Climate Policy Curves:
Linking Policy Choices to Climate Outcomes

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Abstract

The extent of future climate change is a policy choice. Using an integrated climate-economy assessment model, we estimate *climate policy curves* (CPCs) that link the price of carbon dioxide (CO_2) to subsequent global temperatures. The resulting downward sloping CPCs quantify the inverse relationship between carbon prices and future temperatures and illustrate how climate policy choices determine climate outcomes. Our analysis can account for a variety of climate policies—for example, carbon or fuel taxes, emissions trading programs, green subsidies, and energy-efficiency regulations—all of which can be summarized by means of an effective CO_2 price. Importantly, we also examine CPC uncertainty, for example, by perturbing the model's equilibrium climate sensitivity to trace out the temperature range associated with a given CO_2 price. Finally, based on the latest Intergovernmental Panel on Climate Change (IPCC) integrated-assessment model scenarios, we estimate an implicit CPC, which provides a high-level IPCC summary of the climate policy actions required to achieve global climate targets.

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1. Introduction

Understanding the linkage between policy instruments and desired outcomes is important for the design and calibration of public policy actions. For example, formulating good monetary and fiscal policies requires understanding how changes in interest rates or government spending affect the economy. For climate policy, quantifying the linkage between policy actions and subsequent climate outcomes is also crucial, but this connection has often been difficult to perceive given the complexity of the relevant socio-economic and physical climate responses. To better understand the efficacy of climate policy, we propose using Climate Policy Curves (CPCs), which quantify the relationship between the effective price of carbon dioxide (CO_2) and the future increase in global temperature.

CPCs incorporate two important relationships: the link from CO_2 prices to emissions and the link from emissions to climate outcomes and global temperature. The first link involves technology and economics—how much emissions abatement will result from a rise in the *effective* price of CO_2, the subject of many recent evaluations (e.g., Andersson, 2019; Bayer and Aklin, 2020; Best et al., 2020; Leroutier, 2022; Pretis, 2022). This effective CO_2 price is a summary measure of the entire range of possible energy and climate policies—including carbon and fuel taxes, emissions trading programs, green subsidies, energy-efficiency regulations, renewable-energy mandates, or behavioral interventions. These diverse policy levers can all be broadly summarized in terms of a direct price on each ton of CO_2 emitted (e.g., Gillingham and Stock 2018; Gosnell et al. 2020; IMF 2021). In particular, non-price policies can be accommodated by reproducing their associated emission reductions with an equivalent carbon price. Similarly, policies for other greenhouse gases (GHGs) can be translated into a CO_2 equivalence. The second link involves climate and earth system science—and depends on how sensitive the earth's climate is to CO_2 emissions. We use the global average surface temperature as a summary measure to encompass a whole host of other environmental shifts, including rising sea levels, shifted weather extremes, and other related climate hazards.

We obtain CPCs by quantifying these two links using integrated assessment models (IAMs). Such models imply a relationship between carbon prices and global temperature outcomes, but previous work has typically focused on individual CO_2 price paths required to meet a specific temperature goal or maximize social welfare (e.g., Dietz and Venmans, 2019; Gerlagh and Liski, 2018; Golosov et al., 2014; Hänsel et al., 2020; Ricke et al., 2018; Traeger, 2022; van den Bijgaart et al., 2016). Viewed through the lens of a CPC, these estimates typically provide only a single point on the curve. But a complete accounting of climate-economy interactions and alternative climate policy choices requires mapping the entire CPC, which describes the climate consequences of a wide range of possible carbon policies.

Thinking about climate policy in terms of the relationship between CO_2 prices and global temperatures is helpful as it focuses on the key policy question: What climate outcomes will result from a given climate policy setting? In this way, CPCs can describe how much higher the effective CO_2 price path ahead needs to be to reduce future global warming by, say, 0.1ºC. Alternatively, CPCs can quantify the climate-economic trade-off between current and future action that policymakers face. For example, limiting the global temperature increase to 2°C can be achieved with a *high* initial CO_2 price that grows slowly over time or a *low* initial price that grows rapidly. The latter path postpones significant action—and mitigation burden—to the future (Gollier, 2021). Thinking about climate policy in terms of CPCs is helpful precisely because it is an important simplification of an otherwise complex relationship. Furthermore, comparing CPCs from different climate-economy models—including different generations or iterations of the same model—can also be useful as a diagnostic tool for assessing alternative IAMs.

