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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.

Keywords Climate risk · Climate policy · Asset pricing · Cost of carbon

1 Introduction

Climate change's impact on the economy first gained prominence in the economics literature some 30 years ago, when the first climate-economic Integrated Assessment Model (IAM) calculated the cost of a marginal ton of carbon dioxide (CO_2) emissions to society, coined the 'Social Cost of Carbon' (SCC) (Nordhaus 1992). IAMs have since taken center stage in climate policy discussions, with the resulting SCC estimates being utilized as benchmarks by companies and governments worldwide (World Bank 2021). To date the most prominent IAM by far – the dynamic integrated climate-economy, or DICE – evaluates climate change impacts within the context of a standard Ramsey growth economy (Nordhaus 2017; Barrage and Nordhaus 2023). In this approach, a global social planner considers tradeoffs between emitting CO_2 and incurring damages both now and, largely, in the future, versus abating CO_2 emissions now at some cost. Performing a benefit-cost analysis results in a presently-low and

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rising optimal SCC over time, with significant global average warming by 2100. Recent efforts have yielded comparatively higher SCC estimates; Rennert et al. (2022), for example, calculates a central SCC of $185 but did not explore the optimal control problem of weighing the benefits and costs of abating CO_2 emissions.[1] It is notable that DICE's optimal warming projections are significantly larger than each warming target – 1.5 °C and 2 °C by 2100 – established in the 2015 Paris Agreement. While this inconsistency has called into question the authority of such models in the climate policy discussion to some (Pindyck 2013; Stern 2013), DICE has been made consistent with a warming target of 1.5 °C with alternative, updated damages and discount rate modules (Hänsel et al. 2020).

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

To address this, there have been considerable advances in climate-economic modeling that include the effects of risk and uncertainty on the SCC and on optimal policy responses to climate change; see Lemoine and Rudik (2017) for a comprehensive review, while Cai and Lontzek (2019) and Lemoine (2021) represent seminal works for including climate-related risk in IAMs.[2] We contribute to this extensive literature by introducing the carbon asset pricing model AR6 (CAP6), a climate-economy IAM that builds on previous financial asset pricing climate-economy models (Daniel et al. 2016, 2019). Our paper makes three primary contributions. The first is along methodological lines: we distill each working group report in the sixth assessment report (AR6) issued by the Intergovernmental Panel on Climate Change (IPCC) (Intergovernmental Panel on Climate Change 2021, 2022a, b) into workable IAM components.[3] This allows our model to be up-to-date with the state-of-the-art calibrations for critical model components. Notably, we formulate a new marginal abatement cost curve (MACC) based on AR6 data, providing an update to the well-known McKinsey & Company (2013) MACC.

The second contribution is a computation of optimal carbon prices and associated mitigation policy. Following Daniel et al. (2016, 2019), we embed a representative agent in a binomial, path-dependent tree that allows for risk assessment to endogenously evolve over time. The agent maximizes the Epstein-Zin-Weil utility (Epstein and Zin 1989; Weil 1990; Epstein and Zin 1991) at every node in the tree such that the present-day utility is maximized. Agent discount rates are calibrated to be in-line with a recent expert elicitation (Drupp et al. 2018) and the U.S. Environmental Protection Agency (EPA) latest estimates

[1] 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).

[2] We provide a more thorough literature review in Online Appendix A.

[3] 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.

for the SCC (National Center for Energy Economics 2022). Notably, we find that the optimal expected warming in our EPA-consistent calibrations is in line with the 2100 warming targets established in the Paris agreement. We find that even if we were pessimistic about the cost of mitigation estimates provided by the IPCC, the EPA-consistent calibration of CAP6 would still support limiting warming to less than 2 °C by 2100, with a discount rate of 2% or lower.[4]

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

Our final contribution is a sensitivity analysis that allows us to identify how each exogenous assumption drives model output. We show that while the expected carbon price depends on the emissions baseline, the expected temperature rise, level of CO_2 concentrations, and incurred economic damages does not. This suggests that our model robustly calculates an economically optimal temperature level for a given calibration; the price of actualizing this temperature level varies across baselines, owing to assumptions about how much emissions are decreasing independently of the policy implemented in CAP6. We find that price uncertainty is dominated by discounting in the near-term and the technological growth rate in the far-term. On the other hand, temperature rise, CO_2 concentration level, and economic damage uncertainty is dominated by discounting for much longer than CO_2 prices, as early inaction leads to warming that cannot be undone later by spending more on abatement (in the absence of significant net-negative emissions or solar geoengineering).

We proceed by presenting the socio-economic setup of CAP6 in Section 2, the climate emulator in Section 3, and our calibration in Section 4. We discuss our results in Section 5; Section 6 concludes. (For Section 2, we provide a brief summary paragraph with key equations and figures for readers who wish to skip the full technical description of our model components.)

2 Socio-economic framework

We consider a representative agent with Epstein-Weil-Zin utility given by Eq. 2.1, and embed this individual in a binomial tree structure where their utility is maximized. CO_2 emissions (without any agent mitigation action) follow the shared socio-economic projections used by the IPCC (Fig. 2). Climate damage functions are calibrated to IPCC working group (WG) II data (see Fig. 3) and our uncertainty parameterization captures both epistemic and parametric uncertainty in the damage functions. Finally, we employ Eq. 2.12 as our marginal abatement cost curve (Fig. 4) and provide two calibrations: our ‘main specification’ based solely on the data in AR6, and the ‘no free lunches’ calibration, which excludes negative costs in the AR6 data.

[4] 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).

2.1 Economic utility

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

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

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

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

Note that, in the EZ framework, risk aversion across time is parameterized by σ, whereas risk aversion across states of nature is parameterized by ψ.

2.1.1 Tree structure

Following Daniel et al. (2016, 2019), agent utility in CAP6 is optimized within the structure of a binomial tree, therefore embedding the representative agent in a *finite horizon probability landscape*. This follows a standard approach employed in financial economics (Cox et al. 1979), and one useful to solve EZ-style models numerically (Epstein and Zin 1991).

