risk premium in the valuation of a marginal  
699 emission of CO<sub>2</sub> owing to the many compounding uncertainties we model<sup>46</sup>.

## 700 **Software**

701 All our results are computed using open-source software tools. We use the Julia programming  
702 language for the entire replication code of this paper<sup>109</sup>. All models used in this study are  
703 implemented on the Mimi.jl computational platform for integrated assessment models<sup>8</sup>.

704 **Data and Code Availability**

705 The replication code and data for this paper is available at  
706 <https://doi.org/10.5281/zenodo.6932028>, including instructions on how to rerun the entire  
707 analysis for this paper.

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## 804 Author Contributions

805 All authors contributed to the analytical methods underlying the model. D.A., R.C., K.C., D.D., F.E.,  
806 C.K., F.C.M., U.K.M., R.G.N., W.P., B.C.P., A.E.R., L.R., K.R., H.Š., H.S., J.H.S., M.W., and T.W.  
807 contributed to the research underlying the four individual modules of the model. D.A., F.E., C.K.,  
808 B.P., R.J.P., L.R., D.S., T.T., and J.W. programmed the integrated model and performed the  
809 computations. D.A., F.E., R.G.N., B.C.P., L.R., K.R., and J.W. evaluated the results and wrote the  
810 paper with input from all authors.

## 811 Competing Interests

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814 developed; that funding was not affected by this study's results. Diaz is employed at the Electric  
815 Power Research Institute (EPRI), a non-profit public interest research institute supported by a  
816 combination of funding from industry, governments, and foundations that could be affected by  
817 the results of this research, both positively and negatively. Newell is a member of the NASEM  
818 Board on Environmental Change and Society, which oversaw the NASEM consensus study that  
819 guided this research, and which Newell co-chaired. Pizer was also a member of that NASEM  
820 consensus study committee when he was on the faculty at Duke University. Newell is also a  
821 member of the National Petroleum Council since 2016, a federally chartered advisory committee  
822 to the U.S. Secretary of Energy, who appoints its members.