2. Quantifying Climate Policy Curves

To calculate CPCs, we project emissions, CO_2 concentrations, and temperature trajectories under alternative exogenous paths for the carbon price using the Dynamic Integrated Climate-Economy (DICE) model developed by Nordhaus (1992, 2018) as updated by Hänsel et al. (2020). As in the baseline scenario of Nordhaus (2018), we rearrange the marginal abatement cost equation to obtain the emissions path resulting from a pre-specified CO_2 price path. We then vary the CO_2 price in the first period, assume some growth rate for future CO_2 prices, and plot the resulting atmospheric temperature in 2100 and at its maximum over the full modelling horizon (see Appendix A for details). Panels A and B in Figure 1 show the resulting CPCs. The horizontal axis measures the 2025 carbon price in constant (2010) US dollars per ton of CO_2, which is the initial policy choice variable. The vertical axis measures climate outcomes: average global 2100 temperature in panel A and the peak temperature in panel B—in both cases relative to the 1850-1900 average. The shaded regions are uncertainty bands described in the next section.

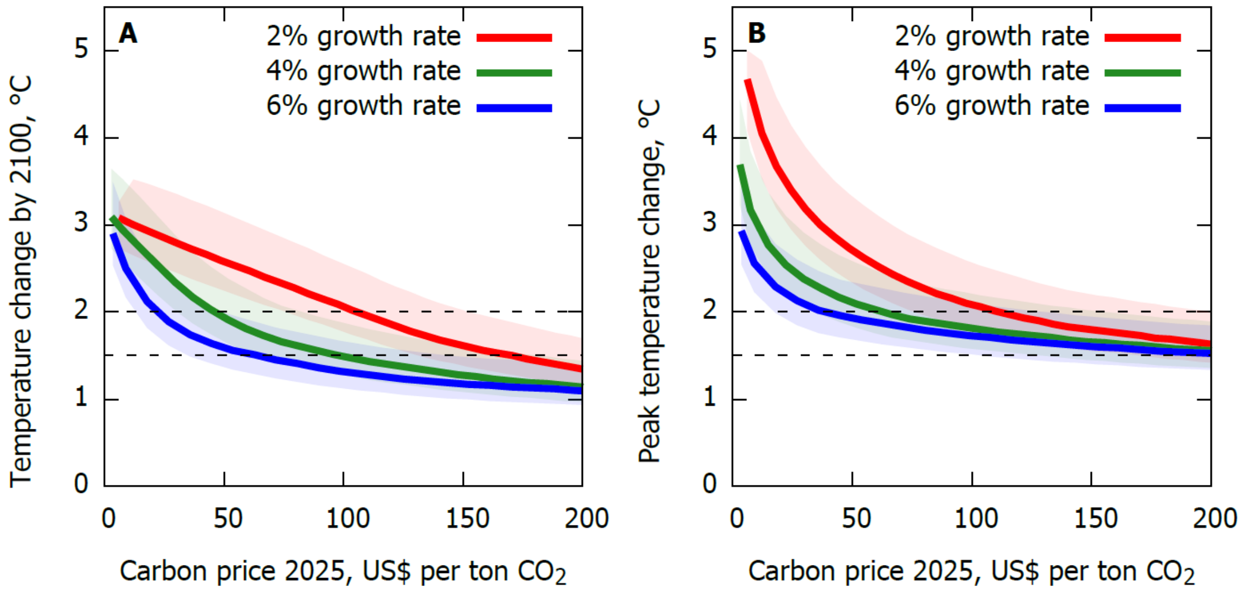

Figure 1 | Climate Policy Curves. The relationship between the carbon price in 2025 and the global temperature for different CO_2 price growth rates. Panel **A** shows global average temperature increases by 2100 (above the 1850-1900 average), and Panel **B** shows overall peak global average temperature increases for three exemplary growth rates of carbon prices of 2% (red), 4% (green) and 6% (blue). Climate sensitivity uncertainty shaded regions are based on 'likely' ranges (66% probability) for the equilibrium climate sensitivity between 2.5-4°C in IPCC (2022) AR6. All prices are in constant 2010 dollars. See Appendix A for a description of methods.

