

<sup>1</sup> Carbon Dioxide as a Risky Asset

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<sup>12</sup> **Abstract**

<sup>13</sup> We develop a financial-economic model for carbon pricing with an explicit representation of de-  
<sup>14</sup> cision making under risk and uncertainty that is consistent with the Intergovernmental Panel on  
<sup>15</sup> Climate Change's sixth assessment report. We show that risk associated with high damages in the  
<sup>16</sup> long term leads to stringent mitigation of carbon dioxide (CO<sub>2</sub>) emissions in the near term, and  
<sup>17</sup> find that this approach provides economic support for stringent warming targets across a variety  
<sup>18</sup> of specifications. Our results provide insight into how a systematic incorporation of climate-related  
<sup>19</sup> risk influences optimal emissions abatement pathways.

<sup>20</sup> **JEL:** G0, G12, Q51, Q54

<sup>21</sup> **Keywords:** Climate risk, climate policy, asset pricing, cost of carbon

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## 1 Introduction

<sup>24</sup> Climate change's impact on the economy first gained prominence in the economics literature some 30  
<sup>25</sup> years ago, when the first climate-economic Integrated Assessment Model (IAM) calculated the cost  
<sup>26</sup> of a marginal ton of carbon dioxide ( $\text{CO}_2$ ) emissions to society, coined the 'Social Cost of Carbon'  
<sup>27</sup> (SCC) (Nordhaus, 1992). IAMs have since taken center stage in climate policy discussions, with the re-  
<sup>28</sup> sulting SCC estimates being utilized as benchmarks by companies and governments worldwide (World  
<sup>29</sup> Bank, 2021). To date the most prominent IAM by far – the dynamic integrated climate-economy,  
<sup>30</sup> or DICE – evaluates climate change impacts within the context of a standard Ramsey growth econ-  
<sup>31</sup> omy (Nordhaus, 2017; Barrage and Nordhaus, 2023). In this approach, a global social planner considers  
<sup>32</sup> tradeoffs between emitting  $\text{CO}_2$  and incurring damages both now and, largely, in the future, versus  
<sup>33</sup> abating  $\text{CO}_2$  emissions now at some cost. Performing a benefit-cost analysis results in a presently-low  
<sup>34</sup> and rising optimal SCC over time, with significant global average warming by 2100. Recent efforts have  
<sup>35</sup> yielded comparatively higher SCC estimates; Rennert et al. (2022), for example, calculates a central  
<sup>36</sup> SCC of \$185 but did not explore the optimal control problem of weighing the benefits and costs of  
<sup>37</sup> abating  $\text{CO}_2$  emissions.<sup>1</sup> It is notable that DICE's optimal warming projections are significantly larger  
<sup>38</sup> than each warming target – 1.5 °C and 2 °C by 2100 – established in the 2015 Paris Agreement. While  
<sup>39</sup> this inconsistency has called into question the authority of such models in the climate policy discussion  
<sup>40</sup> to some (Pindyck, 2013; Stern, 2013), DICE has been made consistent with a warming target of 1.5  
<sup>41</sup> °C with alternative, updated damages and discount rate modules (Hänsel et al., 2020).

<sup>42</sup> A limitation of DICE is that it lacks a comprehensive representation of decision-making under risk  
<sup>43</sup> and uncertainty, a core feature of many 'alternative' climate-economic models (Cai et al., 2016; Cai  
<sup>44</sup> and Lontzek, 2019; Daniel et al., 2019; Barnett et al., 2020). This is important, as climate change  
<sup>45</sup> projections are inherently probabilistic, with low probability, extreme impact outcomes presenting the  
<sup>46</sup> most significant risk to the climate-economic system (Weitzman, 2009). The inherently unpredictable  
<sup>47</sup> nature of the impacts of climate change has led some to think of climate policy as a form of "insur-  
<sup>48</sup> ance" to be taken out against high climate damages (Weitzman, 2012). Conventional IAMs do not  
<sup>49</sup> allow for such considerations in determining their policy projections. Put in financial-economic terms:  
<sup>50</sup> conventional IAMs do not allow individuals to 'hedge' against climate impacts.

<sup>51</sup> To address this, there have been considerable advances in climate-economic modeling that include  
<sup>52</sup> the effects of risk and uncertainty on the SCC and on optimal policy responses to climate change;  
<sup>53</sup> see Lemoine and Rudik (2017) for a comprehensive review, while Cai and Lontzek (2019) and Lemoine  
<sup>54</sup> (2021) represent seminal works for including climate-related risk in IAMs.<sup>2</sup> We contribute to this  
<sup>55</sup> extensive literature by introducing the carbon asset pricing model AR6 (CAP6), a climate-economy  
<sup>56</sup> IAM that builds on previous financial asset pricing climate-economy models (Daniel et al., 2016, 2019).  
<sup>57</sup> Our paper makes three primary contributions. The first is along methodological lines: we distill each  
<sup>58</sup> working group report in the sixth assessment report (AR6) issued by the Intergovernmental Panel on  
<sup>59</sup> Climate Change (IPCC) (Intergovernmental Panel on Climate Change, 2021, 2022a,b) into workable

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<sup>1</sup>This SCC estimate represents a significant increase from the U.S. Interagency Working Group's central estimate of ~\$50 (Committee on Assessing Approaches to Updating the Social Cost of Carbon et al., 2017) and is in line with the U.S. Environmental Protection Agency's recent draft estimates that report a central value of \$190 (National Center for Energy Economics, 2022).

<sup>2</sup>We provide a more thorough literature review in Online Appendix A.

60 IAM components.<sup>3</sup> This allows our model to be up-to-date with the state-of-the-art calibrations for  
61 critical model components. Notably, we formulate a new marginal abatement cost curve (MACC) based  
62 on AR6 data, providing an update to the well-known [McKinsey & Company \(2013\)](#) MACC.

63 The second contribution is a computation of optimal carbon prices and associated mitigation policy.  
64 Following [Daniel et al. \(2016, 2019\)](#), we embed a representative agent in a binomial, path-dependent  
65 tree that allows for risk assessment to endogenously evolve over time. The agent maximizes the Epstein-  
66 Zin-Weil utility ([Epstein and Zin, 1989; Weil, 1990; Epstein and Zin, 1991](#)) at every node in the tree  
67 such that the present-day utility is maximized. Agent discount rates are calibrated to be in-line with  
68 a recent expert elicitation ([Drupp et al., 2018](#)) and the U.S. Environmental Protection Agency (EPA)  
69 latest estimates for the SCC ([National Center for Energy Economics, 2022](#)). Notably, we find that the  
70 optimal expected warming in our EPA-consistent calibrations is in line with the 2100 warming targets  
71 established in the Paris agreement. We find that even if we were pessimistic about the cost of mitigation  
72 estimates provided by the IPCC, the EPA-consistent calibration of CAP6 would still support limiting  
73 warming to less than 2 °C by 2100, with a discount rate of 2% or lower.<sup>4</sup>

74 In computing optimal mitigation strategies, we capture uncertainty associated with both climate  
75 damages and global temperature rise. For damages, we capture both parametric uncertainty inherent  
76 to a given damage function, as well as structural uncertainty associated with different damage function  
77 shapes; in other words, in addition to Monte Carlo sampling damage levels for a given damage function,  
78 we also account for the fact that it is difficult to determine which damage function is correct in the  
79 first place ([Pindyck, 2013; Intergovernmental Panel on Climate Change, 2022a](#)). To our knowledge,  
80 we are the first to capture this dimension of climate-economic uncertainty. We also account for the  
81 marginal damages associated with a probabilistic assessment of climate tipping points ([Lenton et al.,  
82 2008; Dietz et al., 2021](#)).

83 Our final contribution is a sensitivity analysis that allows us to identify how each exogenous as-  
84 sumption drives model output. We show that while the expected carbon price depends on the emissions  
85 baseline, the expected temperature rise, level of CO<sub>2</sub> concentrations, and incurred economic damages  
86 does not. This suggests that our model robustly calculates an economically optimal temperature level  
87 for a given calibration; the price of actualizing this temperature level varies across baselines, owing  
88 to assumptions about how much emissions are decreasing independently of the policy implemented in  
89 CAP6. We find that price uncertainty is dominated by discounting in the near-term and the techno-  
90 logical growth rate in the far-term. On the other hand, temperature rise, CO<sub>2</sub> concentration level, and  
91 economic damage uncertainty is dominated by discounting for much longer than CO<sub>2</sub> prices, as early  
92 inaction leads to warming that cannot be undone later by spending more on abatement (in the absence  
93 of significant net-negative emissions or solar geoengineering).

94 We proceed by presenting the socio-economic setup of CAP6 in section 2, the climate emulator in  
95 section 3, and our calibration in section 4. We discuss our results in section 5; section 6 concludes.  
96 (For section 2, we provide a brief summary paragraph with key equations and figures for readers who

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<sup>3</sup> [Nielsen-Gammon and Behl \(2021\)](#) highlight the need and urgency for standardized, state-of-the-art climate and economic components based on the most up-to-date research for climate-economic modeling.

<sup>4</sup>This rate is significantly below [Barrage and Nordhaus \(2023\)](#)’s “preferred” rate of 4.5% in 2020, but well within the range that has emerged as a broad consensus among economists ([Council of Economic Advisors, 2017; Drupp et al., 2018; Newell et al., 2022](#)).

97 wish to skip the full technical description of our model components.)

## 98 2 Socio-economic framework

99 We consider a representative agent with Epstein-Weil-Zin utility given by (2.1), and embed this in-  
100 dividual in a binomial tree structure where their utility is maximized. CO<sub>2</sub> emissions (without any  
101 agent mitigation action) follow the shared socio-economic projections used by the IPCC (Figure 2).  
102 Climate damage functions are calibrated to IPCC working group (WG) II data (see Figure 3) and  
103 our uncertainty parameterization captures both epistemic and parametric uncertainty in the damage  
104 functions. Finally, we employ (2.12) as our marginal abatement cost curve (Figure 4) and provide  
105 two calibrations: our ‘main specification’ based solely on the data in AR6, and the ‘no free lunches’  
106 calibration, which excludes negative costs in the AR6 data.

### 107 2.1 Economic utility

108 CAP6 considers a representative agent with recursive preferences who maximizes their utility through-  
109 out time. We choose Epstein-Zin-Weil preferences (Epstein and Zin, 1989; Weil, 1990; Epstein and Zin,  
110 1991), henceforth abbreviated as ‘EZ’, because of their unique feature of separating risk across states  
111 of time and states of nature. This distinction has been shown to be especially relevant for climate  
112 economic studies, where risk considerations across different dimensions are key to the outcome (e.g.,  
113 Cai and Lontzek, 2019, among many others). The discrete time utility,  $U_t$ , of a representative agent  
114 with EZ preferences is given by

$$U_t = \left( [1 - \beta] c_t^\rho + \beta [\mathbb{E}_t (U_{t+1}^\alpha)]^{\rho/\alpha} \right)^{1/\rho}, \quad (2.1)$$

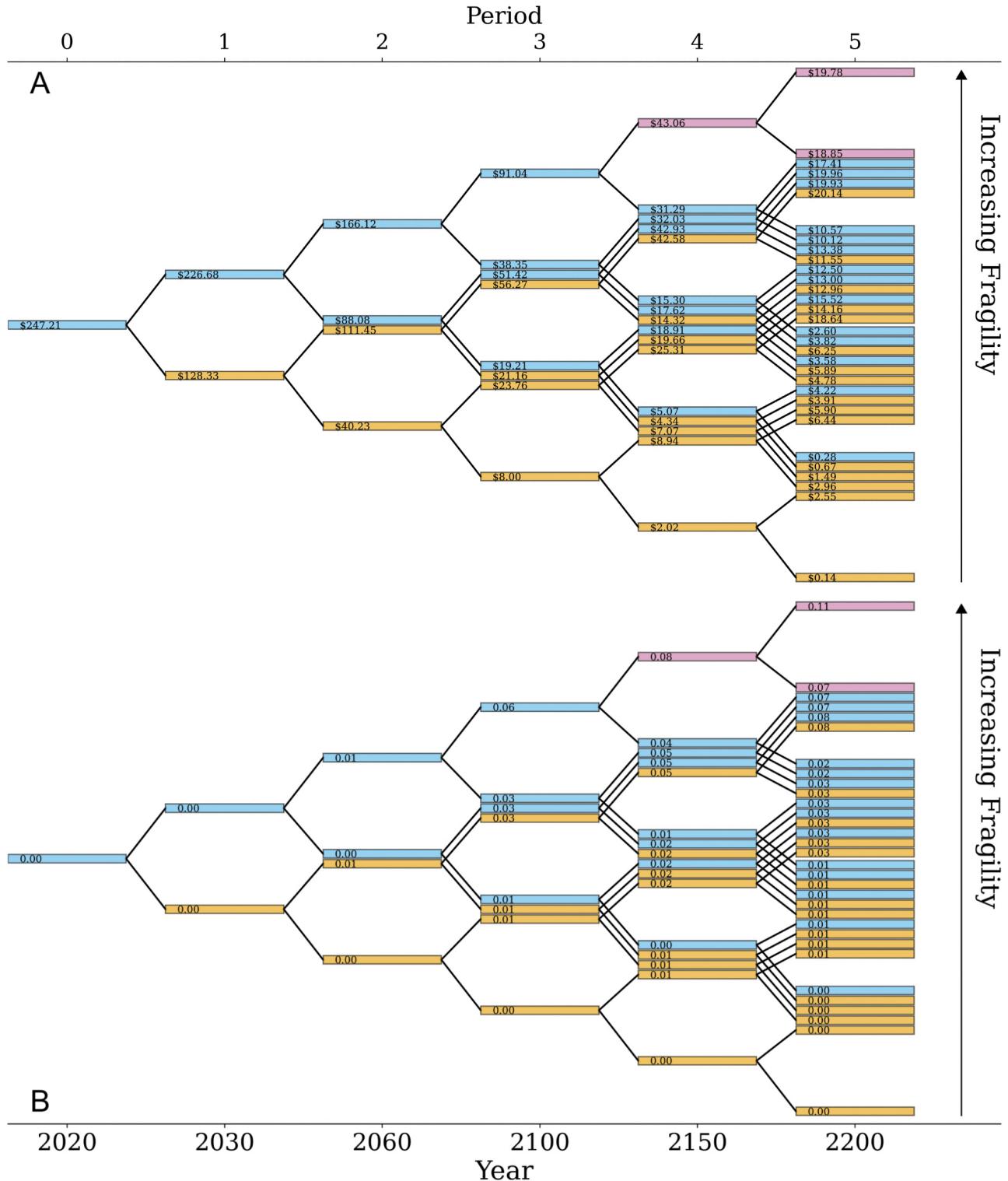
115 where  $\beta := (1 + \delta)^{-1} > 0$  and  $\delta > 0$  is the pure rate of time preference (PRTP),  $c_t > 0$  is the  
116 consumption at time  $t$ ,  $\rho := 1 - 1/\sigma$  and  $\sigma > 0$  is the elasticity of intertemporal substitution (EIS),  
117  $\alpha := 1 - \psi$  and  $\psi > 0$  is agent risk aversion (RA), and  $\mathbb{E}_t$  is the expectation operator at time  $t$ . When  
118  $\alpha = \rho$  (that is, when  $\psi = 1/\sigma$ ), (2.1) collapses into the von Neumann and Morgenstern (1947) expected  
119 utility index. Assuming an exogenous growth rate of consumption  $g > 0$ , in the final period occurring  
120 at time  $T$ , the utility is given by

$$U_T = \left[ \frac{1 - \beta}{1 - \beta(1 + g)^\rho} \right]^{1/\rho} c_T. \quad (2.2)$$

121 Note that, in the EZ framework, risk aversion across time is parameterized by  $\sigma$ , whereas risk aversion  
122 across states of nature is parameterized by  $\psi$ .

#### 123 2.1.1 Tree structure

124 Following Daniel et al. (2016, 2019), agent utility in CAP6 is optimized within the structure of a  
125 binomial tree, therefore embedding the representative agent in a *finite horizon probability landscape*.



**Figure 1:** Cost of CO<sub>2</sub> (panel A) and agent experienced climate damages (panel B) at each node. In both panels, we highlight the accessible future states of two agents: one in 2150 (pink boxes) and one in 2030 (gold boxes).

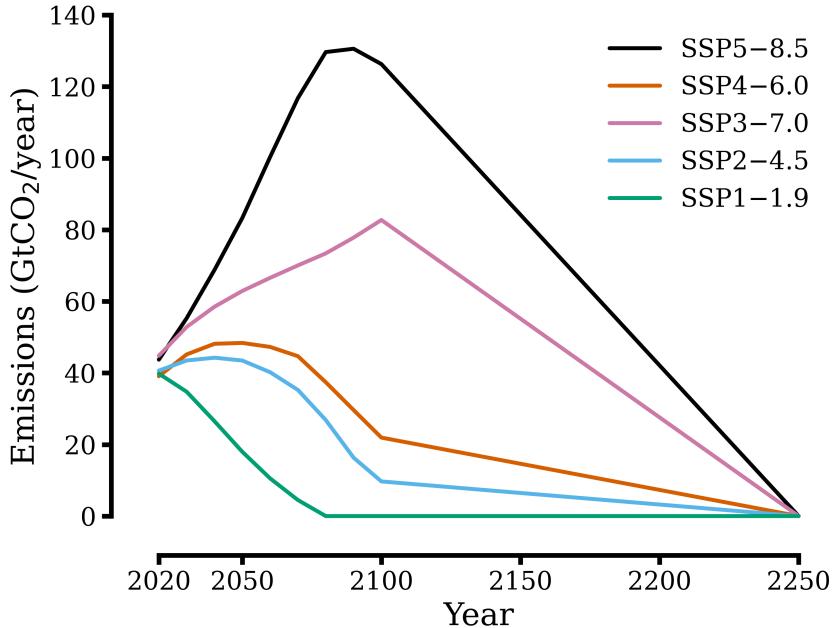
*Note: Values are taken from our 2% discount rate featured model run, main specification.*

126 This follows a standard approach employed in financial economics ([Cox et al., 1979](#)), and one useful to  
127 solve EZ-style models numerically ([Epstein and Zin, 1991](#)).

128 The binomial tree structure of CAP6 is a representation of a time-evolving two dimensional proba-  
129 bility distribution of climate damages (see [Figure 1](#) for a schematic). The first dimension is time, while  
130 the second is “fragility”, the latter of which encodes the potential for high or low climate damages at a  
131 moment in time. Throughout, we will refer to the fragility coordinate at a time  $t$  as  $\theta_t > 0$ . Framing the  
132 tree structure as a representation of a two dimensional probability distribution allows for the roles of  
133  $\sigma$  and  $\psi$  to be clarified:  $\sigma$  parameterizes risk aversion along the *time* dimension, while  $\psi$  parameterizes  
134 risk aversion along the “*fragility*” dimension. We choose to orient the fragility coordinate such that  
135 high (low, resp.) fragility is associated with high (low, resp.) climate damages. By allowing for many  
136 agent decisions, and thus the generation of numerous nodes, we are able to coarsely represent the space  
137 of possible fragilities, therefore spanning many possible states of the climate and climate impacts. Note  
138 that in the limit of infinitely many decisions, fragility is normally distributed owing to every future  
139 state being equally likely, so as to not bias any outcome (be it sanguine or catastrophic) within the  
140 model structure.

141 This structure allows for agent risk assessment to evolve endogenously; as an example, consider  
142 two agents, one in 2150 and one in 2030 (see [Figure 1](#)). The agent in 2150 has only two future  
143 states accessible to them from their position in the tree; this represents an individual who knows well  
144 the impact of the climate on the economy. The agent in 2030 has a significantly higher number of  
145 future states accessible to them; they know less about how climate change impacts the economy, which  
146 influences their decision making, as they have to weigh several possible futures with high and low  
147 climate damages (or “fragility”) all at once.