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

This structure allows for agent risk assessment to evolve endogenously; as an example, consider two agents, one in 2150 and one in 2030 (see Fig. 1). The agent in 2150 has only two future states accessible to them from their position in the tree; this represents an individual who knows well the impact of the climate on the economy. The agent in 2030 has

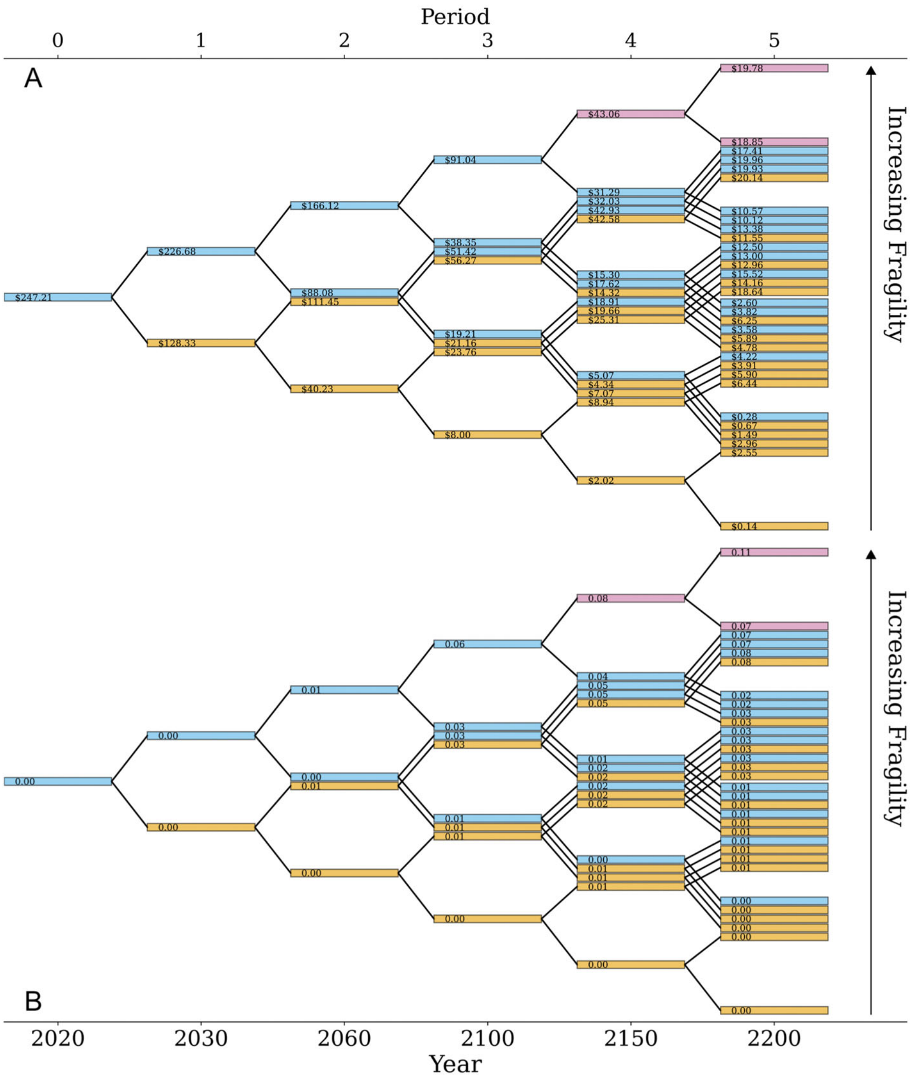

Fig. 1 Cost of CO_2 (panel A) and agent experienced climate damages (panel B) at each node (as a fraction of world GDP loss). In both panels, we highlight the accessible future states of two agents: one in 2150 (pink boxes) and one in 2030 (gold boxes). Note that values are taken from our 2% discount rate featured model run, main specification

a significantly higher number of future states accessible to them; they know less about how climate change impacts the economy, which influences their decision making, as they have to weigh several possible futures with high and low climate damages (or "fragility") all at once.

This approach has the advantage of being easily computationally tractable, while maintaining a structurally endogenous representation of risk and uncertainty resolution. Moreover, it allows for a transparent interpretation of model results and ample sensitivity analyses, which enables our variance decomposition results in Section 5.3.1. However, it does suffer from drawbacks: more modern (and computationally expensive and technically challenging) models are able to solve similar optimization problems in continuous-time, on infinite horizons, or both (Bretschger and Vinogradova 2014; Cai and Lontzek 2019; Van Den Bremer and Van Der Ploeg 2021). These considerations can matter for model results: for example, the time horizon used for climate policy models matters owing to the long residency time of CO_2 in the atmosphere. If one sets the time horizon of the model to 2200, then the net-benefits of a unit of CO_2 abatement in 2190 would matter less than one in 2020 because the benefits would not be given time to materialize. Nevertheless, a number of prominent IAMs used in climate policy consider finite horizons (perhaps most notably, the DICE model is solved on a finite horizon, see Nordhaus 2017; Barrage and Nordhaus 2023) and our model falls into this class. Moreover, our choice to truncate the time horizon at 2250 aligns with the time where we assume the world reaches net zero emissions without any additional policy in CAP6, which would make, from the policy perspective taken in our model, a carbon tax obsolete (see Fig. 2).