## 823 Additional Information

824 Supplementary Information is available for this paper.

825 Correspondence and requests for materials should be addressed to D.A.

826 Reprints and permissions information is available at [www.nature.com/reprints](http://www.nature.com/reprints).

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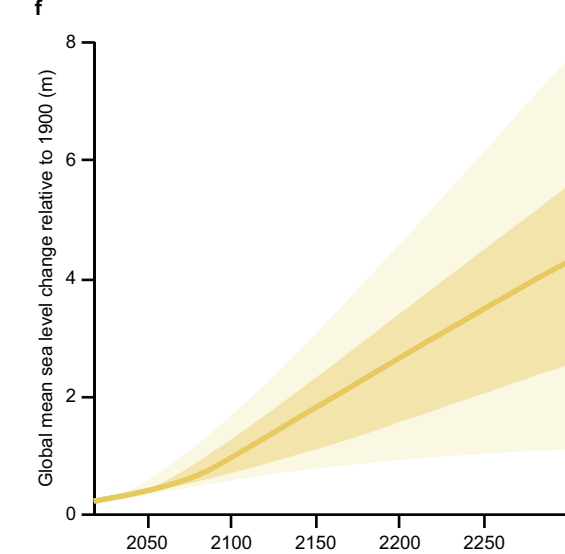
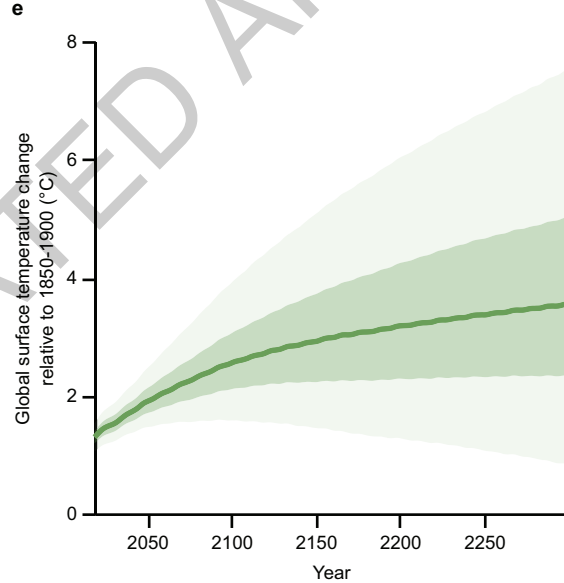
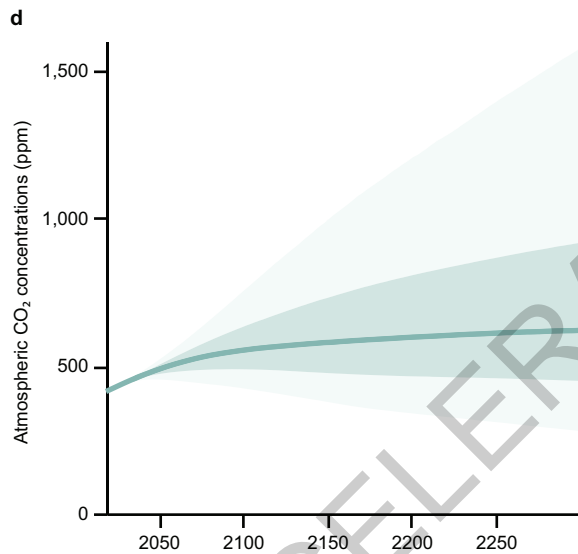
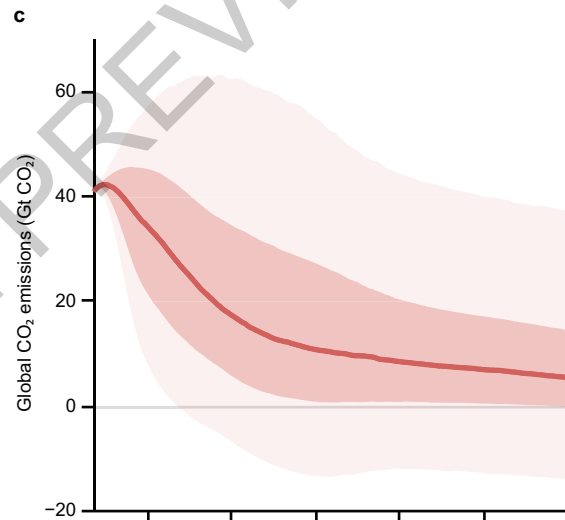
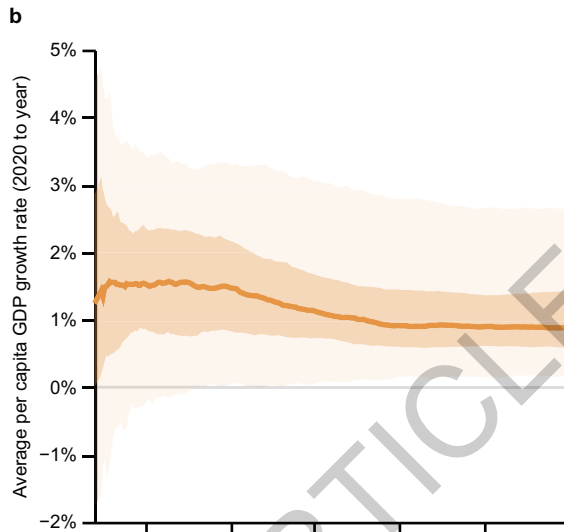
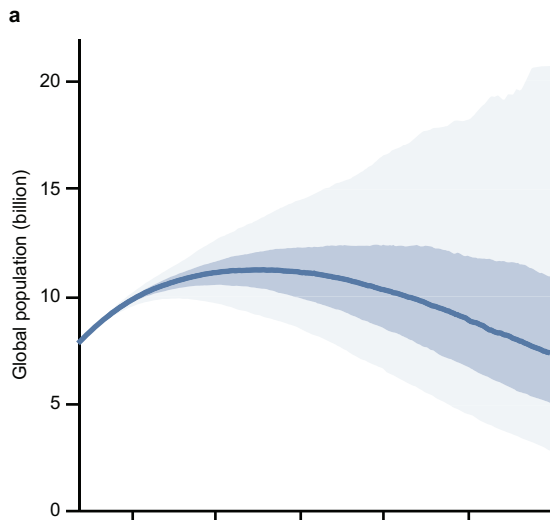
827 Extended data figure/table legends