148 This approach has the advantage of being easily computationally tractable, while maintaining a  
149 structurally endogenous representation of risk and uncertainty resolution. Moreover, it allows for a  
150 transparent interpretation of model results and ample sensitivity analyses, which enables our variance  
151 decomposition results in § [5.3.1](#). However, it does suffer from drawbacks: more modern (and computa-  
152 tionally expensive and technically challenging) models are able to solve similar optimization problems  
153 in continuous-time, on infinite horizons, or both ([Bretschger and Vinogradova, 2014](#); [Cai and Lontzek,](#)  
154 [2019](#); [Van Den Bremer and Van Der Ploeg, 2021](#)). These considerations can matter for model results:  
155 for example, the time horizon used for climate policy models matters owing to the long residency time  
156 of CO<sub>2</sub> in the atmosphere. If one sets the time horizon of the model to 2200, then the net-benefits  
157 of a unit of CO<sub>2</sub> abatement in 2190 would matter less than one in 2020 because the benefits would  
158 not be given time to materialize. Nevertheless, a number of prominent IAMs used in climate policy  
159 consider finite horizons (perhaps most notably, the DICE model is solved on a finite horizon, see [Nord-](#)  
160 [haus, 2017](#); [Barrage and Nordhaus, 2023](#)) and our model falls into this class. Moreover, our choice to  
161 truncate the time horizon at 2250 aligns with the time where we assume the world reaches net zero  
162 emissions without any additional policy in CAP6, which would make, from the policy perspective taken  
163 in our model, a carbon tax obsolete (see [Figure 2](#)).



**Figure 2:** Emissions baselines with their extensions to 2250.

<sup>164</sup> **2.1.2 Statement of utility optimization problem**

Consider a representative agent embedded within a path-dependent binomial tree with  $T$  decision periods, leading to  $2^T - 1$  total tree nodes. The individual resides within a standard endowment economy (Summers and Zeckhauser, 2008), where at every period time  $t$  they are given an amount  $\bar{c}_t > 0$  such that  $\bar{c}_t = \bar{c}_0(1 + g)^t$ . Without loss of generality, set  $\bar{c}_0$  to unity. They cannot consume all of  $\bar{c}_t$ , however, owing to both climate change and climate policy. Climate change can cause the agent to lose some amount of  $\bar{c}_t$  due to climate damages,  $\mathcal{D}_t \geq 0$ . Climate policy allows them to spend some amount of  $\bar{c}_t$  to reduce their impact on future climate by mitigating some fraction of emissions  $x_t$  with total cost  $\kappa_t$ . The consumption of the agent at each time  $t \in \{0, 1, 2, \dots, T\}$  is determined by

$$c_0 = \bar{c}_0 (1 - \kappa_0(x_0)), \quad (2.3)$$

$$c_t = \bar{c}_t (1 - \kappa_t(x_t)) (1 - \mathcal{D}_t(\Psi_t, \theta_t)), \quad \text{for } t \in \{1, 2, \dots, T-1\}, \quad (2.4)$$

$$c_T = \bar{c}_T (1 - \mathcal{D}_T(\Psi_T, \theta_T)), \quad (2.5)$$

<sup>165</sup> where  $\Psi_t$  is the cumulative CO<sub>2</sub> emissions. We choose  $T = 6$  decision periods in all the calculations  
<sup>166</sup> in that follow, with our initial and final year being 2020 and 2250, respectively.<sup>5</sup> The net discounted  
<sup>167</sup> EZ-utility is then maximized to obtain the optimal carbon prices and mitigation policies in § 5; see  
<sup>168</sup> Online Appendix B for more details on our optimization.

169 **2.2 Emission baselines**

170 There is considerable uncertainty when choosing a ‘business-as-usual’ emissions scenario for climate-  
171 economy IAMs ([Hausfather and Peters, 2020](#)). One approach is for the emissions to be a result of  
172 economic output (e.g., [Golosov et al., 2014](#)). This approach has the advantage of making the emissions  
173 baseline endogenous; however, it also tends to exclude important processes relevant to the level and  
174 rate of fossil fuel emissions, such as friction in the diffusion of clean energy technologies, which can be  
175 captured by more sophisticated energy systems IAMs.

176 This concern motivates the second approach commonly used by the IPCC, which is to supply a  
177 given IAM with a stream of CO<sub>2</sub> emissions exogenously based on plausible future emissions scenarios.  
178 The shared socio-economic pathways (SSPs) shown in Figure 2 are an example of this approach,  
179 where each baseline represents a “storyline” for future global and regional economic development based  
180 on the level of challenges faced by policymakers in mitigation and adaptation. For example, SSP5  
181 is a fossil fuel-based development storyline, with high levels of challenge to mitigation (because of  
182 significant fossil fuel development) and low challenges to adaptation (because of expanded wealth).  
183 SSP1, on the other hand, is a more sustainable route, with low challenges to both mitigation (because of  
184 renewable energy expansion) and adaptation (because of equitable growth and investment in education  
185 and health). Combining these socio-economic settings with an energy system model produces the  
186 emissions projections seen in Figure 2; see [Riahi et al. \(2017\)](#) for a complete review of the SSP storylines  
187 and specifics on the underlying assumptions. This approach has been employed by the US Government  
188 in their computations of the SCC ([National Center for Energy Economics, 2022](#)),<sup>6</sup>, and is our approach  
189 here. This implies that our optimal carbon taxes are always with reference to the emissions baseline  
190 we assume; we explore the influence of which emissions baseline we choose on our results in § 5.3.

191 We take emissions data for each SSP at times 2020 – 2100 directly from the SSP database,<sup>7</sup> and select  
192 scenarios which span a range of end-of-century radiative forcing amounts. We make one alteration to  
193 the projections provided in the database: negative emissions are set to zero.<sup>8</sup> As our model extends out  
194 to 2250, we require extensions of the SSPs in the database; we follow the prescription of [Meinshausen  
195 et al. \(2020\)](#) for each baseline, which assumes that (a) positive fossil fuel emissions and any net-negative  
196 fossil fuel emissions are ramped down to zero by 2250, (b) land use CO<sub>2</sub> emissions are zero by 2150, (c)  
197 non-fossil fuel greenhouse gas emissions are ramped down by 2250, and (d) land use-related non-CO<sub>2</sub>  
198 emissions are held constant after 2100. In reality, it is possible that in the absence of a well-designed  
199 policy suite that one or more of these assumptions could not hold, which would imply that we are  
200 underestimating potential emissions levels in the far-future, and thus long-term climate-economic risk;  
201 we explore the relative influence of which emissions baseline we choose in § 5.3. See Figure 2 for the  
202 results of our extension procedure.

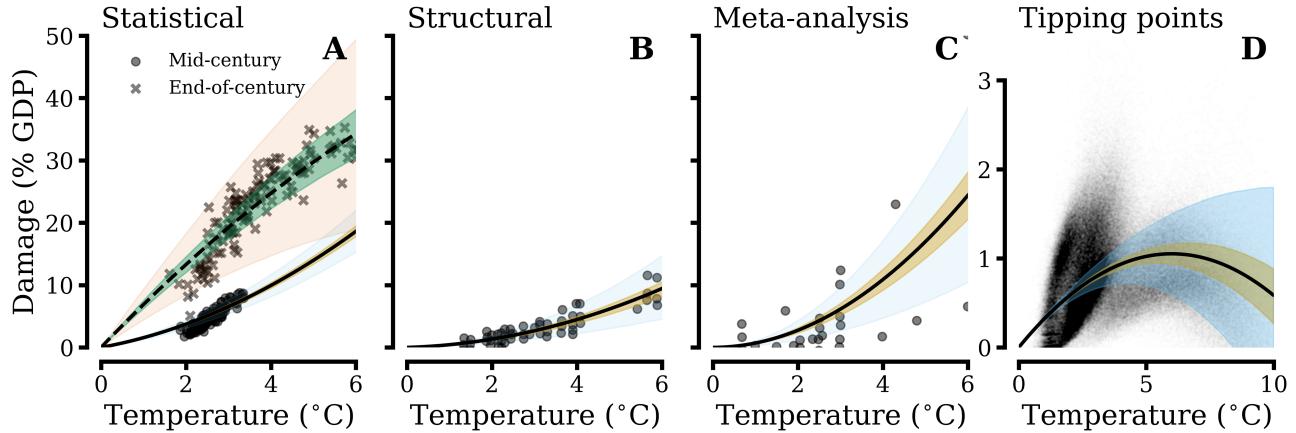
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<sup>5</sup>While one may question the coarseness of our time discretization, it has been shown that including more decision periods in similar models does not significantly affect their output ([Coleman et al., 2021](#)).

<sup>6</sup>Note the US EPA uses the so-called RFF-SPs ([Rennert et al., 2022](#)) rather than the SSPs used here.

<sup>7</sup>See <https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10>

<sup>8</sup>This assumption only impacts SSP1–1.9, as SSP1–1.9 makes more optimistic assumptions around backstop technology than we do in our cost formulation.



**Figure 3:** Each of our damage functions by methodology (statistical, structural, and meta-analytic) as well as the marginal damages owing to tipping points.

*Note: In each panel, yellow shows  $\pm 1$  standard deviation in the damage function, while the blue shaded region shows  $\pm 2$  standard deviations. For the end-of-century estimates in panel A, the green region shows  $\pm 1$  standard deviation and the salmon shows  $\pm 2$  standard deviations. The statistical damage function shown assumes SSP2–4.5.*

### 203 2.3 Damage functions

204 Our climate damage calculation can be broken down into two components: an *aggregate* climate dam-  
 205 age, owing to the total damages incurred by climate change, and a marginal *tipping point* climate  
 206 damage, which accounts for damages which are incurred by, for example, permafrost melt.

#### 207 2.3.1 Aggregate climate change damages

208 Aggregate damages are defined as global damages owing to climate change, and their magnitude is  
 209 estimated in AR6 by WGII ([Intergovernmental Panel on Climate Change, 2022a](#)) (see their Figure  
 210 Cross-Working Group Box ECONOMIC.1, panels (a)-(c), p. 16-114). We specify three aggregate  
 211 damage functions: one that is modeled after statistical climate damage modeling efforts ([Burke et al.,](#)  
 212 [2018](#)), one estimated using structural estimation techniques ([Rose et al., 2017](#)), and a meta-analysis of  
 213 climate damage estimates ([Howard and Sterner, 2017](#)), such that for each we have

$$\mathcal{D}(T') = T'(\varpi_1 + \varpi_2 T') \quad (2.6)$$

214 where  $\varpi_1, \varpi_2 \in \mathbb{R}^+$  are fitted coefficients. We refer to each of these damage functions by their estimation  
 215 methodology in what follows, i.e., “the statistical damage function” and so on. We supply the fitted  
 216 coefficients and their uncertainty, as well as a discussion of the qualifications and the limitations of  
 217 each individual damage function we use, in Online Appendix D. We present the data and fitted curves  
 218 in Figure 3 (ft. <sup>9</sup>).

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<sup>9</sup>We present CAP6 output using only one of each damage function, and compare it to when each damage function is sampled in Online Appendix H.

219 **2.3.2 Tipping point damages**

220 In addition to the aggregate damages accrued owing to climate change, an additional damage potential  
221 exists for climate-related tipping points, such as permafrost melt or Amazon dieback. Previous studies  
222 parameterize climate tipping points as instantaneous shocks that immediately result in damages (e.g.,  
223 Lemoine and Traeger, 2016b); however, this is unrealistic, as the consequences of “hitting a tipping  
224 point” will take time to be fully realized (Kopp et al., 2016; Armstrong McKay et al., 2022). This  
225 effect was captured by Cai and Lontzek (2019); they found that the presence of climate tipping points  
226 significantly increases the social cost of carbon.

227 A recent analysis allows the effect of a given tipping element to be dynamic over time in an IAM,  
228 and estimates the marginal damage associated with ten climate tipping points as a function of global  
229 average temperature (Dietz et al., 2021). This approach has the advantage of aggregating over the  
230 complex dynamic aspects of tipping points and provides a simple “damage function” for marginal  
231 damages owing to tipping points. Moreover, this “damage function” implicitly captures the “domino”  
232 effect of hitting a tipping point (Lemoine and Traeger, 2016b; Cai et al., 2016) in its damage estimates.  
233 However, our use of this approach has the drawback of not capturing aversion to ambiguity surrounding  
234 the location of tipping points (Lemoine and Traeger, 2016a), which has been shown to slightly increase  
235 the stringency of climate policy. This provides some context to our results, as including the effects of  
236 ambiguity aversion to tipping points would increase the resulting carbon price and optimal mitigation  
237 level.

238 We take this additional “damage function” owing to tipping points,  $\mathcal{D}_{tp}(T')$ , from Dietz et al. (2021)  
239 (see their Figure 5c), such that the total damages are given by

$$\mathcal{D}_{tot}(T') = \mathcal{D}(T') + \mathcal{D}_{tp}(T'). \quad (2.7)$$

240 Note that  $\mathcal{D}_{tp}(T')$  has the same functional form as the aggregate damage function, i.e., Eqn. (2.6). See  
241 Figure 3D for a visualization and Table 1 in Online Appendix D for the coefficients of this damage  
242 function and corresponding uncertainties.

243 **2.3.3 Sampling damage function uncertainty**

244 We sample uncertainty in the damage function in two ways. The first is by sampling the parametric  
245 uncertainty in each damage function; that is, the uncertainty in the values of  $\varpi_1, \varpi_2$  in (2.6). The  
246 distributions of  $\varpi_1, \varpi_2$  are assumed Gaussian with mean and variance provided in Online Appendix D,  
247 Table 1. The second source of uncertainty in the damage function pertains to which damage function  
248 (i.e., statistical, structural, or meta-analytic) we specify in the first place. As the IPCC WGII makes no  
249 recommendations in this regard, we assign a hyper-parameter in our simulated climate damages that  
250 randomly chooses a damage function, thus sampling epistemic uncertainty in the damage function.  
251 This methodology allows us to remain agnostic with respect to which damage function we choose.

252 **2.3.4 Calculating damages at a particular decision node**

253 A representative agent in our model at a given decision node only knows the possible end states which  
254 can be accessed from their state. They do not know the exact fragility at their own node, or any  $\theta_t$   
255 for  $t < T$ , owing to the inherent uncertainty surrounding both the climate system (such as the precise  
256 value of climate sensitivity) and economic impacts (such as damage functions). Owing to the agent not  
257 knowing the current fragility, the damages assessed at their decision time are dependent on proxies for  
258 the relevant damage variables. The two proxies used in our model is the set of possible end states,  $\Theta$   
259 (which tells us which end states are accessible) and the cumulative CO<sub>2</sub> emissions,  $\Psi_t$  (which tells us  
260 approximately how warm the world should be, but does not immediately map to the temperature at  
261 time  $t$  owing to uncertainty in the climate sensitivity). These two variables in concert give us a basis  
262 from which we can interpolate end state climate damages backwards in time to any decision node.  
263 Moreover, a continually-updating fragility parameter allows the expectation of future damages to co-  
264 evolve with agent decisions about mitigation, therefore making risk assessment endogenous within our  
265 modeling structure. We calculate the damage at a given node as a probability-weighted average of the  
266 current-period damages accessible to each end node across states of fragility, such that

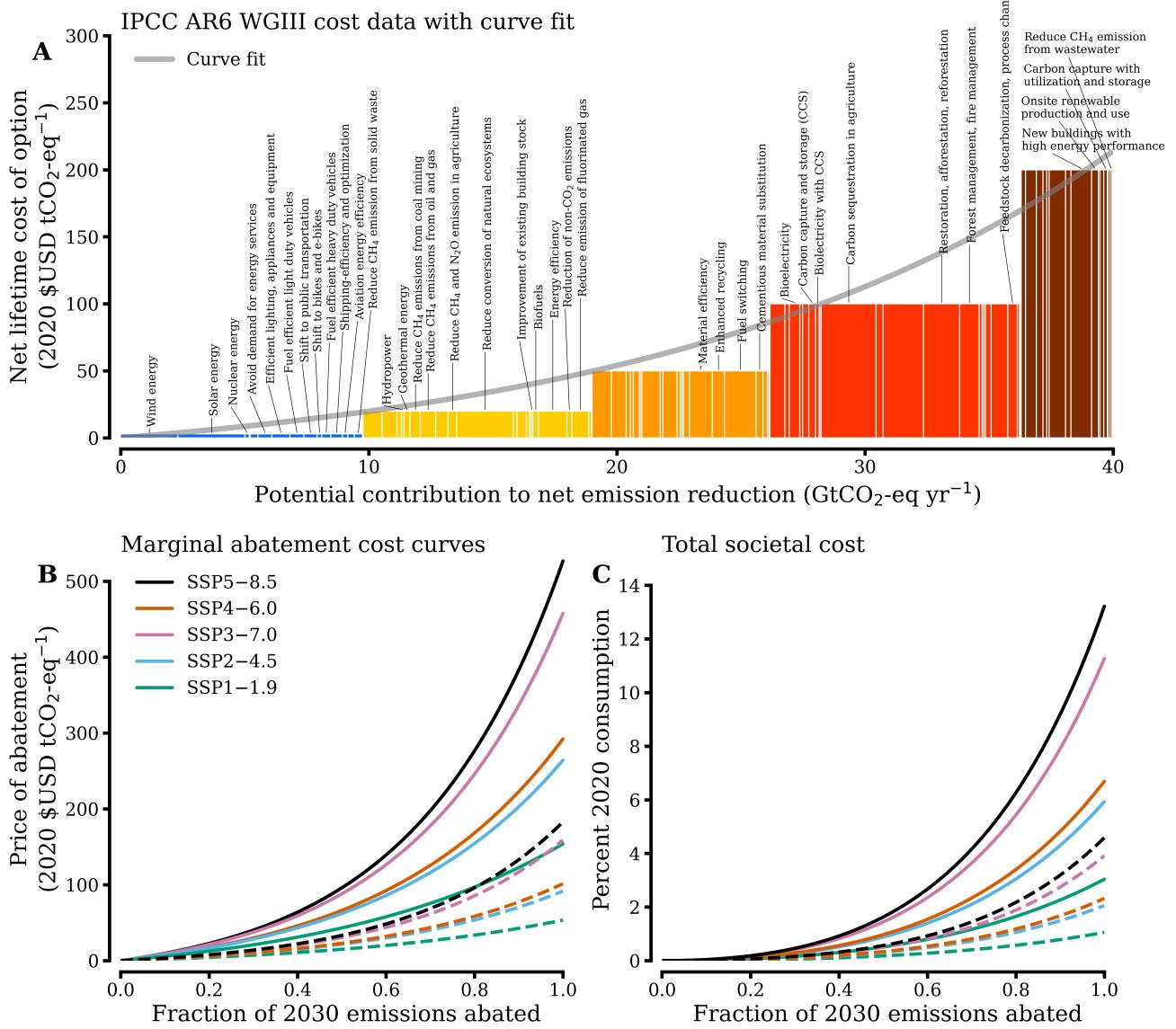
$$\mathcal{D}_{node}(\Psi_t, \theta_t) = \sum_{\theta_T \in \Theta} P(\theta_T | \theta_t) \mathcal{D}_{tot}(\Psi_t, \theta_t). \quad (2.8)$$

267 **2.4 Cost of mitigation**

268 Calculating the cost of mitigation requires specifying a marginal abatement cost curve (MACC), which  
269 relates the price of abatement to the fraction of emissions abated. Such a curve will vary depending on  
270 three factors: (1) the current state of emissions mitigation technologies, which in aggregate represent  
271 the abatement potential as a function of cost, (2) the availability of a backstop technology, which  
272 allows for net-negative emissions, and (3) technological advancement, which makes mitigation costs  
273 cheaper over time ([Gillingham and Stock, 2018](#)). We discuss the limitations to our approach in Online  
274 Appendix E.