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

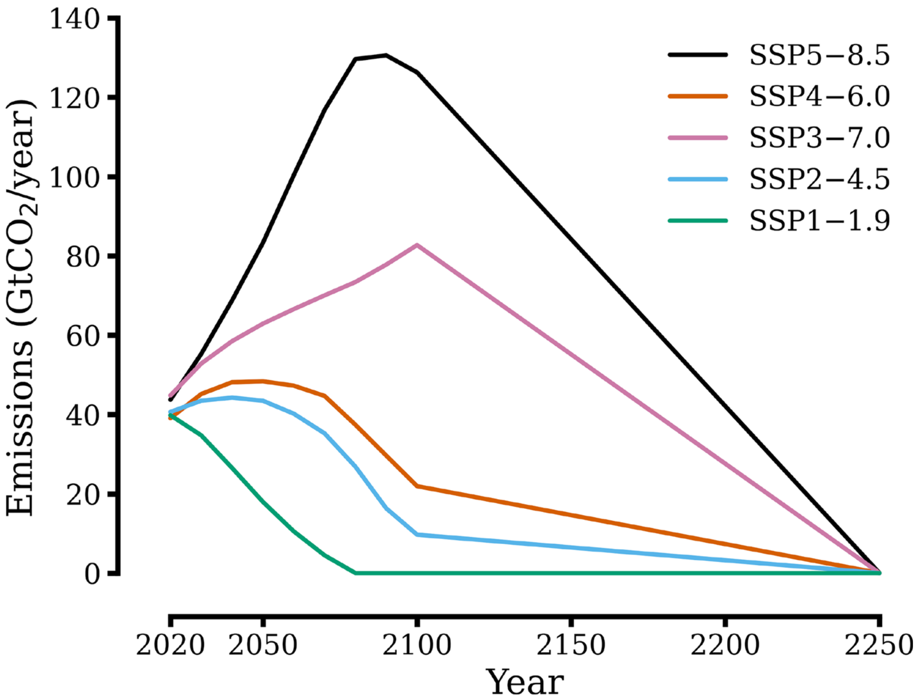

Fig. 2 Emissions baselines with their extensions to 2250

future climate by mitigating some fraction of emissions x_t with total cost κ_t. The consumption of the agent at each time $t \in \{0, 1, 2, ..., T\}$ is determined by

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

$$c_t = \bar{c}_t \left(1 - \kappa_t(x_t)\right)\left(1 - \mathcal{D}_t(\Psi_t, \theta_t)\right), \qquad \text{for } t \in \{1, 2, ..., T-1\}, \tag{2.4}$$

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

where Ψ_t is the cumulative CO_2 emissions. We choose $T = 6$ decision periods in all the calculations in that follow, with our initial and final year being 2020 and 2250, respectively.[5] The net discounted EZ-utility is then maximized to obtain the optimal carbon prices and mitigation policies in Section 5; see Online Appendix B for more details on our optimization.

2.2 Emission baselines

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

This concern motivates the second approach commonly used by the IPCC, which is to supply a given IAM with a stream of CO_2 emissions exogenously based on plausible future emissions scenarios. The shared socio-economic pathways (SSPs) shown in Fig. 2 are an example of this approach, where each baseline represents a "storyline" for future global and regional economic development based on the level of challenges faced by policymakers in mitigation and adaptation. For example, SSP5 is a fossil fuel-based development storyline, with high levels of challenge to mitigation (because of significant fossil fuel development) and low challenges to adaptation (because of expanded wealth). SSP1, on the other hand, is a more sustainable route, with low challenges to both mitigation (because of renewable energy expansion) and adaptation (because of equitable growth and investment in education and health). Combining these socio-economic settings with an energy system model produces the emissions projections seen in Fig. 2; see Riahi et al. (2017) for a complete review of the SSP storylines and specifics on the underlying assumptions. This approach has been employed by the US Government in their computations of the SCC (National Center for Energy Economics 2022)[6], and is our approach here. This implies that our optimal carbon taxes are always with reference to the emissions baseline we assume; we explore the influence of which emissions baseline we choose on our results in Section 5.3.

We take emissions data for each SSP at times 2020 – 2100 directly from the SSP database,[7] and select scenarios which span a range of end-of-century radiative forcing amounts. We make one alteration to the projections provided in the database: negative emissions are set to zero.[8] As our model extends out to 2250, we require extensions of the SSPs in the database; we

[5] 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).

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

[7] See https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10

[8] 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.

follow the prescription of Meinshausen et al. (2020) for each baseline, which assumes that (a) positive fossil fuel emissions and any net-negative fossil fuel emissions are ramped down to zero by 2250, (b) land use CO2 emissions are zero by 2150, (c) non-fossil fuel greenhouse gas emissions are ramped down by 2250, and (d) land use-related non-CO2 emissions are held constant after 2100. In reality, it is possible that in the absence of a well-designed policy suite that one or more of these assumptions could not hold, which would imply that we are underestimating potential emissions levels in the far-future, and thus long-term climate-economic risk; we explore the relative influence of which emissions baseline we choose in Section 5.3. See Fig. 2 for the results of our extension procedure.

2.3 Damage functions

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

2.3.1 Aggregate climate change damages

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

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

where $\varpi_1, \varpi_2 \in \mathbb{R}^+$ are fitted coefficients. We refer to each of these damage functions by their estimation methodology in what follows, i.e., "the statistical damage function" and so on. We supply the fitted coefficients and their uncertainty, as well as a discussion of the qualifications and the limitations of each individual damage function we use, in Online Appendix D. We present the data and fitted curves in Fig. 3 (ft. [9]).

2.3.2 Tipping point damages

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

[9] 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.

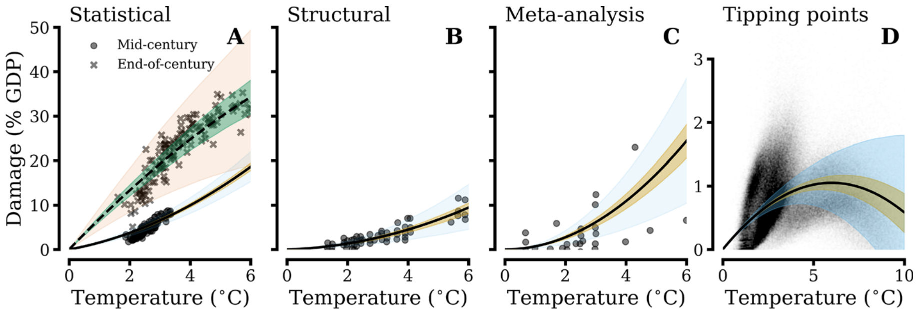

Fig. 3 Each of our damage functions by methodology (statistical, structural, and meta-analytic) as well as the marginal damages owing to tipping points. In each panel, yellow shows ± 1 standard deviation in the damage function, while the blue shaded region shows ± 2 standard deviations. For the end-of-century estimates in panel A, the green region shown ± 1 standard deviation and the salmon shows ± 2 standard deviations. The statistical damage function shown assumes SSP2–4.5

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

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

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

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

2.3.3 Sampling damage function uncertainty

We sample uncertainty in the damage function in two ways. The first is by sampling the parametric uncertainty in each damage function; that is, the uncertainty in the values of ϖ_1, ϖ_2 in Eq. 2.6. The distributions of ϖ_1, ϖ_2 are assumed Gaussian with mean and variance provided in Online Appendix D, Table 1. The second source of uncertainty in the damage function pertains to which damage function (i.e., statistical, structural, or meta-analytic) we specify in the first place. As the IPCC WGII makes no recommendations in this regard, we assign a hyper-parameter in our simulated climate damages that randomly chooses a damage function, thus sampling epistemic uncertainty in the damage function. This methodology allows us to remain agnostic with respect to which damage function we choose.