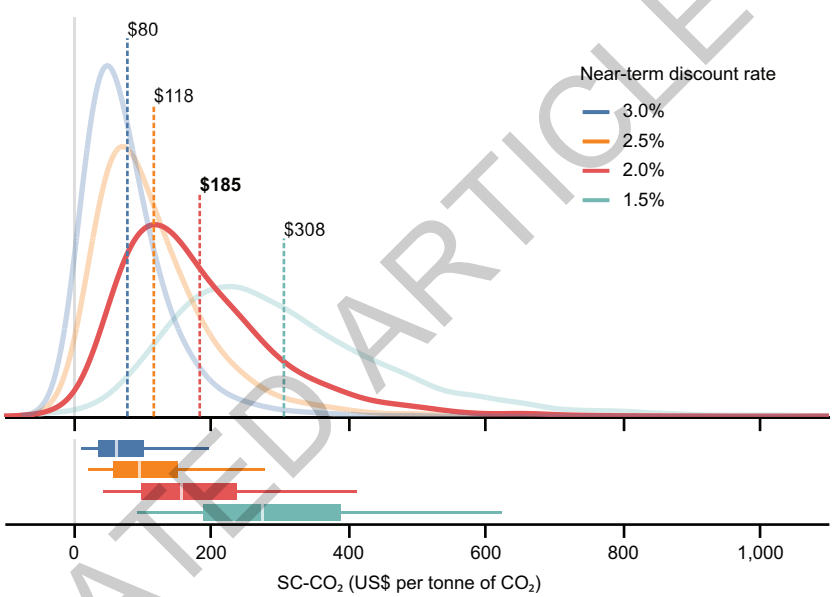
828 **Extended Data Table 1 | Mean SC-CO<sub>2</sub> values (with 5<sup>th</sup>–95<sup>th</sup> quantile ranges), by damage**  
829 **function and discount rate (\$/t-CO<sub>2</sub>).** Our preferred estimates correspond to the GIVE sectoral  
830 damage functions at a 2% near-term discount rate, shown in bold. All results use the RFF-SP  
831 scenarios, a stochastic growth-linked discounting framework, and sample uncertain climate, sea  
832 level, and damage function parameters, including for DICE-2016R and Howard & Sterner  
833 damage functions. The DICE-2016R damage function is based on Nordhaus 2016 (see page 2 of  
834 Nordhaus 2016 Supplemental Information)<sup>32</sup>. The Howard & Sterner damage function is based  
835 on the base coefficient in their Table 2, specification (8). All SC-CO<sub>2</sub> values are expressed in  
836 2020 US dollars per metric tonne of CO<sub>2</sub>.

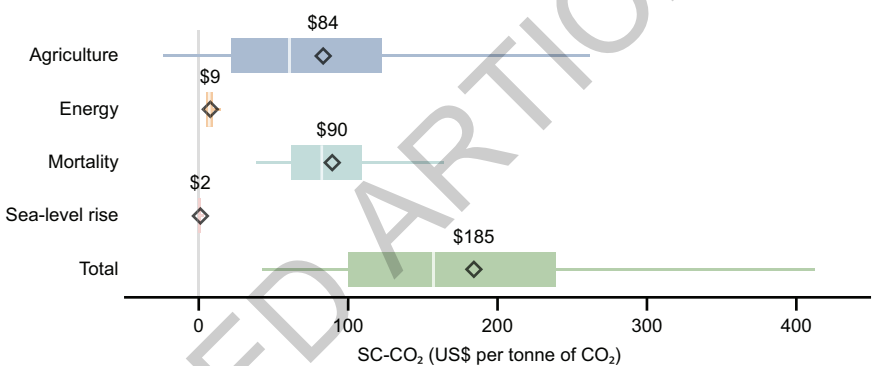
837 **Extended Data Table 2 | Sources of SC-CO<sub>2</sub> uncertainty.** The left column shows the inputs and  
838 components of the GIVE model that contribute to uncertainty in the SC-CO<sub>2</sub>. The right column  
839 briefly describes these uncertainties and their sources.