275 **2.4.1 Marginal abatement cost curve estimation**

276 Estimating MACCs requires a functional relationship between the fraction of emissions abated,  $x$ , the  
277 per-ton tax rate,  $\tau$ , and the emission pathway,  $E$ . We use the most recent estimates for the cost  
278 of CO<sub>2</sub> emission abatement presented in AR6 WGIII ([Intergovernmental Panel on Climate Change,](#)  
279 [2022b](#)) (see their Figure SPM.7, p. SPM-50). We make four important assumptions in interpreting the  
280 data from AR6 WGIII. First, we assume cost estimates are additive, which is not necessarily the case;  
281 however, we expect changes in costs and abatement potential to be small enough to consider them as  
282 negligible in this study. Second, we neglect negative costs; that is, whenever WGIII data dictates that  
283 costs are < \$0, we set the cost to zero. Third, for abatement potentials outside the range provided  
284 by the IPCC, we assume the functional relationship between  $\tau$  and  $x$  established for lower abatement  
285 potentials holds. Lastly, we assume that the cost of each option is equal to its maximum cost in its  
286 respective range, i.e., the cost of an option in the IPCC \$0–\$20 range is assumed to be \$20. Taken



**Figure 4:** Panel A shows the mitigation potential and cost for each methodology given by the IPCC using their WGIII data. Blue represents zero costs (listed as negative in AR6), yellow is \$0-\$20 range, orange is \$20-\$50, red is \$50-\$100, and maroon is \$100-\$200. Panel B shows the fitted marginal abatement cost curves given by (2.9) and panel C shows the total cost to society given by (2.10) in our ‘main specification’. In panels B–C, solid lines correspond to 2030 MACCs, while dashed lines are 2100 MACCs, assuming an exogenous technological growth rate of 1.5% and no endogenous technological growth.

*Note: In panel A, the abatement methodology label is only on the bar with the most mitigation potential for a given methodology.*

287 together, these assumptions make our MACC estimation conservative. We then fit an exponential  
 288 curve to the cost data (see Figure 4A), such that

$$\tau(x) = \tau_0 \left( e^{\xi x} - 1 \right), \quad (2.9)$$

289 where  $\tau_0, \xi > 0$  are constants. To evaluate (2.3)–(2.5), we are interested in the total cost to society,  
 290  $\kappa(\tau)$  for each particular tax rate  $\tau$ , in units of the fraction of 2020 consumption lost. We use the  
 291 envelope theorem to calculate  $\kappa(\tau)$ , such that (see Online Appendix E for the full derivation),

$$\kappa_{MACC}(x) = \frac{E_0 \tau_0}{c_{2020}} \left( \frac{e^{\xi x} - 1}{\xi} - x \right), \quad (2.10)$$

292 where  $c_{2020}$  is the 2020 global consumption in billions of 2020 USD, set to \$61880 (taken from the  
 293 World Bank<sup>10</sup>) and  $E_0$  is the emissions rate in 2030 in GtCO<sub>2</sub> yr<sup>-1</sup>. A table of fitted values for  $\tau_0$  and  
 294  $\xi$  for each SSP are provided in Table 3 in Online Appendix E, as well as a calculation for the percent  
 295 of consumption required to abate all emissions. Fits for (2.9) and (2.10) are shown in Figure 4B and  
 296 Figure 4C, respectively.

#### 297 2.4.2 Direct air capture technology

298 Our model represents direct air capture (DAC) via permitting CO<sub>2</sub> removal (National Research Council,  
 299 2015). Net CO<sub>2</sub> removal occurs whenever the mitigation exceeds unity; this leads to negative emissions  
 300 and thus net carbon removal from the atmosphere. The price of net carbon removal is a major source  
 301 of uncertainty in assessing future climate policy (Johnson et al., 2017), with estimates ranging from  
 302 \$50 – \$1000 2020 USD per ton of CO<sub>2</sub> removed. Regardless of the specific dollar estimates provided in  
 303 the literature, DAC faces a common hurdle: scalability (Intergovernmental Panel on Climate Change,  
 304 2022b). The parameter  $x$  in our MACC is the fraction of 2030 emissions abated; therefore, removing  
 305 even a small percentage of these emissions from the atmosphere is equivalent to abating billions of tons  
 306 of CO<sub>2</sub> from the atmosphere in short order. The technology to carry out this task is simply unavailable  
 307 at present, and it is unclear when it will become fully mature and available at scale.

308 Note that, before mitigation reaches unity, there is some carbon capture and storage that is as-  
 309 sumed to be occurring concurrent with emissions reductions; indeed, by considering the technology-  
 310 by-technology breakdown of the IPCC’s WGIII cost data in Figure 4A, carbon capture and storage  
 311 is placed in the \$200 2020 USD tCO<sub>2</sub>-eq<sup>-1</sup> cost bracket. Hence our inclusion of DAC in our MACC  
 312 formulation represents an abrupt shift from purchasing various abatement technologies (such as solar  
 313 power or equipment to retrofit buildings) to installing exclusively, and at scale, DAC facilities. The  
 314 costs of this process are currently assumed to be rather large (International Energy Agency, 2022).  
 315 However, a breakthrough could certainly occur sometime in the future where DAC becomes deployable  
 316 at scale for a more economically viable cost (for example, as a result of the uncapped subsidies in the  
 317 Inflation Reduction Act of 2022 (Yarmuth, 2022)), which would lower the price of DAC considerably  
 318 and would require a reassessment of our quantitative analysis in § 5.

319 In light of these considerations, we take a simple approach to adjusting our cost curve to account

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<sup>10</sup><https://data.worldbank.org/indicator/NE.CON.TOTL.CD>

320 for DAC technologies by imposing a DAC premium,  $\tau_{DAC} > 0$ , which is an extra price for carbon  
 321 removal which shifts  $\tau_0$  to  $\tau_0 \rightarrow \tau_0 + \tau_{DAC}$ . Throughout, we essentially price out to-scale DAC leading  
 322 to net-negative emissions before 2100. This alters our MACC cost curve (2.10) when  $x > 1$ , such that

$$\kappa_{MACC}(x) = \begin{cases} \frac{E_0\tau_0}{c_{2020}} \left( \frac{e^{\xi x} - 1}{\xi} - x \right), & 0 \leq x \leq 1, \\ \frac{E_0(\tau_0 + \tau_{DAC})}{c_{2020}} \left( \frac{e^{\xi x} - 1}{\xi} - x \right), & x > 1. \end{cases} \quad (2.11)$$

### 323 2.4.3 Technological progress

324 Technological progress in CAP6 is captured by allowing the cost of mitigation to society  $\kappa_{MACC}(x)$   
 325 to decrease in time as technological proficiency makes mitigation cheaper. Technological progress  
 326 can occur in two ways: (1) exogenously, where general technological improvement independent of  
 327 agent choices make mitigation cheaper, and (2) endogenously, where if a given individual invests in  
 328 mitigation early, the cost of mitigation goes down more over time (Acemoglu et al., 2012). The  
 329 exogenous (endogenous, resp.) technology advancement rate is given by  $\varphi_0 \geq 0$  ( $\varphi_1 \geq 0$ , resp.).  
 330 Incorporating these factors into our cost curve results in our final expression for the cost of mitigation  
 331 to society,

$$\kappa_t(x_t) = \kappa_{MACC}(x_t) (1 - \varphi_0 - \varphi_1 X_t)^{t-10}, \quad (2.12)$$

332 where

$$X_t := \frac{\int_0^t x(\zeta) E(\zeta) d\zeta}{\Psi(t)}, \quad (2.13)$$

333 is the weighted average mitigation up to time  $t$  (ft. <sup>11</sup>).

334 We note that our formulation of endogenous technological change – or “learning by doing” – follows a  
 335 formulation akin to Wright’s law (Wright, 1936), where the reduction in costs of mitigation technologies  
 336 is proportional to the total deployed mitigation, as opposed to directed technical change in the spirit  
 337 of Acemoglu et al. (2012) or Lans Bovenberg and Smulders (1995). This is because in our formulation,  
 338 the social planner chooses levels of abatement, which (via proxy) corresponds to the deployment of  
 339 clean technologies. As more and more renewable technologies are “deployed” by the planner, Wright’s  
 340 law would suggest that their costs will decrease. Hence the Wright’s law-based formulation is the most  
 341 natural way to incorporate endogenous technological change into our model. This framework has the  
 342 additional advantage of allowing us to only focus on carbon tax levels rather than including additional  
 343 policy instruments, such as renewable energy subsidies.

### 344 2.4.4 “No free lunches” calibration

345 Estimating the cost of CO<sub>2</sub> abatement is notoriously challenging. The cost estimates presented above  
 346 are static, in the sense that they represent the costs of the lifetime of the project and, for example, ignore

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<sup>11</sup>Note the technological growth factor is offset by ten years as the cost data from AR6 is for 2030 technologies and our first model period is in 2020.

347 spillover effects ([Intergovernmental Panel on Climate Change, 2022b](#)). However, static estimates fail  
 348 to capture the impact of the costs (or savings) associated with a given project that outlive the project  
 349 lifetime itself ([Gillingham and Stock, 2018](#)). Such considerations lead some to argue that costs should  
 350 not be estimated from the “bottom up” as done here, but rather from the “top down.” “Top down”  
 351 estimates generally paint a more pessimistic picture than the “bottom up” methods, positing that the  
 352 cost of abating CO<sub>2</sub> emissions is actually larger than adding up the cost of each individual option,  
 353 owing to inertia and friction in the economic system, a set of barriers typically summarized as the  
 354 “energy paradox” ([Jaffe and Stavins, 1994](#)).

355 To address this concern, we provide an alternative calibration of CAP6 that is more closely aligned  
 356 to “top-down” MACCs (see, e.g., [Barrage and Nordhaus, 2023](#)) by adjusting the MACC to exclude  
 357 zero-cost abatement technologies; indeed, it has been shown that the degree to which one believes  
 358 in zero-cost mitigation explains much of the difference between “top-down” and “bottom-up” MACC  
 359 estimates ([Kotchen et al., 2023](#)). We do so by shifting all of the mitigation potential in the IPCC  
 360 dataset up by one cost bracket; for example, the zero cost methodologies (the blue bars in Figure 4)  
 361 now have \$20 2020 USD tCO<sub>2</sub>-eq<sup>-1</sup> lifetime cost, and so on. The highest cost abatement technologies  
 362 are set to cost \$400 2020 USD tCO<sub>2</sub>-eq<sup>-1</sup>. We coin this MACC calibration as the “no free lunches”  
 363 MACC, and provide its parameter values in Online Appendix E, Table 3. (ft. <sup>12</sup>).

### 364 3 Climate model

365 Here we present the climate component of our model. We map CO<sub>2</sub> emissions to the temperature  
 366 anomaly above preindustrial levels, denoted as  $T'$ , using the transient climate response to emissions  
 367 (TCRE) ([Damon Matthews et al., 2021](#)). The TCRE is defined as a linear scale factor  $\lambda > 0$  that maps  
 368 the cumulative CO<sub>2</sub> emissions,  $\Psi(t) := \int_0^t E(\zeta)d\zeta$ , to temperature, where  $E(t)$  is the emissions baseline.  
 369 The physical basis for TCRE is a compensation between the diminishing sensitivity of radiative forcing  
 370 to CO<sub>2</sub> at higher atmospheric concentration and the diminishing ability of the ocean to take up heat  
 371 and carbon at higher cumulative emissions ([Intergovernmental Panel on Climate Change, 2021](#)). We  
 372 follow the framework laid out in [Damon Matthews et al. \(2021\)](#) to use a TCRE that accounts for non-  
 373 CO<sub>2</sub> forcing via the parameter  $f_{nc} > 0$  which increases the average value and variance of the TCRE.  
 374 We write our “effective” TCRE – the TCRE including non-CO<sub>2</sub> forcing factors – as

$$\lambda_{eff} := \frac{\lambda}{1 - f_{nc}}. \quad (3.1)$$

375 The mean value of  $\lambda$ ,  $f_{nc}$ , and  $\lambda_{eff}$  and their uncertainties are provided in Online Appendix F, Table 4.  
 376 Using this approach, we are able to reproduce central estimates of warming levels this century reported  
 377 by WGI in AR6 for each SSP reasonably well, see Online Appendix F, Table 5. Therefore in our

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<sup>12</sup>The analogous figure to Figure 4 for the “no free lunches” MACC is provided in Online Appendix E. We also performed a second recalibration that sets the costs of the the < \$0 mitigation options to infinity, coined the “infinite cost” calibration. The figure associated with this calibration is also in Online Appendix E. We do not show the results of CAP6 with this calibration as the final costs of abatement are lower than in the “no free lunches” case, but higher than the ‘main specification.’ Hence, the results will simply be an interpolation between the main specification and the “no free lunches” results.

378 calculations of temperature, we use

$$T'(t) = \lambda_{eff}\Psi(t). \quad (3.2)$$

379 The TCRE approach has a number of advantages: (i) it captures short- and long-term uncertainty in  
380 climate warming, (ii) it is relatively simple and transparent, and (iii) emulates state-of-the-art climate  
381 models well (Allen et al., 2009; Dvorak et al., 2022).<sup>13</sup> Moreover, the TCRE framework has been used  
382 in a number of other climate-economic models (e.g., Dietz and Venmans, 2019; Campiglio et al., 2022).

## 383 4 Model calibration

### 384 4.1 Featured runs

385 To calibrate CAP6, we use discount rates in line with recommendations from the US government.  
386 Previous analyses use a discount rate of 3% (Committee on Assessing Approaches to Updating the  
387 Social Cost of Carbon et al., 2017), but recent studies use 2% in light of recent economic trends (such  
388 as falling interest rates) and expert elicitation (Council of Economic Advisors, 2017; Drupp et al., 2018).  
389 Indeed, New York State adopted a 2% discount rate in their social cost of carbon calculations (New  
390 York State Energy Research and Development Authority and Resources for the Future, 2020). We  
391 calibrate our featured runs using 1.5%, 2% and 2.5% discount rates to be consistent with the recent  
392 report issued by the EPA (National Center for Energy Economics, 2022) and use the term structures  
393 from Bauer and Rudebusch (2020). We also show results using a 3% discount rate for consistency with  
394 prior US government estimates (Committee on Assessing Approaches to Updating the Social Cost of  
395 Carbon et al., 2017).<sup>14</sup> See Online Appendix G, Table 6 for specifics. We assume  $g = 1.5\%$  for all  
396 runs. For each discount rate, we assume that  $\psi = 10$ , in line with trends observed in the U.S. financial  
397 market (Schroyen and Aarbu, 2017). For our emissions baseline, we choose SSP2–4.5, as it aligns with  
398 recent projections of emissions used by the US EPA (Rennert et al., 2022). Lastly, we assume a modest  
399 exogenous technological growth rate of 1.5% and no endogenous technological growth, owing to an  
400 inability to reliably calibrate the endogenous technological growth rate parameter  $\varphi_1$ . The choice of  
401 no endogenous technological growth makes our technological growth assumptions conservative, given  
402 the known link between agent investment in mitigation and rates of growth in clean sectors (Acemoglu  
403 et al., 2012).<sup>15</sup>

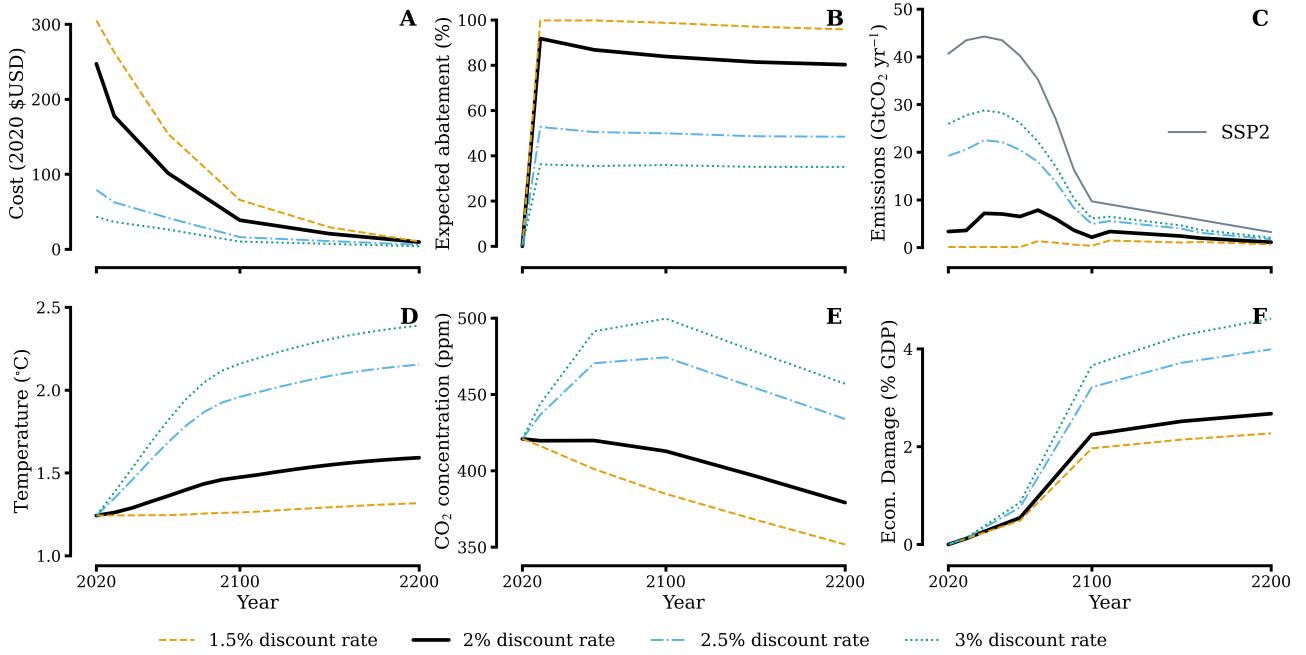
### 404 4.2 Ensemble runs

405 While risk associated with temperature rise and damage function uncertainty are holistically evaluated  
406 in a given run of CAP6, other sources of uncertainty exist and are excluded, such as uncertainty in

<sup>13</sup>Dvorak et al. (2022) showed that the TCRE adequately emulates the response of the more comprehensive FaIR model (Smith et al., 2018), itself a combination of carbon cycle models (Joos et al., 2013) and physical response models (Geoffroy et al., 2013b,a). The TCRE can deviate from more sophisticated models slightly depending on the forcing scenario (Intergovernmental Panel on Climate Change, 2021), but the differences are minor and are therefore ignored in this study.

<sup>14</sup>We do not here take a stand on which discount rate is correct, but do consider the 2% rate as our benchmark, as it is the central rate used by the EPA.

<sup>15</sup>We demonstrate how including endogenous technological growth influences model output in Online Appendix K.



**Figure 5:** CAP6 output for four discount rates in our main specification.

the rate of technological growth, or which exogenous emissions baseline or discount rate is assumed. Each of these represent a source of epistemic uncertainty in the climate-economic system; indeed, not knowing how much CO<sub>2</sub> will be emitted over the next century, for example, strongly influences the range of possible climate realizations, and thus, climate-related risk (Hawkins and Sutton, 2009; Lehner et al., 2020). To probe the impact of assumptions associated with each of these parameters on model output, we carry out a Monte Carlo analysis. We sample discount rates between the range of 1.5% and 4.25%; we chose the lower bound based on the lower bound considered by the EPA and the upper bound is the preferred rate used in DICE–2016R (Nordhaus, 2017). The value of agent RA has been measured to as high as 15 in wealthy countries and as low as 3 in some European nations (Schroyen and Aarbu, 2017), which defines our range. We choose the modest ranges of 0%–3% for both the exogenous and endogenous rate of technological growth. Note that we use our ‘main specification’ MACC for the ensemble run analysis. See Online Appendix G, Table 7 for our numerical values.