2.3.4 Calculating damages at a particular decision node

A representative agent in our model at a given decision node only knows the possible end states which can be accessed from their state. They do not know the exact fragility at their own node, or any θ_t for $t < T$, owing to the inherent uncertainty surrounding both the climate system (such as the precise value of climate sensitivity) and economic impacts (such as damage functions). Owing to the agent not knowing the current fragility, the damages assessed at their decision time are dependent on proxies for the relevant damage variables. The two proxies used in our model is the set of possible end states, Θ (which tells us which end states are accessible) and the cumulative CO_2 emissions, Ψ_t (which tells us approximately how warm the world should be, but does not immediately map to the temperature at time t owing to uncertainty in the climate sensitivity). These two variables in concert give us a basis from which we can interpolate end state climate damages backwards in time to any decision node. Moreover, a continually-updating fragility parameter allows the expectation of future damages to co-evolve with agent decisions about mitigation, therefore making risk assessment endogenous within our modeling structure. We calculate the damage at a given node as a probability-weighted average of the current-period damages accessible to each end node across states of fragility, such that

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

2.4 Cost of mitigation

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

2.4.1 Marginal abatement cost curve estimation

Estimating MACCs requires a functional relationship between the fraction of emissions abated, x, the per-ton tax rate, τ, and the emission pathway, E. We use the most recent estimates for the cost of CO_2 emission abatement presented in AR6 WGIII (Intergovernmental Panel on Climate Change 2022b) (see their Figure SPM.7, p. SPM-50). We make four important assumptions in interpreting the data from AR6 WGIII. First, we assume cost estimates are additive, which is not necessarily the case; however, we expect changes in costs and abatement potential to be small enough to consider them as negligible in this study. Second, we neglect negative costs; that is, whenever WGIII data dictates that costs are <\$0, we set the cost to zero. Third, for abatement potentials outside the range provided by the IPCC, we assume the functional relationship between τ and x established for lower abatement potentials holds. Lastly, we assume that the cost of each option is equal to its maximum cost in its respective range, i.e., the cost of an option in the IPCC \$0–\$20 range is assumed to be \$20. Taken together, these assumptions make our MACC estimation conservative. We then fit an

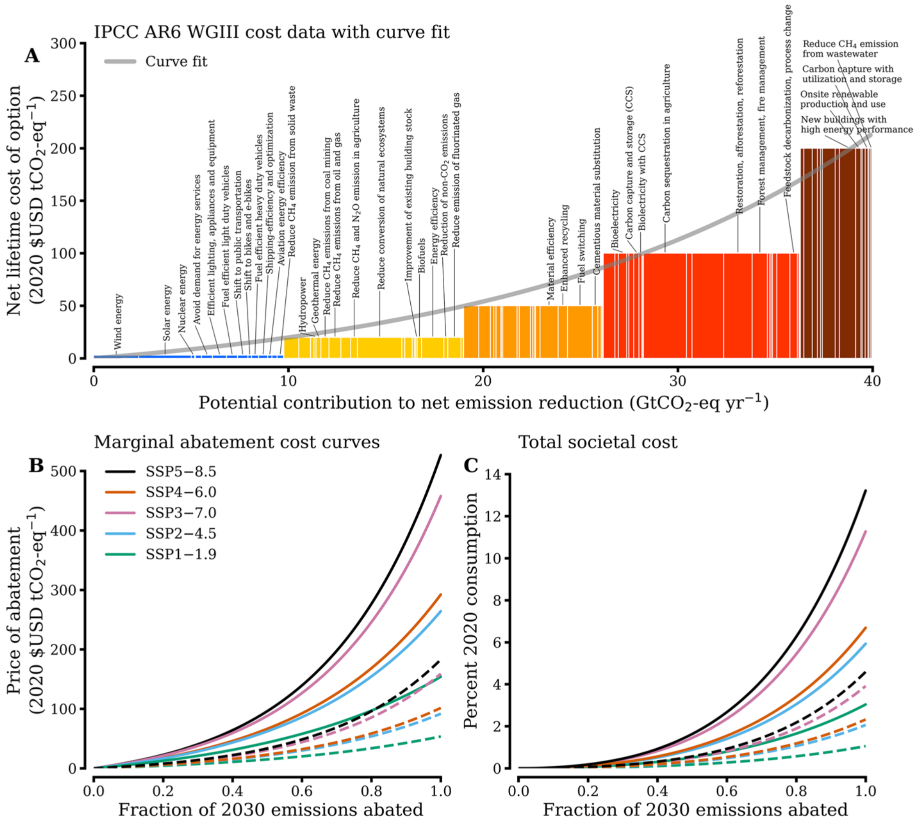

Fig. 4 Panel A shows the mitigation potential and cost for each methodology given by the IPCC using their WGIII data. Blue represents zero costs (listed as negative in AR6), yellow is \$0-\$20 range, orange is \$20-\$50, red is \$50-\$100, and maroon is \$100-\$200. Panel B shows the fitted marginal abatement cost curves given by Eq. 2.9 and panel C shows the total cost to society given by Eq. 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 that, in panel A, the abatement methodology label is only on the bar with the most mitigation potential for a given methodology

exponential curve to the cost data (see Fig. 4A), such that

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

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

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

where c_{2020} is the 2020 global consumption in billions of 2020 USD, set to \$61880 (taken from the World Bank[10]) and E_0 is the emissions rate in 2030 in $GtCO_2$ yr^{-1}. A table of fitted values for τ_0 and ξ for each SSP are provided in Table 3 in Online Appendix E, as well as a

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

calculation for the percent of consumption required to abate all emissions. Fits for Eqs. 2.9 and 2.10 are shown in Fig. 4B and 4C, respectively.