840 **Extended Data Fig. 1 | SC-CO<sub>2</sub> distributions are robust to different damage function**  
841 **specifications (\$/t-CO<sub>2</sub>).** Distributions of the SC-CO<sub>2</sub> using the damage functions from GIVE  
842 (orange, our preferred specification), DICE-2016R<sup>32</sup> (blue), and Howard & Sterner<sup>33</sup> (red) for near-  
843 term discount rates of 1.5%, 2.0%, 2.5%, and 3.0%. All results use the RFF-SP scenarios, a  
844 stochastic growth-linked discounting framework, and sample uncertain climate, sea level, and  
845 damage function parameters, including for DICE-2016R and Howard & Sterner damage functions.  
846 The DICE-2016R damage function is based on Nordhaus 2016 (see page 2 of Nordhaus 2016  
847 Supplemental Information)<sup>32</sup>. The Howard & Sterner damage function is based on the base  
848 coefficient in their Table 2, specification (8). All SC-CO<sub>2</sub> values are expressed in 2020 US dollars  
849 per metric tonne of CO<sub>2</sub>.

850 **Extended Data Fig. 2 | Discounted marginal damages by year, preferred 2% near-term discount**  
851 **rate case.** Solid line represents mean discounted marginal damages for a one-tonne CO<sub>2</sub>  
852 emissions pulse in 2020, dotted line represents the median, with darker shading spanning the  
853 25-75% quantile range and lighter shading spanning the 5-95% quantile range. All SC-CO<sub>2</sub> values  
854 are expressed in 2020 US dollars per metric tonne of CO<sub>2</sub>.







Damage function	Near-term discount rate			
	1.5%	2%	2.5%	3%
GIVE sectoral	\$308 (\$94–\$626)	<b>\$185</b> <b>(\$44–\$413)</b>	\$118 (\$23–\$280)	\$80 (\$12–\$197)
DICE-2016R	\$275 (\$35–\$690)	\$152 (\$20–\$390)	\$91 (\$12–\$233)	\$59 (\$8–\$149)
Howard & Sterner	\$370 (\$106–\$828)	\$205 (\$56–\$468)	\$123 (\$33–\$286)	\$80 (\$22–\$183)

**Extended Data Table 1**

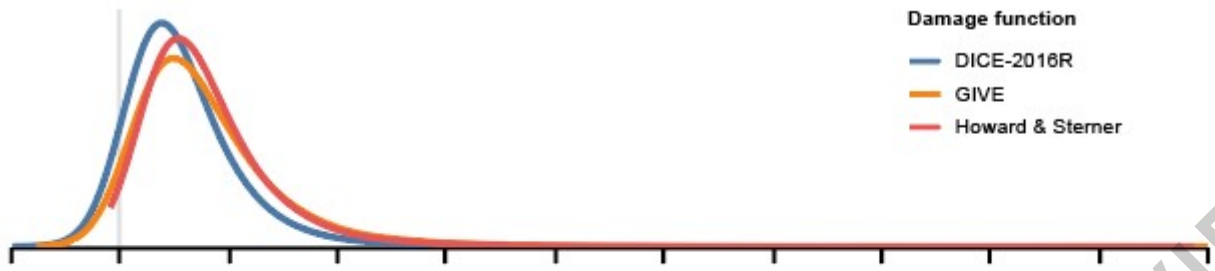
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Model Component	Uncertainty Source
Global CO <sub>2</sub> , CH <sub>4</sub> , and N <sub>2</sub> O emission trajectories	RFF-SPs <sup>3</sup>
Country-level GDP growth rates	RFF-SPs <sup>3,10</sup>
Country-level population	RFF-SPs <sup>9</sup>
FaIR climate-carbon cycle model	2,237-member constrained ensemble of the uncertain parameters (sampled with replacement) from IPCC AR6 report <sup>74</sup>
BRICK sea-level model	10,000-member ensemble of the uncertain parameters derived from a Bayesian calibration framework <sup>15,16</sup>
Agriculture damage function	Uncertain damage coefficient distributions based on Moore et al. <sup>18</sup>
Temperature-related mortality damage function	Uncertain damage coefficient distributions based on Cromar et al. <sup>19</sup>