## 5 Results

### 5.1 Main specification

We show the featured model runs of CAP6 in Figure 5. We find that the 2% discount rate policy implies a high cost of carbon and stringent abatement policies, see panels 5A–B. The cost of carbon declines over time; this, however, should not be confused with reduced abatement action over time. Rather, the declining dynamics of carbon prices can be entirely attributed to the improved ability to abate CO<sub>2</sub> emissions owing to technological improvements (see Eqn. (2.12)). This set of mitigation actions leads emissions peaking in 2070, with CO<sub>2</sub> concentrations stabilizing before starting to decrease by mid-century. The expected global temperature change resulting from this emissions policy is less

428 than 1.5 °C by 2100 ( $\sim 1.47$  °C) and less than 2 °C in 2200 ( $\sim 1.6$  °C).

429 Decreasing the discount rate to 1.5% leads to complete and immediate cessation of emissions (see  
430 panel 5B), thus maximizing costs and decreasing 2100 (2200, resp.) warming by 0.2 °C (0.3 °C, resp.)  
431 in comparison to the 2% run. Larger discount rates relax the stringent abatement policies seen in  
432 the 2% and 1.5% discount rate cases. This results in lower costs and less mitigation action, and  
433 consequentially, larger warming and damages. We find that both the 2.5% and 3% discount rates  
434 warm beyond the warming target of 1.5 °C by 2100 established in the Paris Agreement. Moreover,  
435 the 3% discount rate policy exceeds 2 °C warming by 2100, and the 2.5% discount rate policy barely  
436 holds temperatures below 2 °C by 2100 ( $\sim 1.96$  °C by 2100). In the case of the 2.5% and 3% discount  
437 rates, CO<sub>2</sub> concentrations rise before falling as emissions cease.<sup>16</sup> The 2.5% (3%, resp.) discount rate  
438 individual also tends to lose  $\sim 1\%$  ( $\sim 1.4\%$ , resp.) more GDP in 2100 and  $\sim 1.3\%$  ( $\sim 2\%$ , resp.) more  
439 in 2200 than in the 2% discount rate case, showing the expensive consequences of delayed action in  
440 combating climate change.

441 The intuition behind our declining carbon prices can be found in our structural representation of  
442 risk. In the early periods of the model, the social planner faces the risk of catastrophic long-term  
443 damages if they choose not to abate any CO<sub>2</sub> emissions ( $\sim 50\%$  GDP or higher, if the worst-case  
444 climate sensitivity and damage function concurrently materialize); this causes the social planner to  
445 mitigate aggressively early on to effectively rule out such catastrophic futures from ever materializing.  
446 Technological progress then brings down abatement costs over time (especially if learning-by-doing  
447 effects are considered, see Online Appendix K), and drives down the carbon price over time. These  
448 two factors combine to cause carbon prices to start high and decline over time.

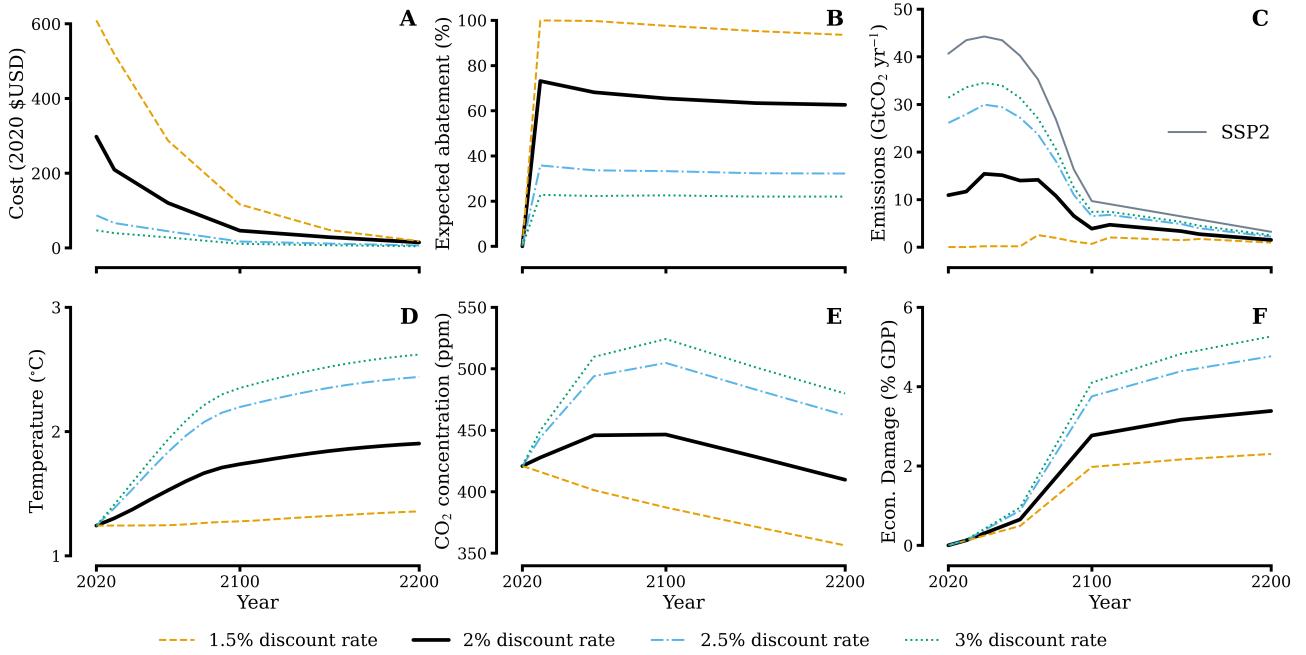
449 From this analysis, we find that modeling the cost of climate risk with CAP6 supports stringent  
450 mitigation action. We find that the carbon price and corresponding mitigation policy associated with  
451 the 2% discount rate saves at least \$22 trillion 2020 USD globally in 2100 (assuming global GDP grows  
452 annually by 4%) in comparison to the higher discount rate policies. In addition, employing policies  
453 with discount rates considered by the EPA result in an expected warming level in line with the targets  
454 set forth in the Paris agreement (United Nations Framework Convention on Climate Change, 2015),  
455 providing the targets with explicit economic support. When faced with potentially severe damages, the  
456 representative agent makes a clear choice: they sacrifice consumption today to abate CO<sub>2</sub> emissions,  
457 consistent with our understanding of how risk influences climate mitigation policy.

## 458 5.2 Alternative calibration: “no free lunches”

459 We recalculate our featured runs using the “no free lunches” MACC and show the results in Figure 6.  
460 The “no free lunches” cost curve leads to an increase in the optimal price of carbon; the 2020 CO<sub>2</sub> price  
461 increases by 20% in the 2% discount rate case. However, the “no free lunches” MACC significantly  
462 influences the efficacy of the optimal price in abating CO<sub>2</sub> emissions. For example, the 2% discount  
463 rate policy now abates only 70% of emissions (as opposed to  $\sim 85\%$  in the main specification). This  
464 emissions pathway reaches  $\sim 1.7$  °C of warming by 2100 and  $\sim 1.9$  °C warming by 2200, notably

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<sup>16</sup>We use the carbon cycle model of Joos et al. (2013) to compute carbon concentrations for our optimal mitigation pathways, see Online Appendix F.



**Figure 6:** CAP6 output for four discount rates using the “no free lunches” cost curve calibration.

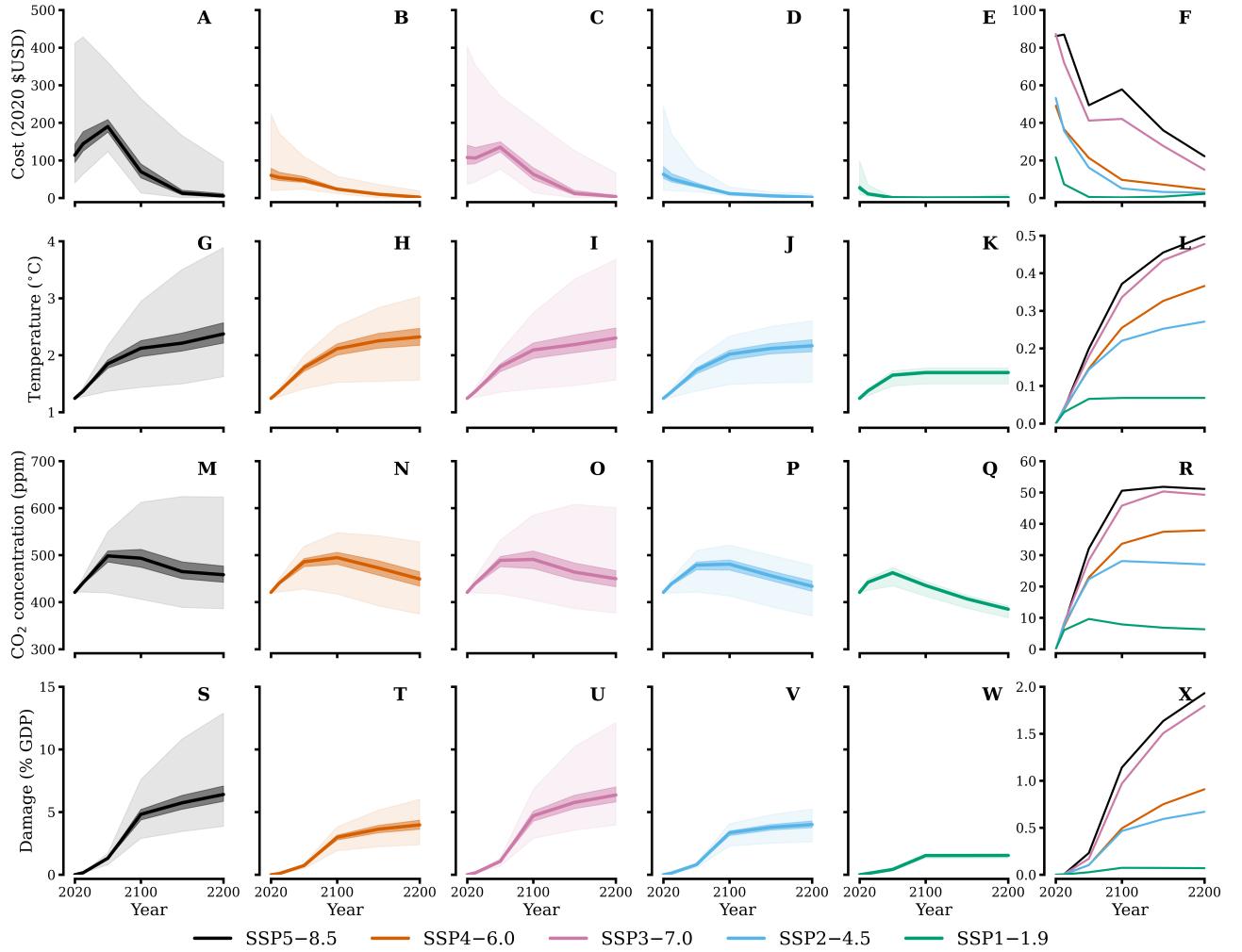
465 maintaining less than 2 °C warming. This shows that even if the cost of abatement is considerably  
 466 higher than the IPCC foretells, keeping total warming below 2 °C is still optimal within CAP6 when  
 467 a 2% discount rate is used.

468 Running CAP6 with the “no free lunches” calibration and a 2.5% or 3% discount rates show  
 469 similar results as the 2% rate, with higher optimal prices, more near-term warming, and higher CO<sub>2</sub>  
 470 concentrations. In this case, however, we find that using a 2.5% or 3% discount rate exceeds 2 °C  
 471 warming in 2100, thus exceeding the upper bound of targeted warming in the Paris agreement. This  
 472 shows that if abatement turns out to be more costly than we expect, using a higher discount rate in  
 473 climate policy makes the world’s ability of achieving the warming targets in the Paris agreement far  
 474 more tenuous.

475 The only exception to the pattern above – the “no free lunches” MACC leading to less abatement  
 476 and more warming – is the 1.5% discount rate policy, which still abates nearly 100% of emissions in the  
 477 near term. This can be explained by this agent having both a low discount rate and low risk tolerance,  
 478 and therefore sacrifices considerable consumption to minimize both experienced and potential future  
 479 damages owing to climate change.

### 480 5.3 Ensemble model analysis

481 We probe the influence of uncertainty in exogenous model parameters on CO<sub>2</sub> price paths, temperature  
 482 change, CO<sub>2</sub> concentrations, and economic damages incurred in our ensemble runs, shown in Figure 7.  
 483 We find that CO<sub>2</sub> price paths decline over time, regardless of socio-economic specification, owing to  
 484 agent risk response and technological progress. The level of CO<sub>2</sub> price varies between baselines because  
 485 the MACC is baseline dependent (see Eqn. (2.12)); for the same fraction of emissions abated, agents  
 486 pay different prices depending on the baseline. Finally, cost variance is highly stratified across baselines,



**Figure 7:** Cost (top row, panels A–E), temperature (second from top, panels G–K), CO<sub>2</sub> concentrations (third from top, panels M–Q), and economic damages (bottom row, panels S–W) from our ensemble model runs. Dark (light, resp.) shaded region represents the 36<sup>th</sup>–64<sup>th</sup> (1<sup>st</sup>–99<sup>th</sup>, resp.) percentile range, solid lines represent the median time series. In the final column (panels F, L, R, and X) we plot the standard deviation of each parameter distribution in time.

487 see panel 7F.

488 Central estimates of temperature, CO<sub>2</sub> concentrations, and economic damages,<sup>17</sup> however, do not  
489 see significant differences in central estimates across baselines as was observed in CO<sub>2</sub> prices. This  
490 owes to suggested policy in CAP6 being consistent across baselines; the only difference is the price of  
491 implementing said policy. Hence, the impact variables are relatively insensitive to baseline choice. This  
492 is a notable result, as it implies CAP6 finds an optimal outcome across emissions baselines for a given  
493 calibration. The variance in each impact variable however, displayed in panels 7L,R,X, is sensitive to the  
494 choice in baseline, with high (low, resp.) emissions scenarios having the highest (lowest, resp.) amount  
495 of variance. This can be explained by considering the consequences of inaction (i.e., high discount rate  
496 policies). In a high emissions scenario such as SSP5–8.5, inaction leads to more emissions, and thus  
497 higher impacts than in a low emissions scenario such as SSP2–4.5. Hence, the variance in each impact  
498 variable are all higher for high emissions scenarios than in low emissions scenarios.

499 **5.3.1 Variance decomposition of ensemble results**

500 The significant stratification of uncertainty in our output variables shown in Figure 7 motivates further  
501 study; is it high discount rates that control prices, for example, or rates of technological change? To  
502 this end, we perform a regression analysis of CO<sub>2</sub> price and the impact variables studied above at every  
503 point in time against parameter values, and plot the fraction of total  $r^2$  attributable to each parameter  
504 in Figure 8 (see Online Appendix I for details and supporting figures).

505 For prices, we find that the discount rate (i.e., EIS and PRTP) dominate uncertainty in the near term  
506 (i.e., prior to 2100). This owes to these parameters dictating individual attitudes towards time-related  
507 risk and discounting. In early periods of the model, climate damages are highly uncertain. Therefore,  
508 any abatement action that is taken is with the intent to rule out the most catastrophic outcomes and  
509 secure future welfare; the extent to which individuals respond to this threat of catastrophe is governed  
510 by the discount rate, thus determining the level of early mitigation action and driving costs. On longer  
511 timescales (past 2100), climate damages have been more distinctly realized, and the number of possible  
512 futures have narrowed. Individuals must come to grips with their damaged future, and generally begin  
513 investing more stringently in emissions abatement. This comes at a cost, a cost that is determined  
514 by how much cheaper abatement technologies have become in the time it took to reach this decision.  
515 In particular, high prices in late periods are almost entirely attributable to low rates of technological  
516 change across SSPs.

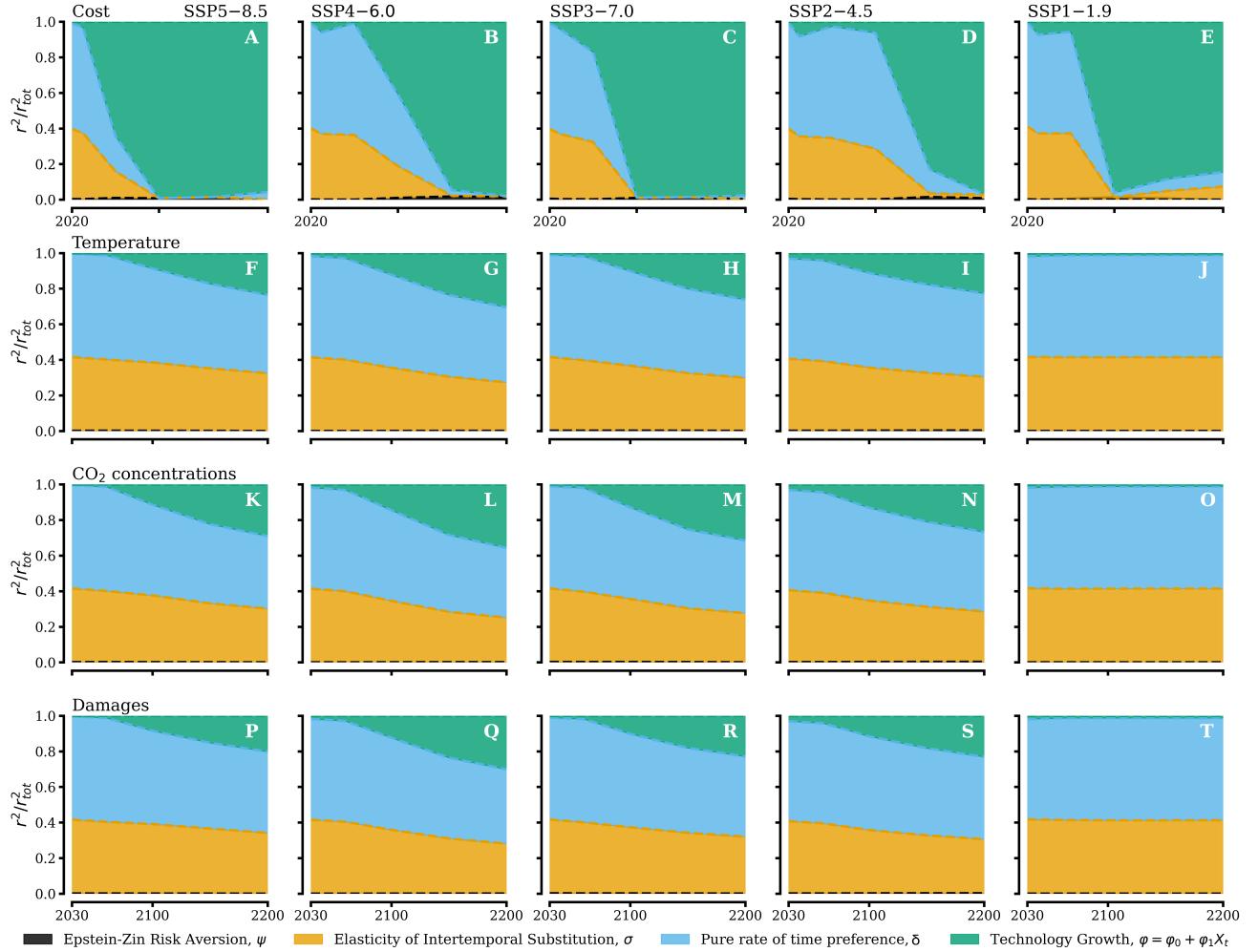
517 For the impact variables, however, a different story emerges: the influence of the discount rate is  
518 pronounced for much longer than in the case of CO<sub>2</sub> prices. This owes to inactivity early on leading to  
519 long-term consequences in the form of climate-economic impacts that cannot simply be fixed by more  
520 spending on abatement.<sup>18</sup> Indeed, while technological change can certainly halt any further increase in  
521 global mean surface temperature, for example, it cannot undo past malfeasance.<sup>19</sup> Hence, the discount

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<sup>17</sup>We refer to this set of variables as “impact variables” for the remainder of this discussion.