2.4.2 Direct air capture technology

Our model represents direct air capture (DAC) via permitting CO_2 removal (National Research Council 2015). Net CO_2 removal occurs whenever the mitigation exceeds unity; this leads to negative emissions and thus net carbon removal from the atmosphere. The price of net carbon removal is a major source of uncertainty in assessing future climate policy (Johnson et al. 2017), with estimates ranging from \$50 − \$1000 2020 USD per ton of CO_2 removed. Regardless of the specific dollar estimates provided in the literature, DAC faces a common hurdle: scalability (Intergovernmental Panel on Climate Change 2022b). The parameter x in our MACC is the fraction of 2030 emissions abated; therefore, removing even a small percentage of these emissions from the atmosphere is equivalent to abating billions of tons of CO_2 from the atmosphere in short order. The technology to carry out this task is simply unavailable at present, and it is unclear when it will become fully mature and available at scale.

Note that, before mitigation reaches unity, there is some carbon capture and storage that is assumed to be occurring concurrent with emissions reductions; indeed, by considering the technology-by-technology breakdown of the IPCC's WGIII cost data in Fig. 4A, carbon capture and storage is placed in the \$200 2020 USD $tCO_2\text{-eq}^{-1}$ cost bracket. Hence our inclusion of DAC in our MACC formulation represents an abrupt shift from purchasing various abatement technologies (such as solar power or equipment to retrofit buildings) to installing exclusively, and at scale, DAC facilities. The costs of this process are currently assumed to be rather large (International Energy Agency 2022). However, a breakthrough could certainly occur sometime in the future where DAC becomes deployable at scale for a more economically viable cost (for example, as a result of the uncapped subsidies in the Inflation Reduction Act of 2022 (Yarmuth 2022)), which would lower the price of DAC considerably and would require a reassessment of our quantitative analysis in Section 5.

In light of these considerations, we take a simple approach to adjusting our cost curve to account for DAC technologies by imposing a DAC premium, $\tau_{DAC} > 0$, which is an extra price for carbon removal which shifts τ_0 to $\tau_0 \to \tau_0 + \tau_{DAC}$. Throughout, we essentially price out to-scale DAC leading to net-negative emissions before 2100. This alters our MACC cost curve Eq. 2.10 when $x > 1$, such that

$$\kappa_{MACC}(x) = \begin{cases} \dfrac{E_0\tau_0}{c_{2020}}\left(\dfrac{e^{\xi x}-1}{\xi} - x\right), & 0 \leq x \leq 1, \\[2ex] \dfrac{E_0(\tau_0+\tau_{DAC})}{c_{2020}}\left(\dfrac{e^{\xi x}-1}{\xi} - x\right), & x > 1. \end{cases} \tag{2.11}$$

2.4.3 Technological progress

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

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

where

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

is the weighted average mitigation up to time t (ft. [11]).

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

2.4.4 "No free lunches" calibration

Estimating the cost of CO_2 abatement is notoriously challenging. The cost estimates presented above are static, in the sense that they represent the costs of the lifetime of the project and, for example, ignore spillover effects (Intergovernmental Panel on Climate Change 2022b). However, static estimates fail to capture the impact of the costs (or savings) associated with a given project that outlive the project lifetime itself (Gillingham and Stock 2018). Such considerations lead some to argue that costs should not be estimated from the "bottom up" as done here, but rather from the "top down." "Top down" estimates generally paint a more pessimistic picture than the "bottom up" methods, positing that the cost of abating CO_2 emissions is actually larger than adding up the cost of each individual option, owing to inertia and friction in the economic system, a set of barriers typically summarized as the "energy paradox" (Jaffe and Stavins 1994).

To address this concern, we provide an alternative calibration of CAP6 that is more closely aligned to "top-down" MACCs (see, e.g., Barrage and Nordhaus 2023) by adjusting the MACC to exclude zero-cost abatement technologies; indeed, it has been shown that the degree to which one believes in zero-cost mitigation explains much of the difference between "top-down" and "bottom-up" MACC estimates (Kotchen et al. 2023). We do so by shifting all of the mitigation potential in the IPCC dataset up by one cost bracket; for example, the zero cost methodologies (the blue bars in Fig. 4) now have \$20 2020 USD $tCO_2\text{-eq}^{-1}$ lifetime cost, and so on. The highest cost abatement technologies are set to cost \$400 2020 USD

[11] 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.

tCO_2-eq^{-1}. We coin this MACC calibration as the "no free lunches" MACC, and provide its parameter values in Online Appendix E, Table 3 (ft. [12]).

3 Climate model

Here we present the climate component of our model. We map CO_2 emissions to the temperature anomaly above preindustrial levels, denoted as T', using the transient climate response to emissions (TCRE) (Damon Matthews et al. 2021). The TCRE is defined as a linear scale factor $\lambda > 0$ that maps the cumulative CO_2 emissions, $\Psi(t) := \int_0^t E(\zeta)d\zeta$, to temperature, where $E(t)$ is the emissions baseline. The physical basis for TCRE is a compensation between the diminishing sensitivity of radiative forcing to CO_2 at higher atmospheric concentration and the diminishing ability of the ocean to take up heat and carbon at higher cumulative emissions (Intergovernmental Panel on Climate Change 2021). We follow the framework laid out in Damon Matthews et al. (2021) to use a TCRE that accounts for non-CO_2 forcing via the parameter $f_{nc} > 0$ which increases the average value and variance of the TCRE. We write our "effective" TCRE – the TCRE including non-CO_2 forcing factors – as

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

The mean value of λ, f_{nc}, and λ_{eff} and their uncertainties are provided in Online Appendix F, Table 4. Using this approach, we are able to reproduce central estimates of warming levels this century reported by WGI in AR6 for each SSP reasonably well, see Online Appendix F, Table 5. Therefore in our calculations of temperature, we use

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

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

4 Model calibration

4.1 Featured runs

To calibrate CAP6, we use discount rates in line with recommendations from the US government. Previous analyses use a discount rate of 3% (Committee on Assessing Approaches to

[12] The analogous figure to Fig. 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.

[13] 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.