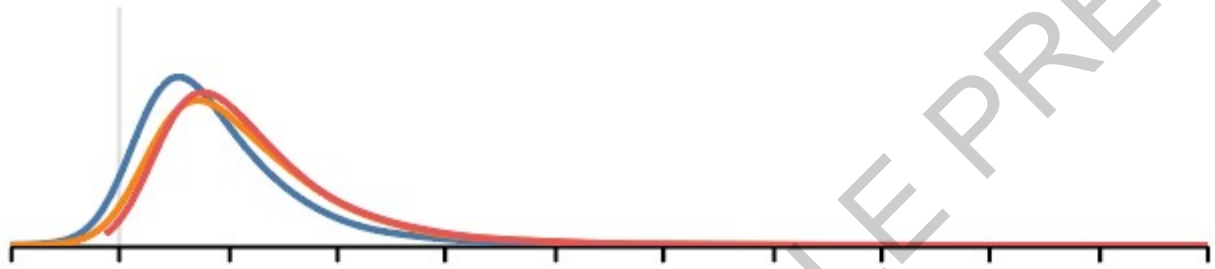
## Extended Data Table 2



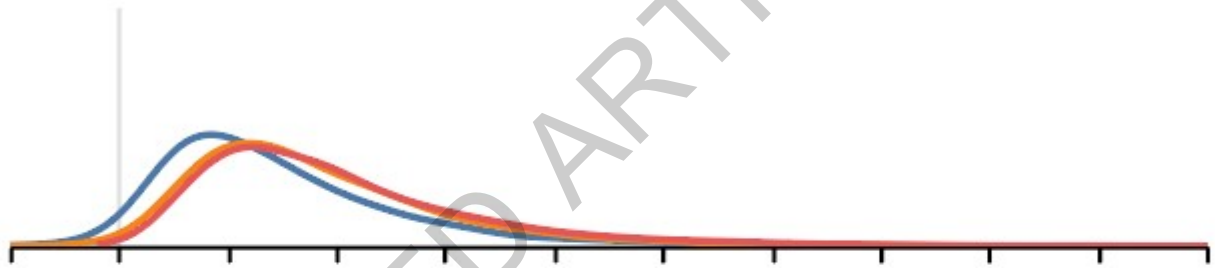
**a: 3.0% near-term discount rate**



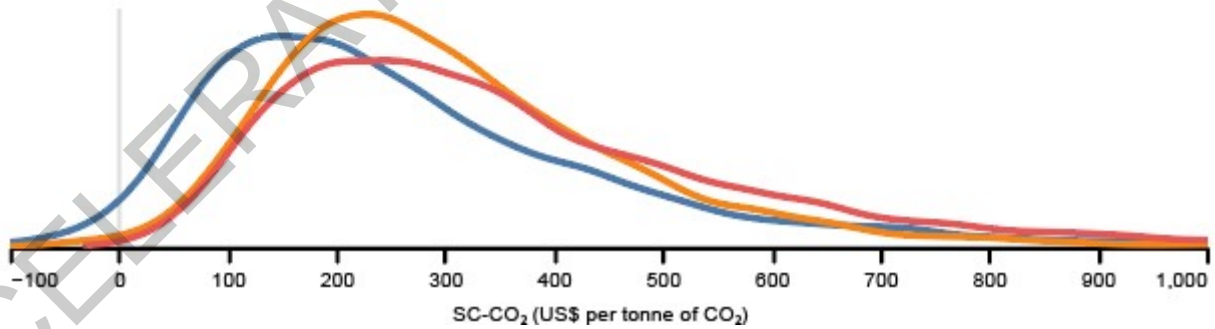