<sup>18</sup>This conclusion relies on a high cost of net-negative emissions; if a breakthrough in direct air capture (DAC) technologies occurs, then we would expect the variance explained in impact variables owing to technological growth to be higher, as net-negative emissions would enable long-run temperatures, CO<sub>2</sub> concentrations, and economic losses to be changed, perhaps significantly so, depending on how expensive DAC turns out to be.

<sup>19</sup>An important qualification to this conclusion is that we do not consider solar geoengineering, which could lead to



**Figure 8:** Fraction of total variance (calculated as total  $r^2$ ) attributable to each model parameter for carbon prices (top row, panels A–E), temperature (second row, panels F–J), CO<sub>2</sub> concentrations (third row, panels K–O), and economic damages (bottom row, panels P–T). Each column represents a different SSP.

Note: Cost variance (top row) begins in 2020 whereas temperature, CO<sub>2</sub> concentrations, and economic damages (bottom three rows) begin in 2030, as the model is initialized with the same climate conditions and no damages incurred, leading to zero variance in 2020 for the latter three variables.

522 rate has a much more pronounced influence on far-distant temperature rise, atmospheric CO<sub>2</sub> levels,  
523 and economic damages than in the case of CO<sub>2</sub> prices.

524 Interestingly, Figure 8 shows that the influence of RA (i.e., the value of  $\psi$ ) is suppressed for CAP6  
525 output uncertainty<sup>20</sup> relative to other model inputs. We postulate that this owes to the risk aversion  
526 captured by  $\psi$  (i.e., the Epstein-Weil-Zin sense of risk aversion across states of nature) is relatively less  
527 important to risk across states of time. Given the large residence time of CO<sub>2</sub> in the atmosphere, it  
528 stands to reason that the impact of risk aversion with respect to time would dwarf the impact of risk  
529 aversion across states of nature. Indeed, the results of Figure 8 provide resounding support for this  
530 theory: risk aversion across states of time (captured by EIS) drowns out the influence of risk across  
531 states of nature (as captured by RA).

## 532 6 Conclusion

533 Over a decade ago, Lord Nicholas Stern wrote that “Presenting the [climate] problem as risk-management  
534 is likely to point strongly towards a policy for a rapid transition to a low-carbon economy” ([Stern, 2013](#)).<sup>21</sup> Our framework takes this view seriously, and, in the final analysis, shows the wisdom in  
535 Stern’s words. By treating CO<sub>2</sub> as a risky asset and calculating the optimal CO<sub>2</sub> price and associated  
536 abatement policy using U.S. EPA-consistent discount rates, we find that optimal policy limits warming  
537 below 2 °C in 2100 for each discount rate we considered. Practically speaking, this corresponds to  
538 cutting > 70% of CO<sub>2</sub> emissions in relatively short order; a “rapid transition to a low-carbon econ-  
539 omy” indeed. Our results flip the conventional view of climate policy on its head; rather than abating  
540 progressively more CO<sub>2</sub> emissions as time goes on (and damages are felt more acutely), our model  
541 suggests stringent early abatement as a ‘hedge’ against potentially severe damages associated with  
542 climate change.

544 Evidently our framework for computing optimal climate policies is idealized, and in practice, a  
545 number of additional considerations are necessary for formulating robust climate policy. For example,  
546 we compute a globally “optimal carbon tax” as a proxy for the overall strength of climate policy, not  
547 as an actual policy guide.<sup>22</sup> Prospects for such a common global carbon tax are bleak, to put it mildly.  
548 Therefore, useful extensions of this work would analyze the transition risk towards zero emissions  
549 policies, i.e., by considering asset stranding and adjustment costs ([Campiglio et al., 2022](#)), the potential  
550 for a ‘run on fossil fuels’ induced by an expected transition away from fossil fuel use ([Barnett, 2023](#)),  
551 or considering the distributional effects of heterogeneous climate policy mixes in different nations (as  
552 explored in [Clausing and Wolfram, 2023](#)). More work in this direction could prove both scientifically  
553 and economically insightful as well as immediately applicable in a wide variety of policy settings.

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increased spending influencing temperature, CO<sub>2</sub> concentration, and economic damages levels in both the short- and long-term.

<sup>20</sup>This is not to say that RA has no impact on price levels, as increasing (decreasing, resp.) RA does slightly raise (lower, resp.) near term prices, see Online Appendix J.

<sup>21</sup>Others, like [Nordhaus \(2007\)](#), criticized Stern at the time, while [Weitzman \(2007\)](#) argued that Stern was “right for the wrong reasons”, reasons subsequently developed in [Weitzman \(2009, 2012\)](#).

<sup>22</sup>Another limitation is that we compute the optimal carbon tax with a single exogenous discount rate. In reality, the discount rate will respond to the level of risk ([Lucas, 1976](#)) and is uncertain on long time horizons ([Weitzman, 1998](#)). Allowing for a dynamic discount rate in our framework is a potentially fruitful avenue of future work.

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576 **Disclosure statements**

577 *Adam Michael Bauer*

578 At the time of submission, I hold a short-term consultancy position at the World Bank's Climate Change  
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582 *Cristian Proistosescu*

583 I have no conflicts of interest to disclose.

584 *Gernot Wagner*

585 I am on the corporate advisory board of CarbonPlan. I have no other conflicts of interest to disclose.

586 **Author contributions**

587 Cristian Proistosescu and Gernot Wagner conceived of the study. Adam Michael Bauer wrote the code,  
588 designed numerical experiments, performed literature review, and made the figures. The first draft of  
589 the paper was written by Adam Michael Bauer, and all authors assisted in editing this draft to shape  
590 the final submitted manuscript. All authors have approved the submitted verison.

591 **Data Availability**

592 The code for the Carbon Asset Pricing model – AR6 (CAP6) can be found at the following Github  
593 repository: [github.com/adam-bauer-34/cap6](https://github.com/adam-bauer-34/cap6).

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# Online Appendix: Carbon Dioxide as a Risky Asset

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## Abstract

We develop a financial-economic model for carbon pricing with an explicit representation of decision making under risk and uncertainty that is consistent with the Intergovernmental Panel on Climate Change's sixth assessment report. We show that risk associated with high damages in the long term leads to stringent mitigation of carbon dioxide emissions in the near term, and find that this approach provides economic support for stringent warming targets across a variety of specifications. Our results provide insight into how a systematic incorporation of climate-related risk influences optimal emissions abatement pathways.

**JEL:** G0, G12, Q51, Q54

**Keywords:** Climate risk, climate policy, asset pricing, cost of carbon

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## <sup>1</sup> A Brief literature review

<sup>2</sup> There are three primary ways that risk and uncertainty are incorporated into climate-economic integrated assessment models. The first such approach is to augment DICE with stochastic components and reframe the model into a dynamic stochastic optimal control problem. This approach has yielded a number of fruitful insights (see, e.g., [Lemoine and Traeger \(2016a,b\)](#)). For example, the seminal work of [Cai and Lontzek \(2019\)](#) show that the possibility of hitting a climate tipping point substantially increases the SCC, and thus the stringency of optimal mitigation policy, using a continuous-time version of DICE with many stochastic components.

<sup>9</sup> Another approach is to formulate climate policy from the perspective of dynamic stochastic general equilibrium (DSGE) models. This approach was pioneered by [Golosov et al. \(2014\)](#), who derive a simple expression for the marginal externality damage from carbon emissions (analogously, the optimal carbon price or SCC). This expression shows that the optimal carbon price can be – in a stylized setting – decomposed into three contributing factors: (i) the discount rate, (ii) the elasticity of damage associated with a marginal ton of emissions, and (iii) the rate of depreciation of carbon stocks in the atmosphere. However, this study does not include temperature uncertainty, and utilizes a logarithmic utility, which causes the role of uncertainty to be substantially suppressed. [Van Den Bremer and Van Der Ploeg \(2021\)](#) extend the DGSE framework to include recursive preferences, finding that the influence of temperature and climate damage uncertainty increase the SCC. Similar conclusions were drawn by [Hambel et al. \(2021\)](#), whose formulation allows for multiple, additive climate shocks, as well as for considering the influence of climate change on both GDP levels and growth rates.

<sup>21</sup> A third approach is to employ methods from financial economics to explore the influence of uncertainty on carbon prices. [Dietz et al. \(2018\)](#) utilize a simple analytic model derive the consumption-based capital asset pricing model “beta” ([Lucas, 1978](#)) for climate mitigation projects. They find that the sign of the “climate beta” is positive, and that the discounted expected net benefits of carbon emissions abatement are increasing in the “climate beta”. However, they do not utilize recursive preferences in their approach. [Lemoine \(2021\)](#) formulates a simple analytic expression that highlights the various channels of uncertainty associated with the SCC and signs each; the collective effect is positive. [Barnett et al. \(2020\)](#) build a dynamic structural model which includes decision making under uncertainty, nonlinear impulse response functions, and dynamic valuation, and find that the influence of uncertainty is multiplicative across economic and climate channels. Each of these contributions provide relatively simple – yet powerful – explanations, in financial economic terms, of how uncertainty influences optimal carbon pricing.

<sup>33</sup> **B Statement of optimization problem**

Put together, solving CAP6 is equivalent to solving the following optimization problem:

$$\max_{\{x_t\}_{t \in \{0, 1, \dots, T-1\}}} U_0(x_t), \quad (\text{B.1})$$

Such that :  $x_t \in \mathbb{R}^+$ , (B.2)

$$U_t = \left[ (1 - \beta) c_t^\rho + \beta \left( \mathbb{E}_t [U_{t+1}^\alpha]^{1/\rho} \right) \right]^{1/\rho} \quad (\text{B.3})$$

$$U_T = \left( \frac{1 - \beta}{1 - \beta(1 + g)^\rho} \right)^{1/\rho} c_T, \quad (\text{B.4})$$

$$c_t = \bar{c}_t (1 - \kappa_t(x_t)) (1 - \mathcal{D}_t(\Psi_t, \theta_t)), \quad \forall t \in \{0, 1, \dots, T-1\} \quad (\text{B.5})$$

$$c_T = \bar{c}_T (1 - \mathcal{D}_T(\Psi_T, \theta_T)), \quad (\text{B.6})$$

$$\bar{c}_t = \bar{c}_0 (1 + g)^t, \quad (\text{B.7})$$

$$\Psi_t = \int_0^t E_\zeta d\zeta, \quad (\text{B.8})$$

$$\mathcal{D}_t(\Psi_t, \theta_t) = \sum_{\theta_t \in \Theta_t} P(\theta_T | \theta_t) \mathcal{D}_{tot}(\Psi_t, \theta_t) \quad (\text{B.9})$$

$$\kappa_t(x_t) = \kappa_{MACC}(x_t) (1 - \varphi_0 - \varphi_1 X_t)^{t-10}, \quad (\text{B.10})$$

$$X_t = \frac{\int_0^t x_\zeta E_\zeta d\zeta}{\Psi_t}, \quad (\text{B.11})$$

$$\beta = \frac{1}{1 + \delta} \quad (\text{B.12})$$

$$0 \leq P(\theta_T | \theta_t) \leq 1, \quad (\text{B.13})$$

$$\delta, \rho, \alpha, g, \varphi_0, \varphi_1, \tau_{DAC}, E_t \text{ given and positive}, \quad (\text{B.14})$$

$$\mathcal{D}_0(\Psi_t, \theta_t) = 0. \quad (\text{B.15})$$

<sup>34</sup> See the main text for details regarding functional forms, calibrations, and results after numerically  
<sup>35</sup> solving the model.

<sup>36</sup> **C Prototypical model run**

<sup>37</sup> Given that our climate-economy model is unlike most other such models in the literature, an example  
<sup>38</sup> of how each of the components laid out above interact in one model “run” is warranted. First, let us  
<sup>39</sup> establish some important concepts and recurring values that will be essential for our understanding.  
<sup>40</sup> We have chosen  $T = 6$  decision periods. This implies that we have a total of  $n := 2^T - 1 = 63$  decision  
<sup>41</sup> nodes in the tree. Decisions are made at times  $t$  such that  $t \in \{2020, 2030, 2060, 2100, 2150, 2200\}$ , and  
<sup>42</sup> an additional period (with no decisions being made) occurs at  $t = 2250$  to establish the terminal period  
<sup>43</sup> conditions. As the binomial tree is path dependent, it immediately follows that the number of unique  
<sup>44</sup> paths through the tree is equal to the number of nodes in the *final* period, given by  $n_f := 2^{T-1} = 32$ .  
<sup>45</sup> Any vector of length  $n$  (which represents the value of a given variable, say mitigation, at each *node* in  
<sup>46</sup> the tree) can be readily translated into a set of *paths* of shape  $n_f \times T$  through the tree (which represents  
<sup>47</sup> the values of a given variable at the nodes in each *path* through the tree). Note that Figure 1 in the  
<sup>48</sup> main text is a helpful visual guide for our entire discussion.

49 **Step 1: Simulate climate damages**

50 The first step is to simulate potential climate damages. This comes *before* agent utility is optimized,  
51 as decisions about utility are made *within the context* of the landscape of potential damages. Once the  
52 landscape of damages are calculated (and we will be more precise about what is meant by “landscape”  
53 in our discussion below), then damages are interpolated in our utility calculations. Note that in the  
54 following discussion  $N_{MC} = 3 \times 10^6$  refers to the number of draws taken in our Monte Carlo samples  
55 of TCRE and damage function parametric uncertainty.

56 Climate damages are simulated using the following prescription. First, we specify an emissions baseline  
57 by choosing an SSP. Once specified, there is a range of possible cumulatively emitted CO<sub>2</sub> at each point  
58 in time, depending on hypothetical agent mitigation policy. Let the maximum cumulative emissions  
59 (associated with no mitigation) at a time  $t$  be represented by  $\Psi_t^*$ . Cumulative emissions  $\Psi_t$  therefore  
60 always lie in the range  $0 \leq \Psi_t \leq \Psi_t^*$ . We discretize the range of potential cumulative emissions at each  
61 point in time by applying a constant scaling  $0 \leq m \leq 1$  to the SSP and computing damages for each  
62 value of  $m$ . In our runs, we choose  $M = 101$  values of  $m$ . To recapitulate: we choose a value of  $m$  such  
63 that  $0 \leq m \leq 1$ , resulting in a time series of cumulative emissions  $\Psi_t = m\Psi_t^*$  that is manifestly less  
64 than or equal to the maximum permissible amount  $\Psi_t^*$  for all  $t$ .

65 For a given time series of cumulative emissions, the corresponding temperature change is uncertain  
66 owing to the uncertainty in the TCRE. We draw  $N_{MC}$  samples of the TCRE from a rectified normal  
67 distribution with best estimate and variance taken from Table 4 and evaluate (3.2), which results in  
68  $N_{MC}$  time series of global temperature change. For each temperature time series, we at random choose  
69 a damage function (statistical, structural, or meta-analytic) and evaluate (2.6) for the chosen damage  
70 function and the additional tipping points piece. The total damage is given by (2.7). This procedure  
71 results in  $N_{MC}$  time series of climate damages. The climate damage time series are then ordered by  
72 severity of the final period damages (thus establishing an orientation of the “fragility” dimension),  
73 and grouped in  $N_{MC}/n_f$  sized bundles. An average is then taken over each bundle, resulting in  $n_f$   
74 time series of climate damages. The averaging procedure is necessary to make the simulated climate  
75 damages congruent with the dimensionality of the binomial tree.

76 The procedure described above has resulted in a  $n_f \times T$  matrix of climate damages, ordered from high  
77 to low. Continuing for every value of  $m$  results in a  $M \times n_f \times T$  *landscape* of climate damages. This is  
78 coined as a landscape owing to its encapsulation of the potential extent of climate damages. The  $M$ -  
79 dimension contains information about the extent of emissions; the  $T$ -dimension contains information  
80 about the timing of damages; and the  $n_f$ -dimension contains the extent of climate damages based on  
81 the uncertainty in TCRE and the damage function. With this landscape now calculated, we can turn  
82 our attention to how the economic utility is maximized within it.

83 **Step 2: Utility maximization**

84 We optimize the economic utility given by (2.1) using a genetic algorithm (Goldberg, 1989). The genetic  
85 algorithm is a stochastic optimization routine, where a set of random solution vectors are generated  
86 and their “fitness” is determined. The vectors with high fitness are stored for the next round (they  
87 “survive”), and vectors with low fitness are discarded (they “die”). The low fitness vectors are replaced  
88 with another set of random vectors (the “offspring” of the more fit vectors) whose fitness is compared to  
89 the incumbents’. This process continues until minimal changes in the highest fitness value are recorded  
90 for a number of rounds; the vector corresponding to the highest fitness is then said to be the “optimal”  
91 solution vector. The genetic algorithm is best suited for objective functions with unknown or difficult  
92 to evaluate gradients, making it ideal for CAP6. In our use case, the randomly selected solution vectors  
93 are mitigation vectors, and a given vector’s fitness is its 2020 economic utility. In what follows, allow  
94  $\vec{x}$  be a vector of mitigation values with length  $n$ .

95 EZ utility captures future risk by allowing the utility at time  $t$  be dependent on the utility at time  $t + 1$   
96 (see Eqn. (2.1)). Evaluating the utility must therefore begin at the final period, and is then evaluated  
97 *backwards* to  $t = 2020$ . Thus, the first step is to evaluate the final period utility (2.2) where the final  
98 period consumption is given by (2.5) for each final state node. (Recall there are  $n_f = 32$  nodes in  
99 the final period.) The assumed SSP and the mitigation vector  $\vec{x}$  are used to calculate the emissions  
100 time series for every path through the tree, and thus the cumulative emissions at each end node. The  
101 cumulative emissions are used in (2.8) to calculate the damages at each node.

102 For each node before the final period, the mitigation action *up to but not including* a given node is  
103 used to calculate the cumulative emissions at that node. The cost of mitigation is found using (2.12),  
104 and the damages are found using (2.8). These in tandem determine the consumption by (2.4). The  
105 consumption and the following period utility are used in (2.1) to determine the utility. This continues  
106 for each node, and each randomly generated vector, until the genetic algorithm finds the mitigation  
107 vector with the highest utility.

### 108 Step 3: Visualize model output

109 The most fit mitigation vector  $\vec{x}^*$  translates into the output shown in Figures 5, 3, 6, 9, and 7 in the  
110 following way. To calculate the cost, we apply (2.9) at each node, including the technological growth  
111 prefactor found in (2.12). We calculate the expected mitigation using (2.13). We use  $\vec{x}^*$  to calculate the  
112 emissions at each node, which readily translates into the concentrations at each node using (F.4) and  
113 the *expected* warming at each node using (3.2) assuming the mean value of TCRE. Economic damages  
114 for each node are calculated using  $\vec{x}^*$  in (2.8). Averaging over the cost, expected mitigation, emissions,  
115 temperature, CO<sub>2</sub> concentrations, and damage amount in each period gives the time series shown in  
116 Figures in the main text and the Online Appendix.

## 117 D Supplementary discussion: damage functions

118 In Table 1 we show the calibrated values and uncertainties for the free parameters in (2.6). Below, we  
119 provide a technical description of how the values in Table 1 are computed.