Updating the Social Cost of Carbon et al. 2017), but recent studies use 2% in light of recent economic trends (such as falling interest rates) and expert elicitation (Council of Economic Advisors 2017; Drupp et al. 2018). Indeed, New York State adopted a 2% discount rate in their social cost of carbon calculations (New York State Energy Research and Development Authority and Resources for the Future 2020). We calibrate our featured runs using 1.5%, 2% and 2.5% discount rates to be consistent with the recent report issued by the EPA (National Center for Energy Economics 2022) and use the term structures from Bauer and Rudebusch (2020). We also show results using a 3% discount rate for consistency with prior US government estimates (Committee on Assessing Approaches to Updating the Social Cost of Carbon et al. 2017).[14] See Online Appendix G, Table 6 for specifics. We assume $g = 1.5\%$ for all runs. For each discount rate, we assume that $\psi = 10$, in line with trends observed in the U.S. financial market (Schroyen and Aarbu 2017). For our emissions baseline, we choose SSP2–4.5, as it aligns with recent projections of emissions used by the US EPA (Rennert et al. 2022). Lastly, we assume a modest exogenous technological growth rate of 1.5% and no endogenous technological growth, owing to an inability to reliability calibrate the endogenous technological growth rate parameter φ_1. The choice of no endogenous technological growth makes our technological growth assumptions conservative, given the known link between agent investment in mitigation and rates of growth in clean sectors (Acemoglu et al. 2012).[15]

4.2 Ensemble runs

While risk associated with temperature rise and damage function uncertainty are holistically evaluated in a given run of CAP6, other sources of uncertainty exist and are excluded, such as uncertainty in 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_2 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 Fig. 5. We find that the 2% discount rate policy implies a high cost of carbon and stringent abatement policies, see panels Fig. 5A–B. The cost

[14] 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.

[15] We demonstrate how including endogenous technological growth influences model output in Online Appendix K.

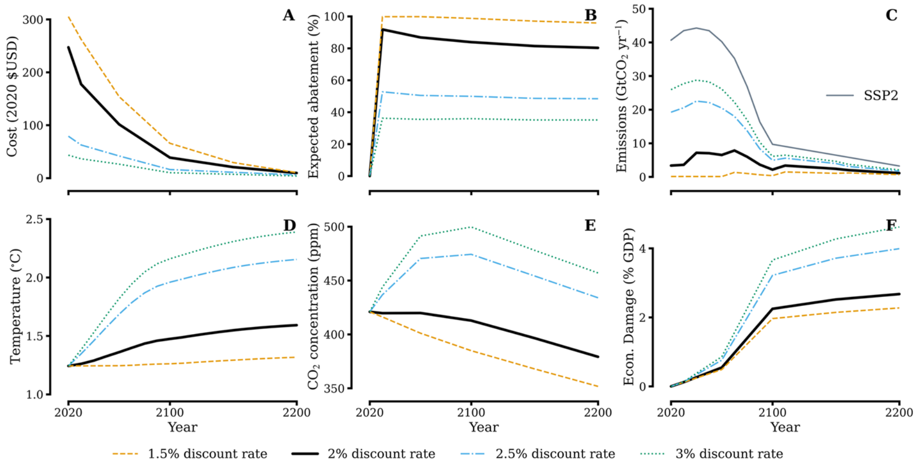

Fig. 5 CAP6 output for four discount rates in our main specification

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_2 emissions owing to technological improvements (see Eq. 2.12). This set of mitigation actions leads emissions peaking in 2070, with CO_2 concentrations stabilizing before starting to decrease by mid-century. The expected global temperature change resulting from this emissions policy is less than 1.5 °C by 2100 ($\sim$ 1.47 °C) and less than 2 °C in 2200 ($\sim$ 1.6 °C).

Decreasing the discount rate to 1.5% leads to complete and immediate cessation of emissions (see panel Fig. 5B), thus maximizing costs and decreasing 2100 (2200, resp.) warming by 0.2 °C (0.3 °C, resp.) in comparison to the 2% run. Larger discount rates relax the stringent abatement policies seen in the 2% and 1.5% discount rate cases. This results in lower costs and less mitigation action, and consequentially, larger warming and damages. We find that both the 2.5% and 3% discount rates warm beyond the warming target of 1.5 °C by 2100 established in the Paris Agreement. Moreover, the 3% discount rate policy exceeds 2 °C warming by 2100, and the 2.5% discount rate policy barely holds temperatures below 2 °C by 2100 ($\sim$ 1.96 °C by 2100). In the case of the 2.5% and 3% discount rates, CO_2 concentrations rise before falling as emissions cease.[16] The 2.5% (3%, resp.) discount rate individual also tends to lose $\sim$1% ($\sim$1.4%, resp.) more GDP in 2100 and $\sim$1.3% ($\sim$2%, resp.) more in 2200 than in the 2% discount rate case, showing the expensive consequences of delayed action in combating climate change.

The intuition behind our declining carbon prices can be found in our structural representation of risk. In the early periods of the model, the social planner faces the risk of catastrophic long-term damages if they choose not to abate any CO_2 emissions ($\sim$50% GDP or higher, if the worst-case climate sensitivity and damage function concurrently materialize); this causes the social planner to mitigate aggressively early on to effectively rule out such catastrophic futures from ever materializing. Technological progress then brings down abatement costs over time (especially if learning-by-doing effects are considered, see Online Appendix K),

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

and drives down the carbon price over time. These two factors combine to cause carbon prices to start high and decline over time.

From this analysis, we find that modeling the cost of climate risk with CAP6 supports stringent mitigation action. We find that the carbon price and corresponding mitigation policy associated with the 2% discount rate saves at least \$22 trillion 2020 USD globally in 2100 (assuming global GDP grows annually by 4%) in comparison to the higher discount rate policies. In addition, employing policies with discount rates considered by the EPA result in an expected warming level in line with the targets set forth in the Paris agreement (United Nations Framework Convention on Climate Change 2015), providing the targets with explicit economic support. When faced with potentially severe damages, the representative agent makes a clear choice: they sacrifice consumption today to abate CO_2 emissions, consistent with our understanding of how risk influences climate mitigation policy.