**b: 2.5% near-term discount rate**



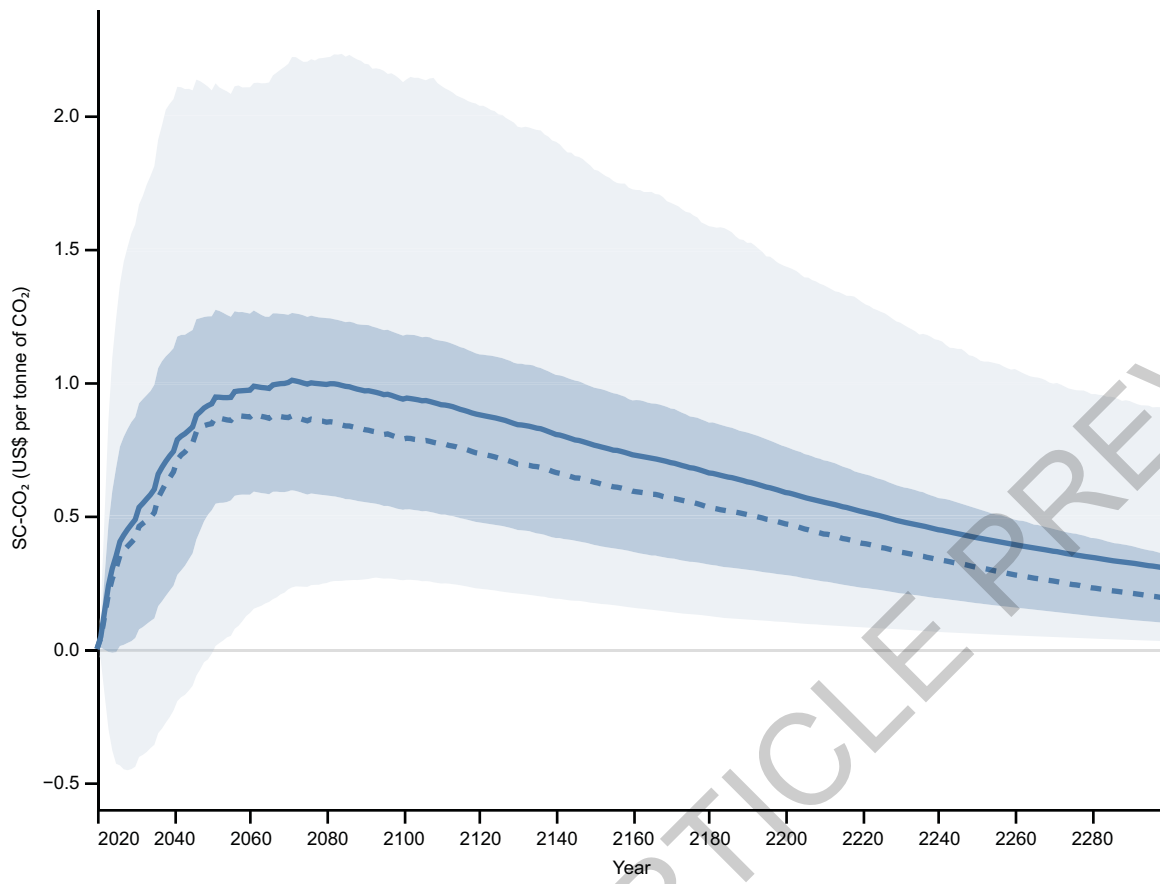
**c: 2.0% near-term discount rate**



**d: 1.5% near-term discount rate**



**Extended Data Fig. 1**



**Extended Data Fig. 2**