### 120 D.1 Discussion of IPCC aggregate damage functions

#### 121 D.1.1 Statistically estimated damage function

122 The statistically estimated damage function (Burke et al., 2018) builds on previous work involving the  
123 nonlinear response of economic productivity to temperature (Burke et al., 2015), following methodolo-  
124 gies laid out more generally in Carleton and Hsiang (2016). This damage function relies on the  
125 specification of a certain horizon where damages set in, and choose the natural markers of 2049 and  
126 2099 (mid-century and end of century, respectively). The mid-century and end of century estimates  
127 are starkly different, as in this framework climate change slows economic growth, therefore requiring  
128 sufficient time for damages to compound. Damages are also different depending on which SSP one  
129 chooses; this owes to the fact that each SSP contains different assumptions around adaptation, techno-  
130 logical growth, and so on. Finally, the warming levels represented in Burke et al. (2018) are relative to  
131 a 1986–2005 baseline, *not* relative preindustrial temperature levels. The IPCC’s representation of this  
132 damage function differs from the original publication in three ways: they only report end-of-century  
133 estimates; they aggregate damage estimates across SSPs without indicating the differences between  
134 each; and they report the temperature change as relative to preindustrial rather than to a 1986–2005  
135 baseline.

**Table 1:** Fitted parameters for the damage function (2.6) based on Burke et al. (2018), Dietz et al. (2021) and Intergovernmental Panel on Climate Change (2022).

Damage function	$\bar{\varpi}_2 [K^{-2}]$	$\sigma_{\varpi_2} [K^{-2}]$	$\bar{\varpi}_1 [K^{-1}]$	$\sigma_{\varpi_1} [K^{-1}]$
Statistically estimated				
SSP1, mid-century	$5.36 \times 10^{-3}$	$7.13 \times 10^{-4}$	$8.93 \times 10^{-3}$	$1.12 \times 10^{-3}$
SSP2, mid-century	$3.09 \times 10^{-3}$	$4.76 \times 10^{-4}$	$1.24 \times 10^{-2}$	$1.90 \times 10^{-3}$
SSP3, mid-century	$2.95 \times 10^{-3}$	$4.74 \times 10^{-4}$	$1.18 \times 10^{-2}$	$1.89 \times 10^{-3}$
SSP4, mid-century	$3.50 \times 10^{-3}$	$7.14 \times 10^{-4}$	$5.83 \times 10^{-3}$	$1.19 \times 10^{-3}$
SSP5, mid-century	$3.40 \times 10^{-3}$	$5.20 \times 10^{-4}$	$1.14 \times 10^{-2}$	$1.75 \times 10^{-3}$
SSP1, end-of-century	$-1.24 \times 10^{-3}$	$2.49 \times 10^{-4}$	$7.07 \times 10^{-2}$	$1.42 \times 10^{-2}$
SSP2, end-of-century	$-2.33 \times 10^{-3}$	$4.75 \times 10^{-4}$	$7.21 \times 10^{-2}$	$1.47 \times 10^{-2}$
SSP3, end-of-century	$-2.81 \times 10^{-3}$	$5.93 \times 10^{-4}$	$7.20 \times 10^{-2}$	$1.52 \times 10^{-2}$
SSP4, end-of-century	$-1.11 \times 10^{-3}$	$3.42 \times 10^{-4}$	$4.67 \times 10^{-2}$	$1.43 \times 10^{-2}$
SSP5, end-of-century	$-1.33 \times 10^{-3}$	$3.45 \times 10^{-4}$	$5.56 \times 10^{-2}$	$1.45 \times 10^{-2}$
Structurally estimated	$2.30 \times 10^{-3}$	$8.53 \times 10^{-4}$	$2.05 \times 10^{-3}$	$7.59 \times 10^{-4}$
Meta analysis	$6.85 \times 10^{-3}$	$2.43 \times 10^{-3}$	$2.98 \times 10^{-4}$	$1.06 \times 10^{-4}$
Climate tipping points	$4.8 \times 10^{-1}$	$4 \times 10^{-2}$	$-4 \times 10^{-2}$	$1 \times 10^{-2}$

136 We correct these inconsistencies in our formulation to be consistent with the original publication. We  
137 include explicitly the time dependence of this damage function in our simulated climate damages,  
138 allowing for the decision periods of 2030 and 2060 to use the mid-century estimates and each decision  
139 period from 2100 onward to use end of century estimates. This of course is not perfect, as damages  
140 are expected to continue growing past 2100 in their framework, but we lack projection data to extend  
141 their framework to longer time horizons. Therefore, our estimates of climate damages in the long run  
142 are to be considered as conservative. We also change the fit to damage function data based on which  
143 SSP we consider. Finally, we correct the temperature baseline by shifting the abscissa by  $\sim 0.8$  °C to  
144 correctly represent temperature anomalies relative to preindustrial levels.

145 A final qualifier to our use of this damage function is our parameterization of uncertainty. The un-  
146 certainty range for these estimates is large, and net-benefits of climate change are not ruled out even  
147 in the long term (though they are exceptionally rare). The extent of this uncertainty is largely driven  
148 by the assumed economic response to climate change and the discount rate chosen in their model, and  
149 no range is given for the estimates of economic damages for a given climate model's projection; only  
150 the median estimate is reported for each climate model. We also suppress climate model uncertainty  
151 in their presented results so as to not double count climate uncertainty, resulting in a more narrow  
152 uncertainty envelope for damages estimates. We present our formulation in Figure 3A, taking care to  
153 allow uncertainty to broaden between 2049 and 2099, consistent with the original publication.

#### 154 D.1.2 Structurally estimated damage function

155 In the case of the structurally estimated damage function (Rose et al., 2017), three IAMs' (DICE (Nord-  
156 haus, 1992), PAGE (Hope et al., 1993), and FUND (Tol, 1999)) output are aggregated to form a range  
157 of climate damages estimates as a function of temperature. The central value of climate damages is  
158 close to that of DICE–2023 (Barrage and Nordhaus, 2023). The uncertainty associated with this dam-  
159 age function results from sampling the input parameter distribution of each IAM (Rose et al., 2017).  
160 We present our formulation of this damage function based on IPCC data in Figure 3B.

#### 161 D.1.3 Meta-analytic damage function

162 The meta-analytic damage function (Howard and Sterner, 2017) is derived from a synthesis of studies  
163 found in the literature, where care was taken to account for duplicates of studies and methodology.  
164 We use the preferred damage function from Howard and Sterner (2017), and assign an uncertainty  
165 envelope which encompasses much of the spread in the data reported by the IPCC, see Figure 3C. One  
166 limitation of this approach is that it is unclear if a set of damage estimates using different models and  
167 estimation types can be joined together in this way to form one unified “damage function”; moreover,  
168 it is also unclear if the uncertainty found in the data can truly be labeled as “parametric” or simply a  
169 by-product of disagreements in the literature.

#### 170 D.1.4 Synthesis

171 The inability to properly compare damage estimates across studies and methodologies led WGI to  
172 conclude that a reliable range of damage estimates could not be determined; there is no single ‘correct’  
173 damage function that we can specify in this work (Intergovernmental Panel on Climate Change, 2022).  
174 We resolve this issue by taking a conservative approach and sampling all of the damage functions  
175 mentioned above with equal probabilities; in this way, we remain agnostic about which damage function  
176 is the ‘correct’ one, and sample the space of possible damage functions in addition to uncertainty  
177 inherent to a specific climate damage estimation methodology.

Despite the issues with individual damage functions described above, our approach to sampling all available damage functions has the benefit that, at minimum, we sample a variety of damage function shapes and scales. The statistically estimated damage function has a concave shape at end-of-century. Furthermore, this damage function is time dependent, capturing the impact of climate change impacting economic growth; this has been shown to be an important factor in climate policy (Moore and Diaz, 2015). The structurally estimated damage function, in contrast, is convex, with low damages in the short run which slowly rise in temperature. Finally, the meta-analytic damage function is also convex, but rises much faster than the structurally estimated damage function.

## D.2 Damage function calibration

We fit the damage function data in the following way. For each damage function, we require that the concavity of the damage function is preserved, i.e.,  $\partial^2\mathcal{D}/\partial T'^2 \geq 0$ , depending on the damage function being considered. To solve for the damage function coefficients as presented in (2.6), we require knowing the damages for two data points, generically labeled as  $(T_1, \mathcal{D}_1)$  and  $(T_2, \mathcal{D}_2)$ . Then we can write

$$\mathcal{D}_1 = T_1(\varpi_2 T_1 + \varpi_1), \quad (\text{D.1})$$

$$\mathcal{D}_2 = T_2(\varpi_2 T_2 + \varpi_1), \quad (\text{D.2})$$

and, solving the above for  $\varpi_1$  and  $\varpi_2$ , results in

$$\varpi_1 = \frac{\mathcal{D}_1 T_2^2 - \mathcal{D}_2 T_1^2}{T_2 T_1 (T_2 - T_1)}, \quad (\text{D.3})$$

$$\varpi_2 = \frac{\mathcal{D}_2 T_1 - \mathcal{D}_1 T_2}{T_2 T_1 (T_2 - T_1)}. \quad (\text{D.4})$$

Having established the mean state, we can now introduce uncertainty into (D.3) and (D.4). We do so by allowing  $\mathcal{D}_1$  to be uncertain, assigning it a Gaussian distribution  $\tilde{\mathcal{D}}_1$  with mean  $\bar{\mathcal{D}}_1$  and standard deviation  $\sigma_{\mathcal{D}_1}$ . We link this to a distribution of  $\mathcal{D}_2$  by invoking the condition  $\partial^2\mathcal{D}/\partial T'^2 \geq 0$ , immediately resulting in the condition  $\varpi_2 \geq 0$ . Using (D.4), we arrive at

$$\tilde{\mathcal{D}}_2 \geq \tilde{\mathcal{D}}_1 \left( \frac{T_2}{T_1} \right). \quad (\text{D.5})$$

Eqn. (D.5) is generic for any damage function, but our model, we want either a concave up or concave down damage function. To accomplish this, we include an additional factor  $\Lambda > 0$  to (D.5) such that the inequality is ensured, i.e.,

$$\tilde{\mathcal{D}}_2 = \Lambda \tilde{\mathcal{D}}_1 \left( \frac{T_2}{T_1} \right), \quad \text{such that } \Lambda \geq 1. \quad (\text{D.6})$$

Therefore, if  $\Lambda > 1$ , we have a concave up damage function, and if  $\Lambda < 1$ , we have a concave down damage function. Setting  $T_1 = 3^\circ\text{C}$  and  $T_2 = 10^\circ\text{C}$ , we fit values for  $\bar{\mathcal{D}}_1$ ,  $\sigma_{\mathcal{D}_1}$ , and  $\Lambda$  to each set of damage function data resulting in the values presented in Table 1. See Table 2 for the values of our calibration coefficients.

## E Supplementary discussion: cost of mitigation

### E.1 Marginal abatement cost curve alternative calibrations

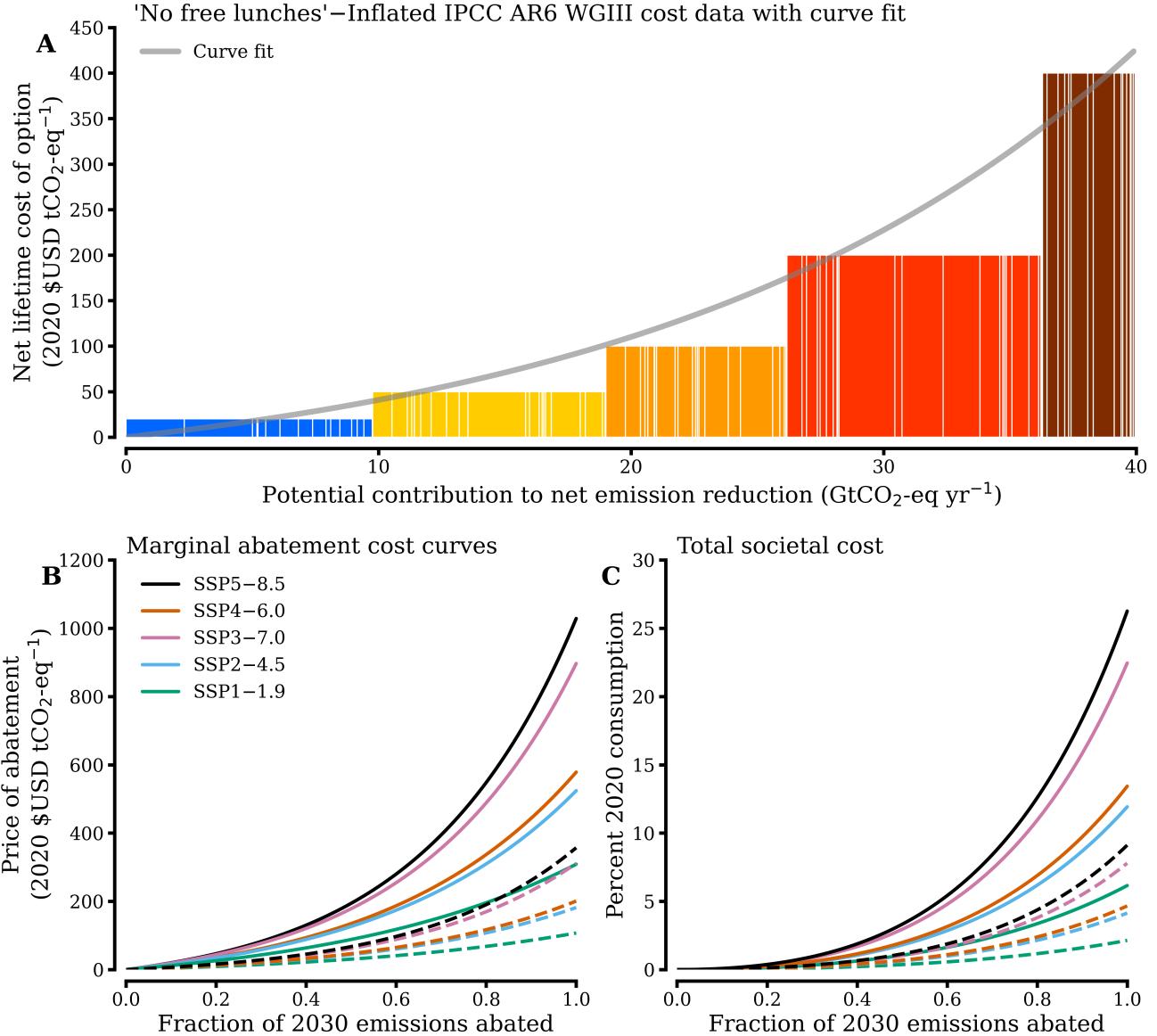
As a sensitivity test of our marginal abatement cost curve (MACC), we increased the cost of each mitigation option by one cost bracket, eliminating the zero-cost mitigation options (i.e., “free lunch” options) that the IPCC reports in their WGIII report. The resulting cost figure is in Figure 1.

**Table 2:** Fitted parameters for the damage function calibration equation (D.6) based on Burke et al. (2018), Dietz et al. (2021) and Intergovernmental Panel on Climate Change (2022).

Damage function	$\bar{\mathcal{D}}_1 [-]$	$\sigma_{\mathcal{D}_1} [-]$	$\Lambda$
Statistically estimated			
SSP1, mid-century	0.075	0.01	2.5
SSP2, mid-century	0.065	0.01	2.0
SSP3, mid-century	0.062	0.01	2.0
SSP4, mid-century	0.049	0.01	2.5
SSP5, mid-century	0.065	0.01	2.1
SSP1, end-of-century	0.2	0.04	0.87
SSP2, end-of-century	0.195	0.04	0.75
SSP3, end-of-century	0.19	0.04	0.69
SSP4, end-of-century	0.13	0.04	0.82
SSP5, end-of-century	0.155	0.04	0.82
Structurally estimated	0.027	0.01	2.8
Meta analysis of climate damages	0.063	0.022	3.3

**Table 3:** Fitted coefficients for (2.9), the cost of abating all emissions,  $\tau_a := \tau(x = 1)$ , and the percent of consumption required to abate all emissions,  $\kappa_a := \kappa_{MACC}(x = 1)$ , based on AR6 WGIII data for each SSP in our ‘main specification’ and our “no free lunches” alternative calibration. All dollar values are in 2020 \$USD.

SSP	$\xi$	$\tau_0 [\$/tCO_2\text{-eq}^{-1}]$	$\tau_a [\$/tCO_2\text{-eq}^{-1}]$	$\kappa_a [\%]$
<i>Main specification</i>				
1	1.9	27.5	153.88	3.0
2	2.4	27.5	264.09	5.9
3	2.9	27.5	457.57	11.3
4	2.5	27.5	292.15	6.69
5	3.0	27.5	526.58	13.2
<i>“No free lunches”</i>				
1	1.8	58.9	297.42	6.1
2	2.3	58.9	528.58	11.9
3	2.8	58.9	909.69	22.5
4	2.3	58.9	528.58	13.4
5	2.9	58.9	1011.56	26.3



**Figure 1:** Panel A shows the mitigation potential and cost for each methodology given by the IPCC using their WGIII data after adjusting for the “no free lunches” calibration. Blue bars represent the \$0–\$20 range, yellow is \$20–\$50, orange is \$50–\$100, red is \$100–\$200, and maroon is our new cost bracket \$400. Our curve fit is in grey. Panel B shows the fitted marginal abatement cost curves and panel C shows the total cost to society. In panels B–C, solid lines correspond to 2030, while dashed lines are cost curves in 2100, assuming an exogenous technological growth rate of 1.5% and no endogenous technological growth.

203 As another sensitivity test of our marginal abatement cost curve (MACC), we cut out the < \$0  
 204 abatement potential reported by the IPCC WGI data and fit a curve to the nonzero cost options.  
 205 The resulting cost figure is in Figure 2. Note that this marginal abatement cost curve (MACC) results  
 206 in costs that are lower than the “no free lunches” calibration. Hence, we do not present Climate Asset  
 207 Pricing model – AR6 runs with this cost curve specified, as the results will be simple interpolations  
 208 between the main specification results and the “no free lunches” results.

## 209 E.2 Limitations of our cost of abatement approach

210 A major qualification to our results regards two assumptions in our cost of CO<sub>2</sub> abatement parame-  
 211 terization. The first major assumption is that abatement technologies are essentially instantly able to  
 212 be deployed; we do not capture real-world inertia, represented in other energy systems IAMs, that cap  
 213 the rate of decarbonization owing to the delayed availability of abatement technologies, stranded as-  
 214 sets, limited construction times, and other factors (Ha-Duong et al., 1997; Richels and Blanford, 2008;  
 215 Vogt-Schilb et al., 2018). This limitation, however, is common in other IAMs such as DICE (Nordhaus,  
 216 2017) which have been widely used to study optimal climate-economic policy (Committee on Assessing  
 217 Approaches to Updating the Social Cost of Carbon et al., 2017). Secondly, our MACC assumes that  
 218 the sacrificed consumption to abate CO<sub>2</sub> emissions does not feedback on other aspects of the economy,  
 219 such as growth or productivity (Hogan and Jorgenson, 1991). Including a more sophisticated abate-  
 220 ment cost parameterization (i.e., through representing investments in abatement capital explicitly) or  
 221 the feedback of mitigation policy on growth would be an interesting direction for future work. These  
 222 limitations provide important context for our results.