5.2 Alternative calibration: "no free lunches"

We recalculate our featured runs using the "no free lunches" MACC and show the results in Fig. 6. The "no free lunches" cost curve leads to an increase in the optimal price of carbon; the 2020 CO_2 price increases by 20% in the 2% discount rate case. However, the "no free lunches" MACC significantly influences the efficacy of the optimal price in abating CO_2 emissions. For example, the 2% discount rate policy now abates only 70% of emissions (as opposed to $\sim$ 85% in the main specification). This emissions pathway reaches $\sim$ 1.7 °C of warming by 2100 and $\sim$ 1.9 °C warming by 2200, notably maintaining less than 2 °C warming. This shows that even if the cost of abatement is considerably higher than the IPCC foretells, keeping total warming below 2 °C is still optimal within CAP6 when a 2% discount rate is used.

Running CAP6 with the "no free lunches" calibration and a 2.5% or 3% discount rates show similar results as the 2% rate, with higher optimal prices, more near-term warming, and higher CO_2 concentrations. In this case, however, we find that using a 2.5% or 3% discount rate exceeds 2 °C warming in 2100, thus exceeding the upper bound of targeted warming in the Paris agreement. This shows that if abatement turns out to be more costly than we

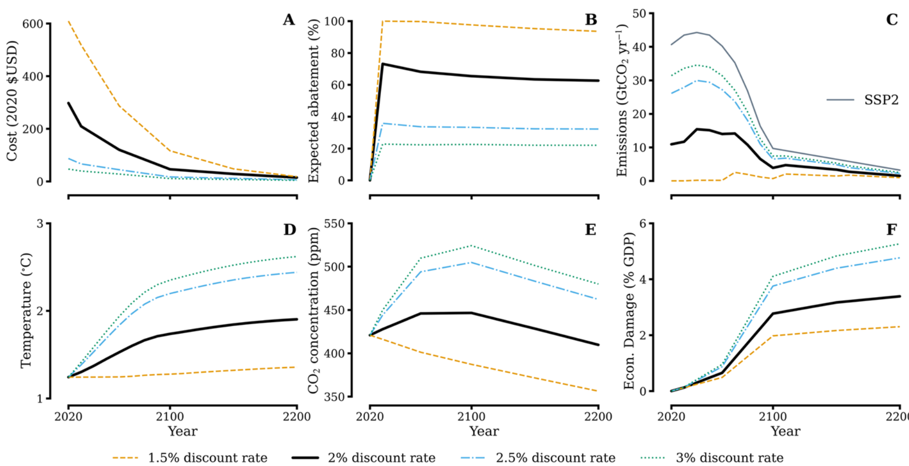

Fig. 6 CAP6 output for four discount rates using the "no free lunches" cost curve calibration

expect, using a higher discount rate in climate policy makes the world's ability of achieving the warming targets in the Paris agreement far more tenuous.

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

5.3 Ensemble model analysis

We probe the influence of uncertainty in exogenous model parameters on CO_2 price paths, temperature change, CO_2 concentrations, and economic damages incurred in our ensemble runs, shown in Fig. 7. We find that CO_2 price paths decline over time, regardless of socio-economic specification, owing to agent risk response and technological progress. The level of CO_2 price varies between baselines because the MACC is baseline dependent (see Eq. 2.12); for the same fraction of emissions abated, agents pay different prices depending on the baseline. Finally, cost variance is highly stratified across baselines, see panel Fig. 7F.

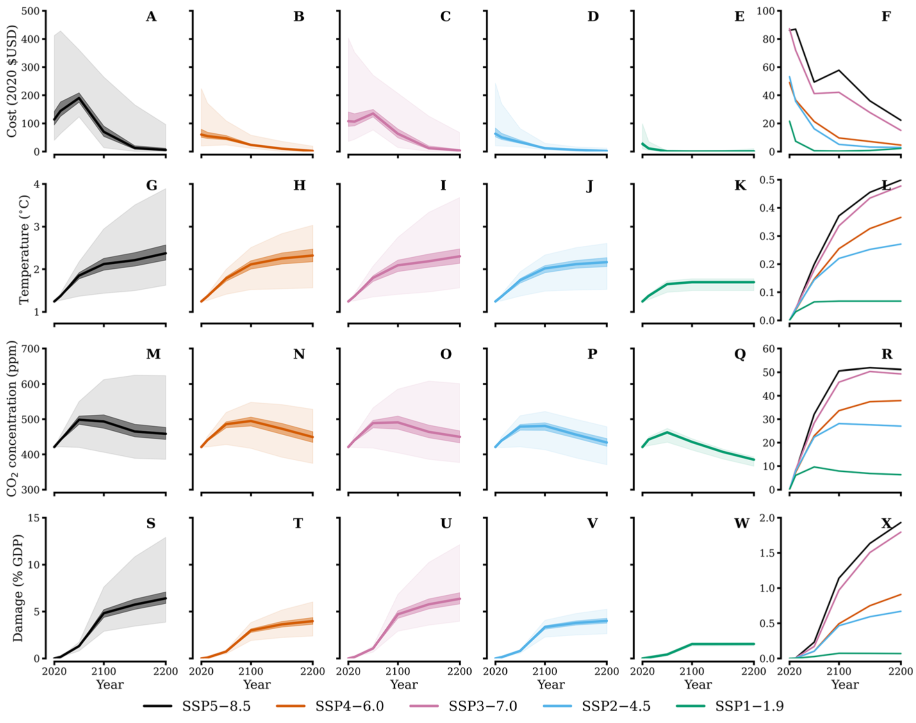

Fig. 7 Cost (top row, panels A–E), temperature (second from top, panels G–K), CO_2 concentrations (third from top, panels M–Q), and economic damages (bottom row, panels S–W) from our ensemble model runs. Dark (light, resp.) shaded region represents the 36^{th}–64^{th} (1^{st}–99^{th}, resp.) percentile 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

Central estimates of temperature, CO_2 concentrations, and economic damages,[17] however, do not see significant differences in central estimates across baselines as was observed in CO_2 prices. This owes to suggested policy in CAP6 being consistent across baselines; the only difference is the price of implementing said policy. Hence, the impact variables are relatively insensitive to baseline choice. This is a notable result, as it implies CAP6 finds an optimal outcome across emissions baselines for a given calibration. The variance in each impact variable however, displayed in panels Fig. 7L,R,X, is sensitive to the choice in baseline, with high (low, resp.) emissions scenarios having the highest (lowest, resp.) amount of variance. This can be explained by considering the consequences of inaction (i.e., high discount rate policies). In a high emissions scenario such as SSP5–8.5, inaction leads to more emissions, and thus higher impacts than in a low emissions scenario such as SSP2–4.5. Hence, the variance in each impact variable are all higher for high emissions scenarios than in low emissions scenarios.

5.3.1 Variance decomposition of ensemble results

The significant stratification of uncertainty in our output variables shown in Fig. 7 motivates further study; is it high discount rates that control prices, for example, or rates of technological change? To this end, we perform a regression analysis of CO_2 price and the impact variables studied above at every point in time against parameter values, and plot the fraction of total r^2 attributable to each parameter in Fig. 8 (see Online Appendix I for details and supporting figures).

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

For the impact variables, however, a different story emerges: the influence of the discount rate is pronounced for much longer than in the case of CO_2 prices. This owes to inactivity early on leading to long-term consequences in the form of climate-economic impacts that cannot simply be fixed by more spending on abatement.[18] Indeed, while technological change can certainly halt any further increase in global mean surface temperature, for example, it cannot undo past malfeasance.[19] Hence, the discount rate has a much more pronounced influence

[17] We refer to this set of variables as “impact variables” for the remainder of this discussion.

[18] 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_2 concentrations, and economic losses to be changed, perhaps significantly so, depending on how expensive DAC turns out to be.

[19] An important qualification to this conclusion is that we do not consider solar geoengineering, which could lead to increased spending influencing temperature, CO_2 concentration, and economic damages levels in both the short- and long-term.

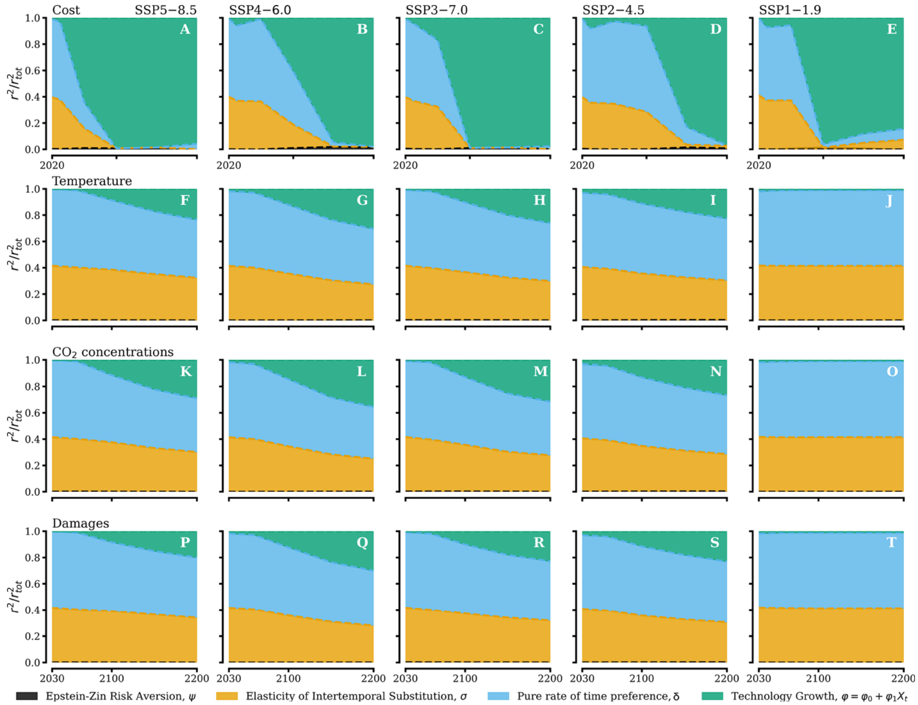

Fig. 8 Fraction of total variance (calculated as total r^2) attributable to each model parameter for carbon prices (top row, panels A–E), temperature (second row, panels F–J), CO_2 concentrations (third row, panels K–O), and economic damages (bottom row, panels P–T). Each column represents a different SSP. Note that cost variance (top row) begins in 2020 whereas temperature, CO_2 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

on far-distant temperature rise, atmospheric CO_2 levels, and economic damages than in the case of CO_2 prices.

Interestingly, Fig. 8 shows that the influence of RA (i.e., the value of ψ) is suppressed for CAP6 output uncertainty[20] relative to other model inputs. We postulate that this owes to the risk aversion captured by ψ (i.e., the Epstein-Weil-Zin sense of risk aversion across states of nature) is relatively less important to risk across states of time. Given the large residence time of CO_2 in the atmosphere, it stands to reason that the impact of risk aversion with respect to time would dwarf the impact of risk aversion across states of nature. Indeed, the results of Fig. 8 provide resounding support for this theory: risk aversion across states of time (captured by EIS) drowns out the influence of risk across states of nature (as captured by RA).

6 Conclusion

Over a decade ago, Lord Nicholas Stern wrote that “Presenting the [climate] problem as risk-management is likely to point strongly towards a policy for a rapid transition to a low-

[20] 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.

carbon economy" (Stern 2013).[21] Our framework takes this view seriously, and, in the final analysis, shows the wisdom in Stern's words. By treating CO_2 as a risky asset and calculating the optimal CO_2 price and associated abatement policy using U.S. EPA-consistent discount rates, we find that optimal policy limits warming below 2 °C in 2100 for each discount rate we considered. Practically speaking, this corresponds to cutting $> 70\%$ of CO_2 emissions in relatively short order; a "rapid transition to a low-carbon economy" indeed. Our results flip the conventional view of climate policy on its head; rather than abating progressively more CO_2 emissions as time goes on (and damages are felt more acutely), our model suggests stringent early abatement as a 'hedge' against potentially severe damages associated with climate change.

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

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

[21] 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).

[22] 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.

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

Declarations

Disclosure *Adam Michael Bauer*
I hold a short-term consultancy position at the World Bank's Climate Change Group unrelated to this work. I have no other conflicts of interest to disclose.
Cristian Proistosescu
I have no conflicts of interest to disclose.
Gernot Wagner
I am on the advisory board of CarbonPlan.org. I have no other conflicts of interest to disclose.

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