## 223 E.3 Full derivation of total cost to society, Eqn. (2.10)

224 First, assume a representative agent optimizes consumption  $c(\tau)$  such that  $dc(\tau)/d\tau = -E(x(\tau)) =$   
 225  $-E(\tau)$ , where we have dropped the dependence of the emissions on mitigation action for clarity. Then  
 226 by simple integration the consumption is given by

$$c(\tau) = \bar{c} - \underbrace{\int_0^\tau E(\zeta)d\zeta}_{=:K(\tau)}, \quad (\text{E.1})$$

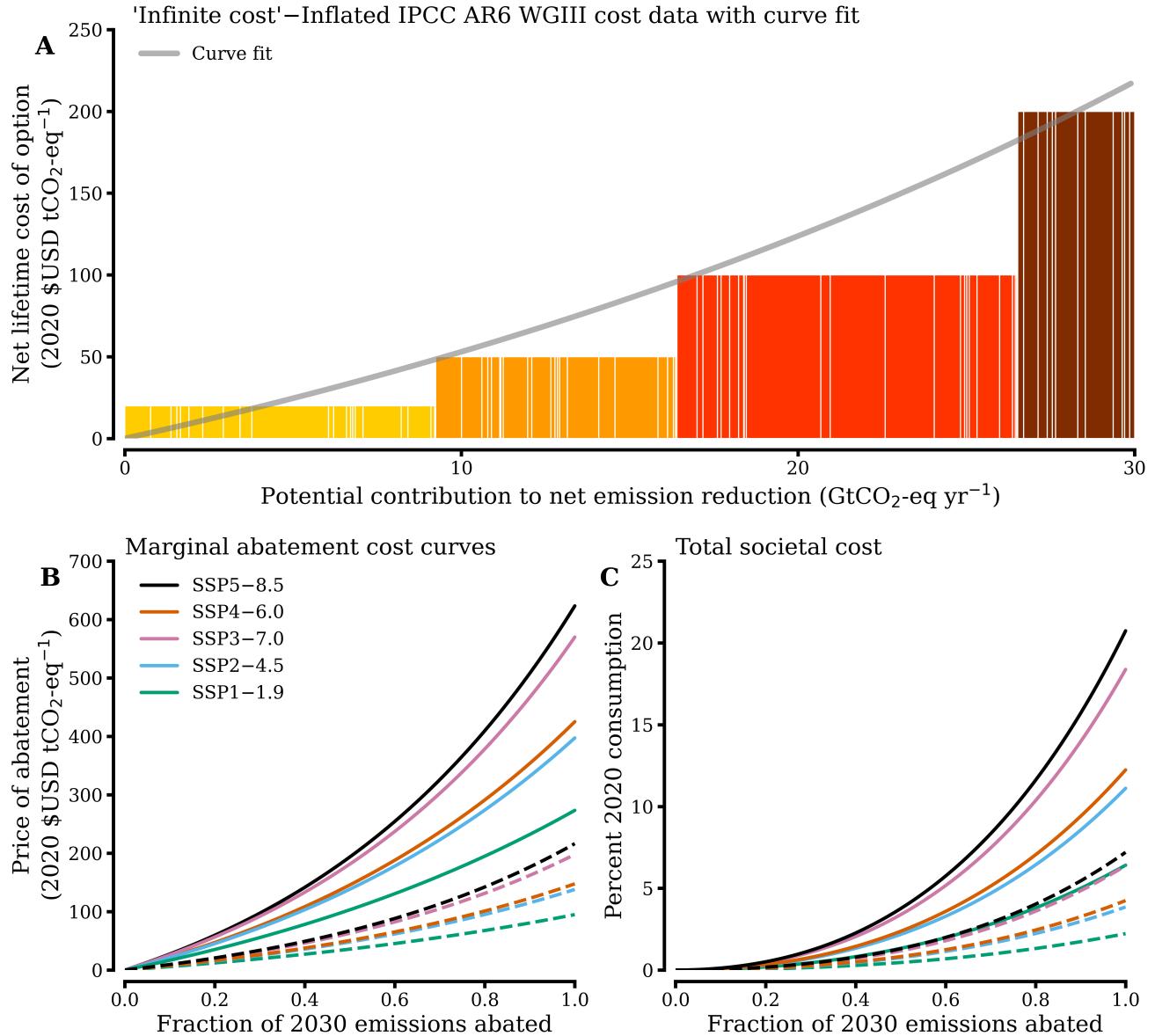
227 where  $\bar{c} > 0$  is the baseline endowed consumption and  $K(\tau)$  is the cost to society in monetary units  
 228 (i.e., dollars). Eqn. (E.1) would be correct if the government was to waste the entirety of the policy  
 229 proceeds, given by  $E(\tau)\tau$ . We instead assume that the proceeds are refunded in a lump sum (Mankiw  
 230 et al., 2009), thus requiring an alteration to  $K(\tau)$  such that

$$K(\tau) = \int_0^\tau E(\zeta)d\zeta - E(\tau)\tau. \quad (\text{E.2})$$

231 The lump sum refund does not allow for CO<sub>2</sub> tax proceeds to be used to decrease distortionary taxes  
 232 unrelated to CO<sub>2</sub> emissions; this would lower the *net* cost of CO<sub>2</sub> even further (Goulder, 1995; Jorgen-  
 233 son, 2013). Rewriting the emissions as  $E(\tau) = E_0(1 - x(\tau))$  where  $E_0$  is the (SSP-dependent) 2030  
 234 emissions in GtCO<sub>2</sub> yr<sup>-1</sup>, we have

$$K(\tau) = E_0 \left( \tau x(\tau) - \int_0^\tau x(\zeta)d\zeta \right). \quad (\text{E.3})$$

235 Note that  $E_0$  is the 2030 emissions for consistency with the cost data presented by WGI. Now  
 236 using (2.9) and its inverse in (E.3), carrying out the integral, and dividing by 2020 consumption results



**Figure 2:** Panel A shows the mitigation potential and cost for each methodology given by the IPCC using their WGIII data after adjusting for the “infinite cost” calibration. Yellow bars are the \$0-\$20 range, orange is \$20-\$50, red is \$50-\$100, and maroon is \$100-\$200. Our curve fit is in grey. Panel B shows the fitted marginal abatement cost curves and Panel C shows the total cost to society. In panels B–C, solid lines correspond to 2030, while dashed lines are cost curves in 2100, assuming an exogenous technological growth rate of 1.5% and no endogenous technological growth.

**Table 4:** Values of fitting coefficients  $a_i$  and timescales  $\tau_i$  used in (F.2) (taken from Joos et al. (2013)), as well as the best estimate and standard deviation of TCRE (taken from Intergovernmental Panel on Climate Change (2021) and Damon Matthews et al. (2021)).

Fitting Coefficient		Timescale [years]	
$a_0$	0.2173	$\tau_1$	394.4
$a_1$	0.2240	$\tau_2$	36.54
$a_2$	0.2824	$\tau_3$	4.304
$a_3$	0.2763		
TCRE Parameters			
$\bar{\lambda} = 0.45 \text{ } ^\circ\text{C (1000 GtCO}_2)^{-1}$		$\sigma_\lambda = 0.18 \text{ } ^\circ\text{C (1000 GtCO}_2)^{-1}$	
$\bar{f}_{nc} = 0.14$		$\sigma_{f_{nc}} = 0.11$	
$\bar{\lambda}_{eff} = 0.52 \text{ } ^\circ\text{C (1000 GtCO}_2)^{-1}$		$\sigma_{\lambda_{eff}} = 0.21 \text{ } ^\circ\text{C (1000 GtCO}_2)^{-1}$	

237 in the total cost to society in terms of fractional 2020 consumption loss, given by  $\kappa_{MACC}(x)$ , as

$$\kappa_{MACC}(x) = \frac{E_0 \tau_0}{c_{2020}} \left( \frac{e^{\xi x} - 1}{\xi} - x \right), \quad (\text{E.4})$$

238 where  $c_{2020}$  is the 2020 global consumption in billions of 2020 \$USD. This completes our derivation.

## 239 F Supplementary discussion: climate model

240 In Table 5 we compare the average warming levels using our effective TCRE approach and the weighted  
241 model averages presented by the IPCC in AR6.

### 242 F.1 Carbon cycle model

243 For a given emission time series the corresponding CO<sub>2</sub> concentration time series can be found by  
244 convolving emissions with the impulse response function (IRF) of a pulse of CO<sub>2</sub> emissions, denoted  
245 as  $\mathcal{I}(t)$ , such that

$$\mathcal{C}_E(t) = E(t) * \mathcal{I}(t). \quad (\text{F.1})$$

246 In Joos et al. (2013), it is shown that the IRF for a pulse of CO<sub>2</sub> can be sufficiently represented by a  
247 superposition of exponentials, given by

$$\mathcal{I}(t) := a_0 + a_1 e^{-t/\tau_1} + a_2 e^{-t/\tau_2} + a_3 e^{-t/\tau_3}. \quad (\text{F.2})$$

248 See Table 4 for the numerical values of the fitting coefficients  $a_i$  and timescales  $\tau_i$  in (F.2).

249 The final component of the concentration time series accounts for pre-2020 CO<sub>2</sub> that is present in the  
250 atmosphere when an agent begins emitting. This ensures that our carbon cycle model not only acts to  
251 take new CO<sub>2</sub> out of the atmosphere, but continues to remove CO<sub>2</sub> from past emissions. To account  
252 for this extra CO<sub>2</sub> in the atmosphere, we make the assumption that the majority of CO<sub>2</sub> before 2020  
253 is old, such that the time it has been in the atmosphere is much greater than  $\tau_2$ . This implies that

**Table 5:** Shown are the central estimate and the 5%-95% range of warming levels in three time periods, for three emissions baselines, using our effective TCRE approach and what is reported by the IPCC in their Table 4.5.

Time period	Effective TCRE range ( $^{\circ}\text{C}$ )	AR6 range ( $^{\circ}\text{C}$ )
SSP2–4.5		
Near-term: 2021–2040	1.5 (1.3 to 1.6)	1.5 (1.2 to 1.8)
Mid-term: 2041–2060	1.9 (1.5 to 2.4)	2.0 (1.6 to 2.5)
Long-term: 2081–2100	2.6 (1.7 to 3.5)	2.7 (2.1 to 3.5)
SSP3–7.0		
Near-term: 2021–2040	1.5 (1.3 to 1.7)	1.5 (1.2 to 1.8)
Mid-term: 2041–2060	2.1 (1.6 to 2.7)	2.1 (1.7 to 2.6)
Long-term: 2081–2100	3.6 (2.1 to 5.1)	3.6 (2.8 to 4.6)
SSP5–8.5		
Near-term: 2021–2040	1.5 (1.3 to 1.7)	1.6 (1.3 to 1.9)
Mid-term: 2041–2060	2.3 (1.6 to 2.9)	2.4 (1.9 to 3.0)
Long-term: 2081–2100	4.6 (2.4 to 6.8)	4.4 (3.3 to 5.7)

254 there is a constant fraction that remains, and a piece that is still decaying. Hence, the remaining CO<sub>2</sub>  
 255 in the atmosphere is given by

$$\mathcal{C}_{\text{pre}-2020}(t) = \mathcal{C}_{2020} \left( \frac{a_0 + a_1 e^{-t/\tau_1}}{a_0 + a_1} \right), \quad (\text{F.3})$$

256 where  $\mathcal{C}_{2020} = 420.87$  ppm.<sup>1</sup> Therefore, we can write the total carbon concentrations time series for a  
 257 given individual as

$$\mathcal{C}(t) = \mathcal{C}_{2020} \left( \frac{a_0 + a_1 e^{-t/\tau_1}}{a_0 + a_1} \right) + E(t) * \mathcal{I}(t). \quad (\text{F.4})$$

258 We note that (F.4) is used only to compute carbon concentrations as a result of optimal policy in  
 259 Figures 5–8; we do not utilize carbon concentrations in our optimization routine, as our temperature  
 260 parameterization relies on cumulative emissions only.

## 261 G Supplementary discussion: discount rate calibration

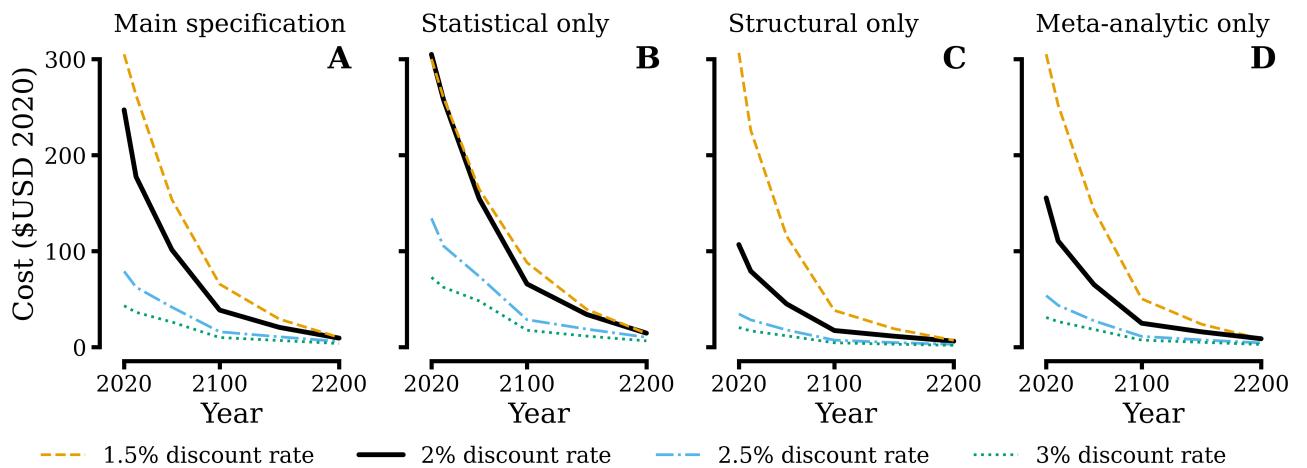
262 In Table 6 we show the term structures of the discount rates used in our featured runs. In Table 7 we  
 263 show the ranges of parameters that are sampled in our ensemble runs.

**Table 6:** Term structures for each discount rate in featured CAP6 runs.

Discount rate [%]	$\delta$ [%]	$\eta$
1.5	0.1	0.93
2	0.2	1.20
2.5	0.5	1.42
3	0.8	1.53

**Table 7:** Ranges of values for each model parameter sampled in the ensemble runs.

Parameter	Symbol	Range
Risk aversion	$\psi$	3 – 15
Elasticity of intertemporal substitution	$\sigma$	0.55 – 1.08
Pure rate of time preference	$\delta$	0.1% – 1.47%
Exogenous rate of technological growth	$\varphi_0$	0% – 3%
Endogenous rate of technological growth	$\varphi_1$	0% – 3%



**Figure 3:** Price paths for each damage function. All damage functions are sampled in panel A.

264 **H Isolating individual damage functions**

265 We isolate the influence of each damage function on carbon price paths in Figure 3 by isolating a single  
266 damage function and re-running our featured model runs. For comparison, we also provide our featured  
267 runs in panel 3A. Beginning with the statistically estimated damage function, we find that prices are  
268 higher in the near term in comparison to the other damage functions, with the exception of the 1.5%  
269 discount rate run. By comparison, running CAP6 with a convex damage function (i.e., the structural  
270 and meta-analytic damage functions) results in lower prices in the near term, with the exception of the  
271 1.5% discount rate runs. This shows that for sufficiently low discount rates, individual preferences can  
272 supercede the specifics of model components in ‘optimal’ policy considerations.

273 **I Regression analysis**

274 Regression coefficients in Figure 8 are calculated by fitting a linear regression between each parameter  
275 value and carbon costs. The one exception is technological growth, which is time dependent and given  
276 by

$$\varphi := \varphi_0 + \varphi_1 X_t. \quad (\text{I.1})$$

277 In 2100 and later, technological change is nonlinearly related to carbon costs. We therefore fit a  
278 quadratic to carbon costs as a function of total technological growth from 2100 on. Figures 4, 5, 6,  
279 and 7 show the intermediate step in computing the results shown in Figure 8.

280 **J Impact of Epstein-Zin risk aversion on prices**

281 Shown in Figure 8 is the influence of changing the Epstein-Zin risk aversion parameter,  $\psi$ , on CO<sub>2</sub>  
282 prices. Increasing (decreasing, resp.)  $\psi$  causes an increase (decrease, resp.) in the optimal carbon tax,  
283 consistent with other studies (e.g., Cai and Lontzek, 2019).

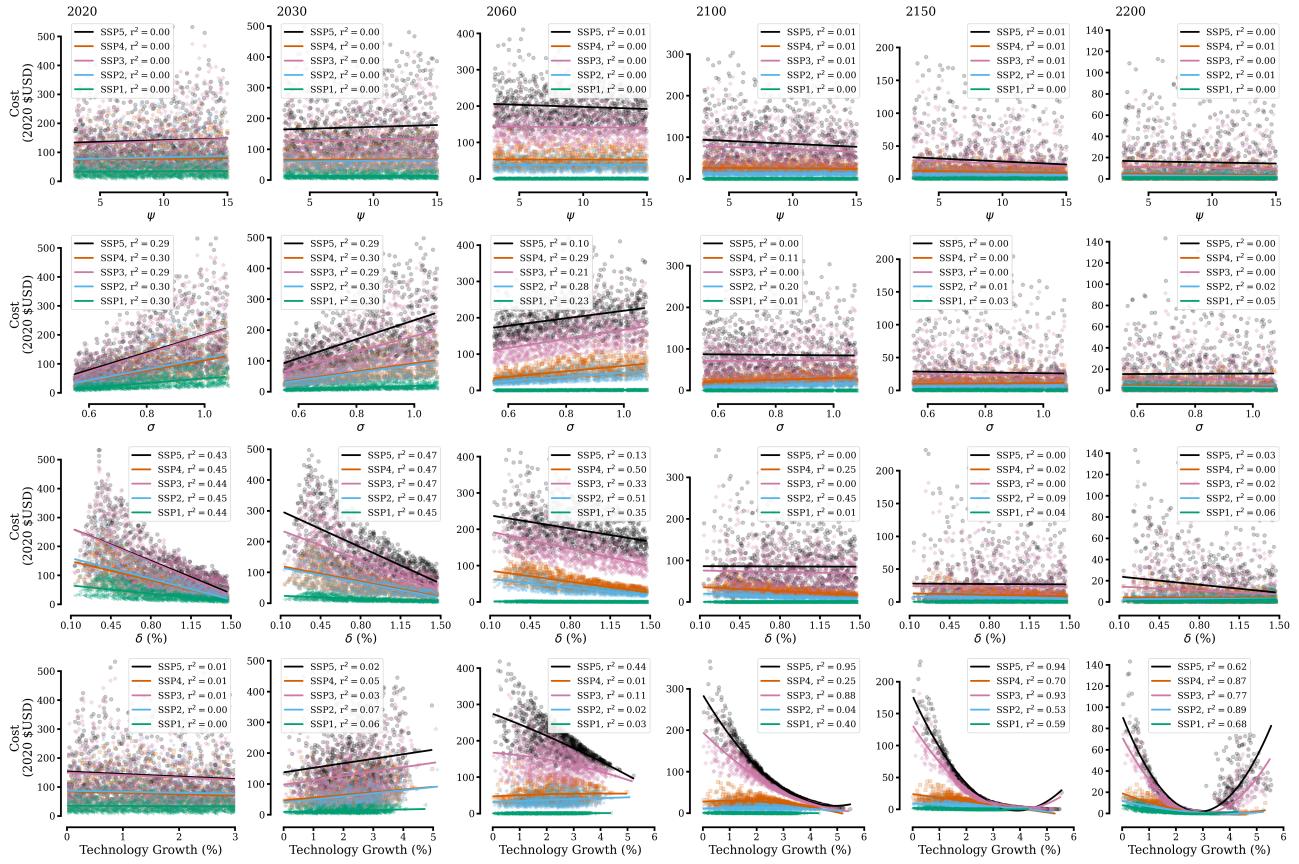
284 **K Including learning by doing**

285 We run CAP6 with learning by doing (LbD) included for both our main specification and “no free  
286 lunches” MACC in Figure 9. Note we use a 2% discount rate for each curve in Figure 9,  $\varphi_1 = 1.5\%$   
287 when LbD is enabled, and all other calibration parameters are the same as in our ‘main specification’  
288 runs above. We find that including LbD causes a relatively minor change in the the present-day carbon  
289 price for both MACC, and lowers the overall cost burden of the optimal abatement policy (i.e., the  
290 integrated cost over time). This is owed to prices declining faster as consumption is spent on mitigation,  
291 thus enabling more abatement in the near-term for cheaper costs. Furthermore, enabling LbD lowers  
292 the expected optimal warming by  $\sim 0.05$  °C in 2100 for both MACCs. For the ‘main specification’  
293 MACC, warming in 2200 is lower by  $\sim 0.1$  °C, whereas for the “no free lunches” MACC 2200 warming  
294 is lower by  $\sim 0.12$  °C.

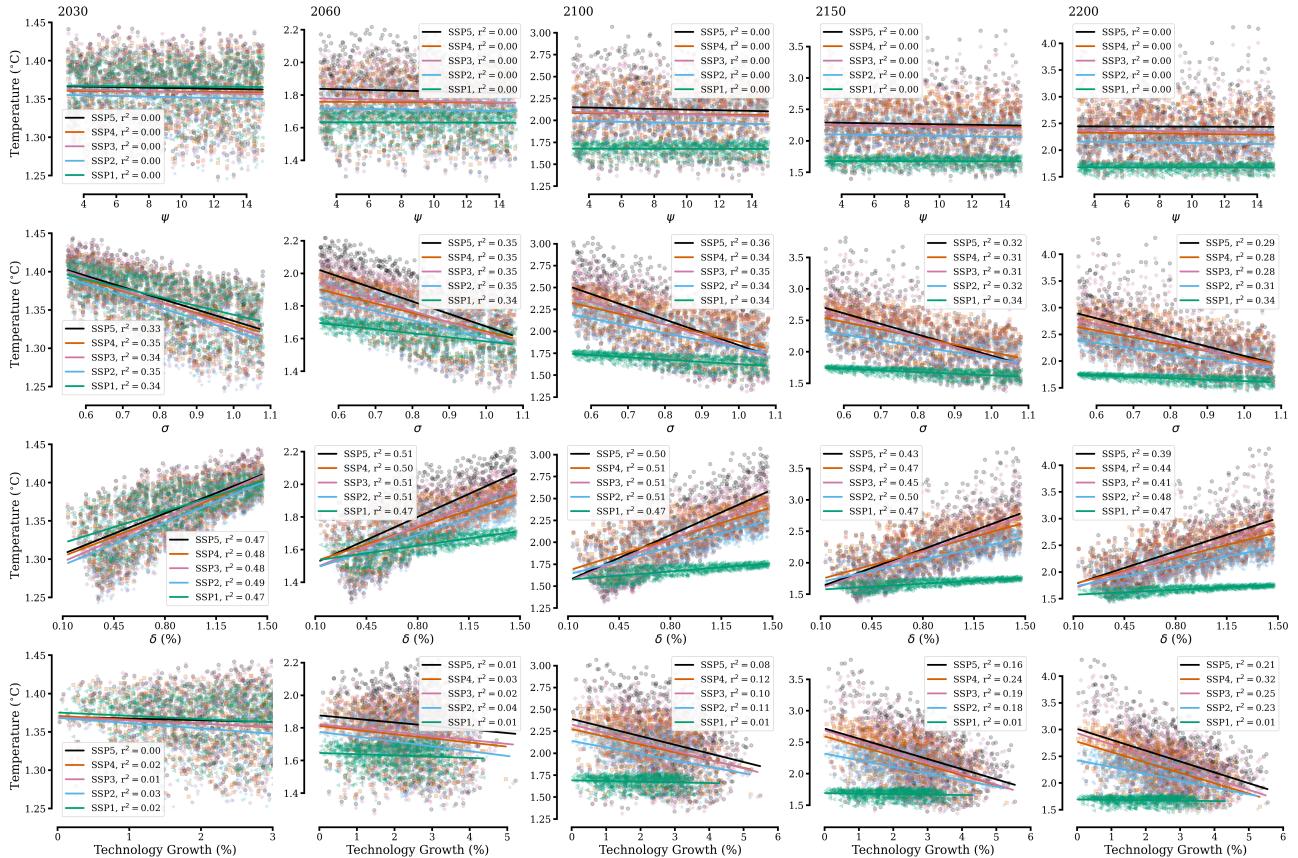
295 A notable result from this exercise is that by including LbD effects, the 2% discount rate policy  
296 with our ‘main specification’ cost curve stays below the 1.5 °C warming target in 2200; recall this  
297 threshold was exceeded when LbD was excluded. Hence, we can expect that the feasibility of reaching  
298 the warming targets set forth in Paris are highly sensitive to such outcomes; given that the rate of  
299 endogenous technological change is difficult to empirically ground, this represents a significant source  
300 of uncertainty in policy projections and a target for future research.

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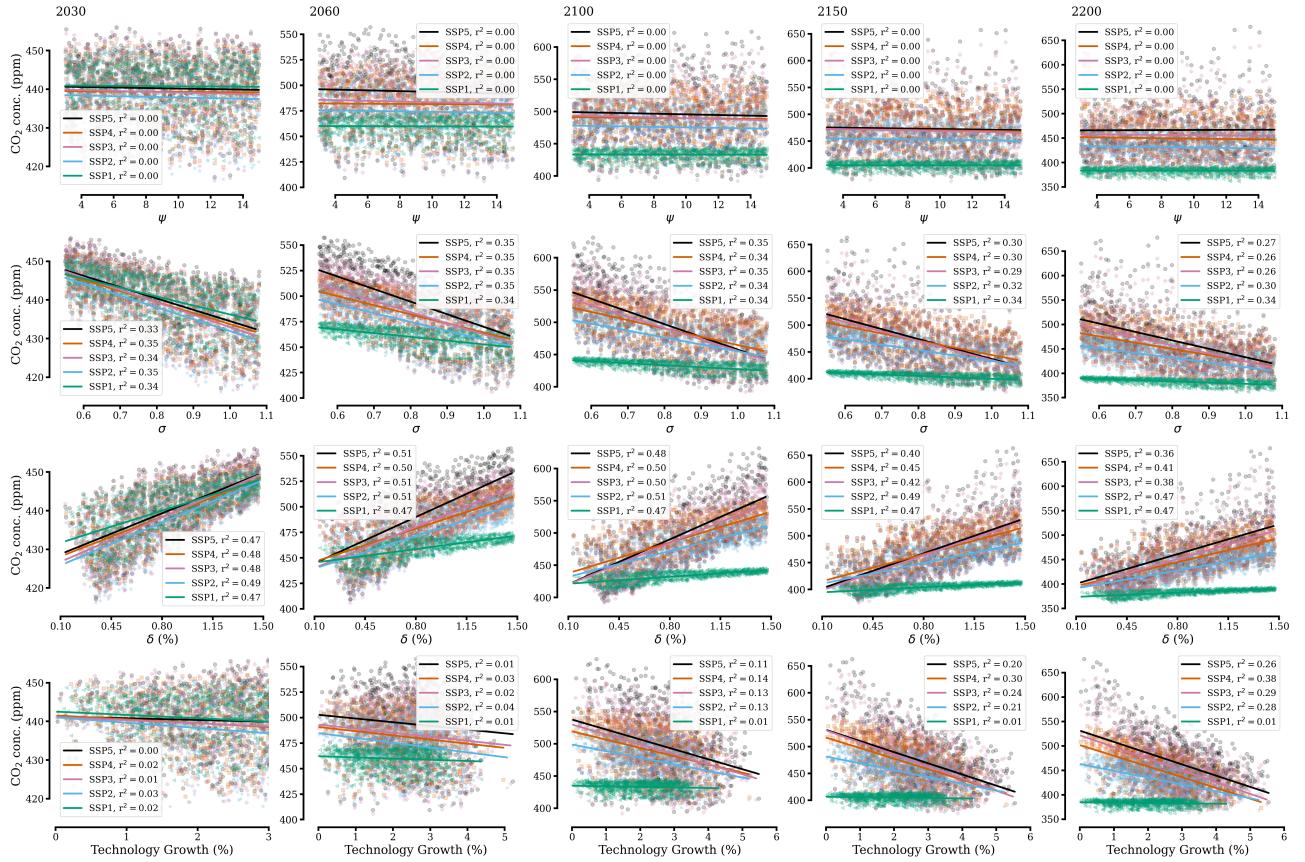
<sup>1</sup>Taken from <https://keelingcurve.ucsd.edu/>



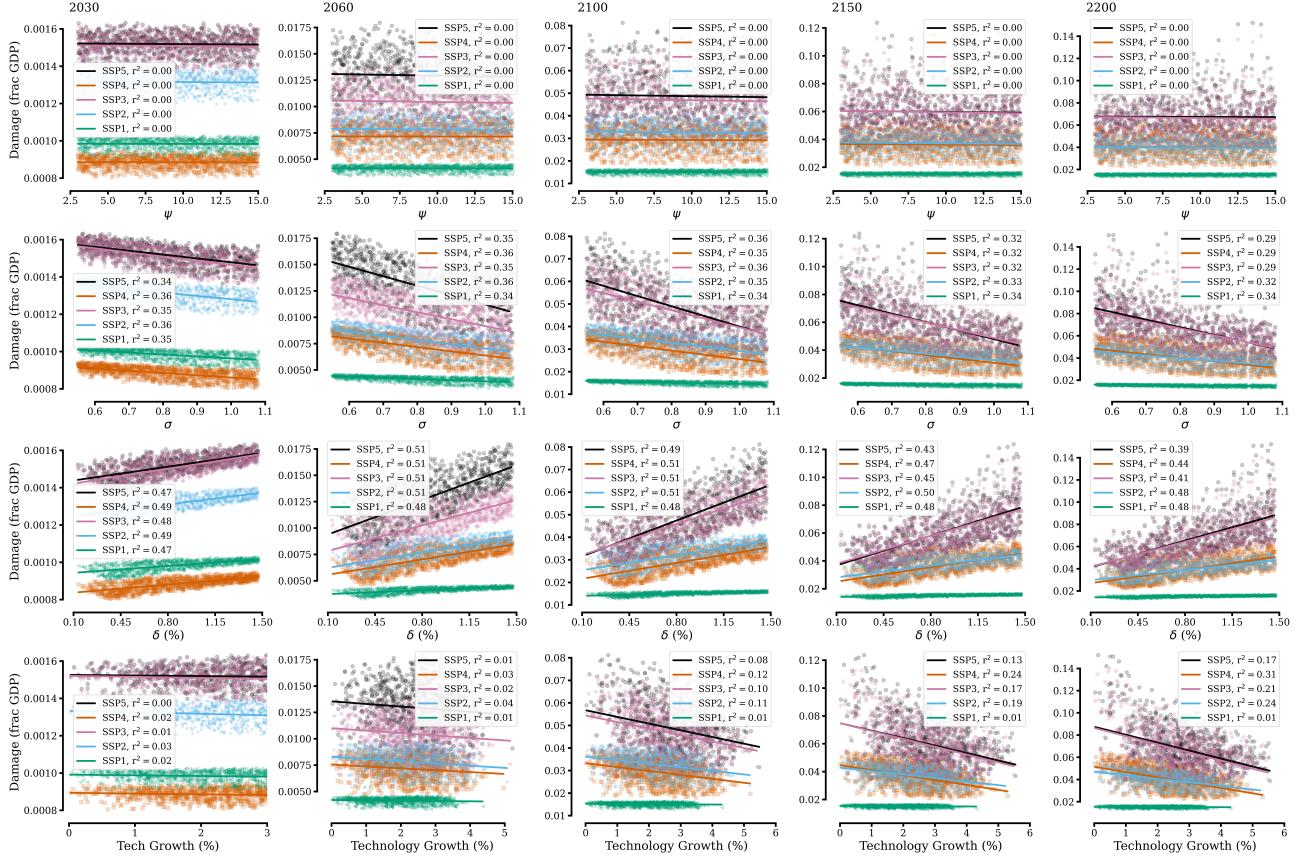
**Figure 4:** In each row, we plot the regression of each parameter against carbon costs in that period.  $r^2$  values are given for each regression in the legend of each panel.



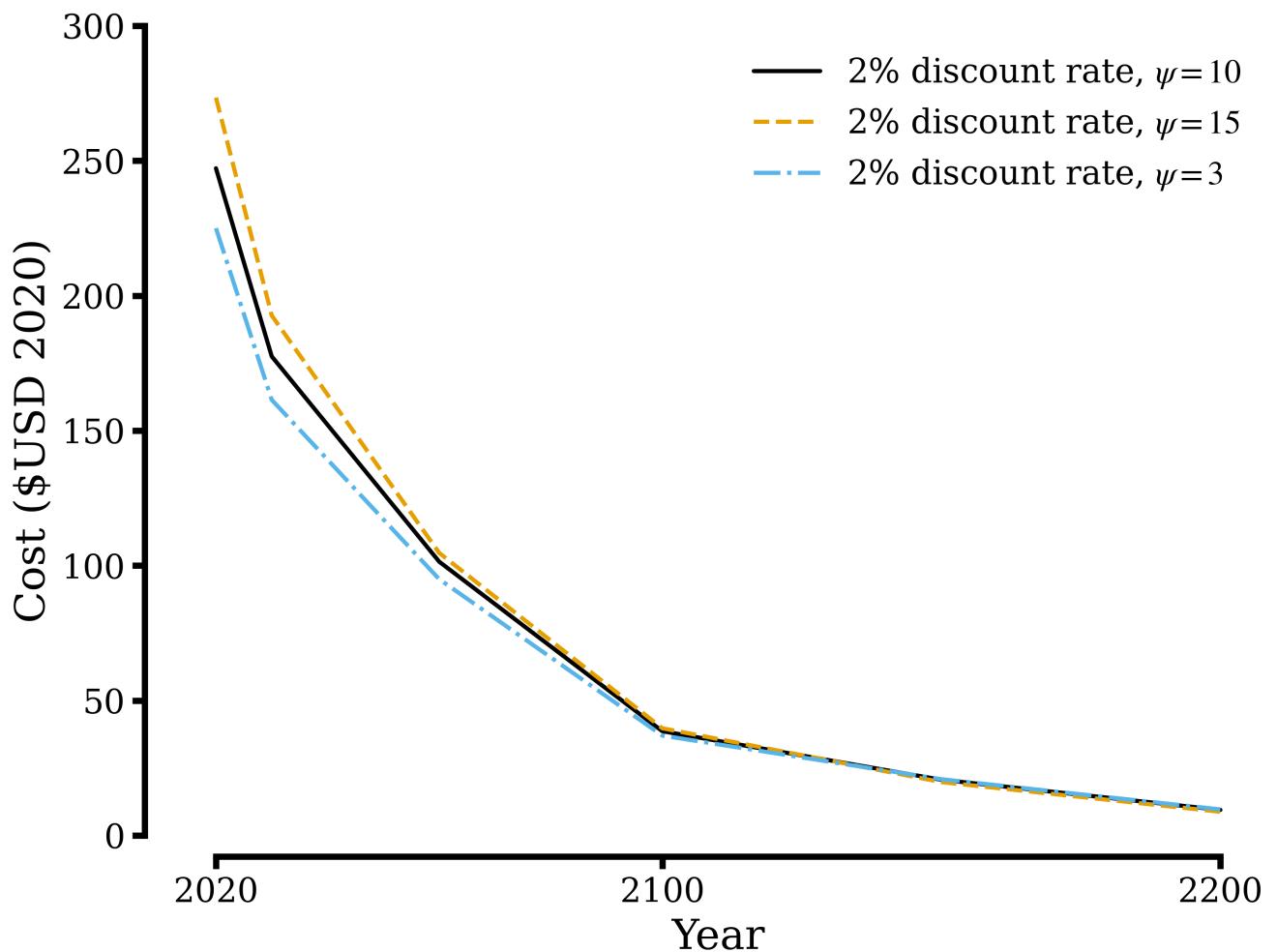
**Figure 5:** In each row, we plot the regression of each parameter against temperature in that period.  $r^2$  values are given for each regression in the legend of each panel.



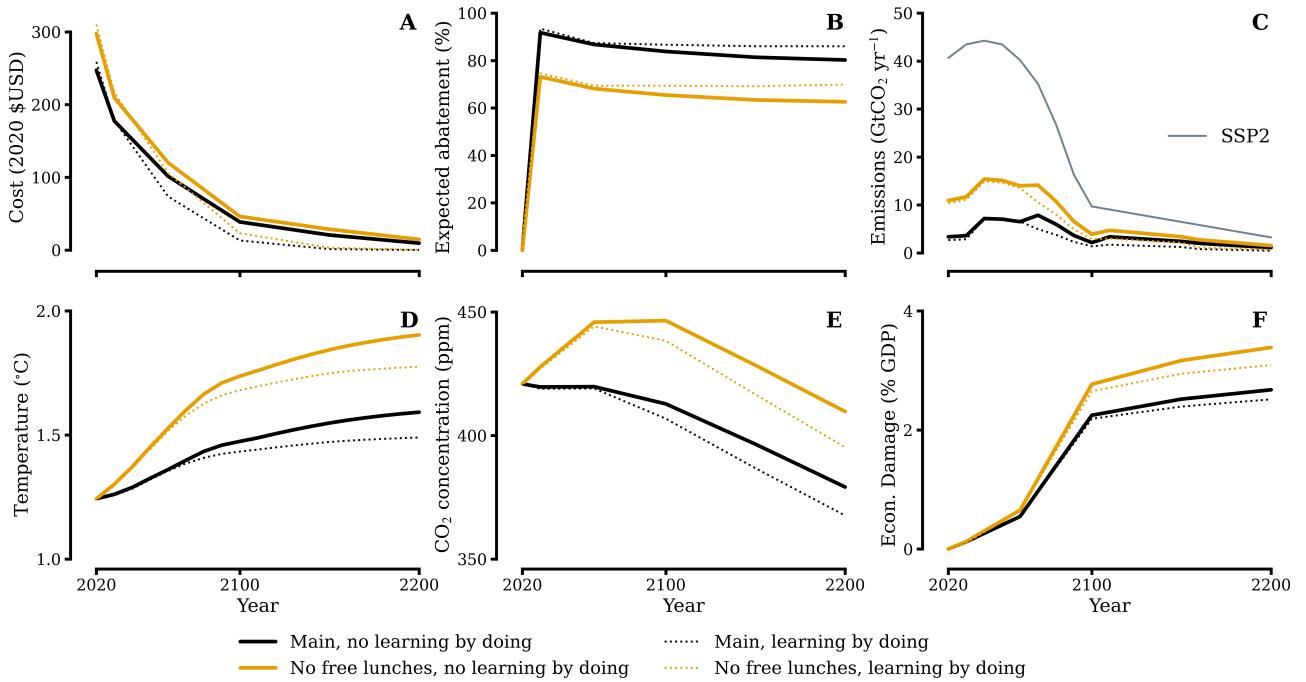
**Figure 6:** In each row, we plot the regression of each parameter against  $\text{CO}_2$  concentrations in that period.  $r^2$  values are given for each regression in the legend of each panel.



**Figure 7:** In each row, we plot the regression of each parameter against economic damages in that period.  $r^2$  values are given for each regression in the legend of each panel.



**Figure 8:** Shown is the resulting price path for different choices of risk aversion, holding all other model inputs constant in our preferred calibration.



**Figure 9:** We show model output using our preferred 2% discount rate and toggling which MACC we use ('main' or "no free lunches") with or without learning by doing.

*Note: Learning by doing implies that  $\varphi_1 = 1.5\%$ ; no learning by doing corresponds to  $\varphi_1 = 0\%$ . All other parameters are the same as in our main specification.*

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