Both the initial level of the effective CO_2 price and its expected future growth rate are fundamental climate policy choices that determine future emissions and global temperatures. Figure 1 plots CPCs for annual CO_2 price growth rates of 2, 4, and 6%, which are consistent with a survey of expert recommendations that revealed a median growth rate of global carbon prices of 4.1% from 2020 to 2050, with a 66-percentile range of 2.3% to 6.5% (Drupp et al., 2022).

Figure 1 illustrates a key climate policy tradeoff. Policymakers need to choose a combination of an initial carbon price and its (expected) growth rate to restrain global warming. At one extreme, an ambitious climate policy starts with a high initial carbon price and a low subsequent growth rate, which may be socially optimal (Hänsel et al., 2020; Nesje et al., 2022). At the other extreme, policymakers might start with a low initial carbon price, but promise a high CO_2 price growth rate, which shifts the bulk of the mitigation burden to the future (Gollier, 2021).

At very low levels for the initial CO_2 price, the CPCs in Panel A imply, in expectation, about 3°C of warming above pre-industrial levels by 2100. This is consistent with other analyses that analyze current global climate policies, which can be approximated with a global effective CO_2 price of just a few dollars (see IPCC, 2018, and Raftery et al., 2017). Clearly, climate policy needs to be substantially more ambitious to attain the UN climate targets of 1.5°C or 2°C. Figure 1 reveals combinations of current carbon prices and future growth rates that are consistent with these targets. For panel A, at a growth rate of 4%, the green CPC shows that limiting global warming to 2°C by 2100 in expectation would require a carbon price around US$50, whereas an increase of only 1.5°C could be accomplished with a current carbon price around US$100. If, instead, we assume a slower growth rate of only 2%, the requisite current carbon prices rise to about US$100 and US$170.

The UN climate targets are often interpreted as trying to limit the *peak* rather than the end-of-century temperature in order to curtail potentially severe and irreversible climate damages (e.g., Drouet et al., 2021; IPCC, 2022). Panel B of Figure 1 plots alternative CPCs, which measure the climate outcome as the peak temperature before year 2515. At currently very low levels of the effective global carbon price, global temperature is substantially higher than in panel A, as temperatures continue to rise after 2100, unless the growth rate of the carbon price is quite high. Panel B shows that limiting the peak temperature increase to 2°C requires a more ambitious climate policy mix—for instance, an initial carbon price of US$70 at a 4% carbon price growth rate.

Figure 2 elaborates on the CPCs to illustrate further how a broad range of alternative policy choices will translate into 2100 (panel A) and peak (panel B) temperatures. These heatmaps illustrate how combinations of initial 2025 carbon prices and subsequent carbon price growth rates (horizontal and vertical scales, respectively) will result in a given temperature—denoted by color. Each CPC in Figure 1 can be represented by a horizontal line in Figure 2. The contour lines for 1.5°C and 2°C temperature increases in Figure 2 illustrate the combinations of initial 2025 carbon prices and subsequent price paths that are compatible with attaining these temperature targets. For example, staying below 2°C by 2100 with only a 1% annual increase in carbon prices would require an initial 2025 carbon price of more than US$160. By contrast, staying below 2°C at an 8% growth rate would require a 2025 carbon price of approximately US$25. Finally, panel B shows that while limiting peak warming to 2°C is still feasible for ambitious climate policy, the 1.5°C target is out of reach within the depicted range for carbon prices and growth rates. Figure 2 illustrates that the UN climate targets cannot be attained without immediate increases in effective carbon prices even assuming sizable future increases in climate policy stringency.

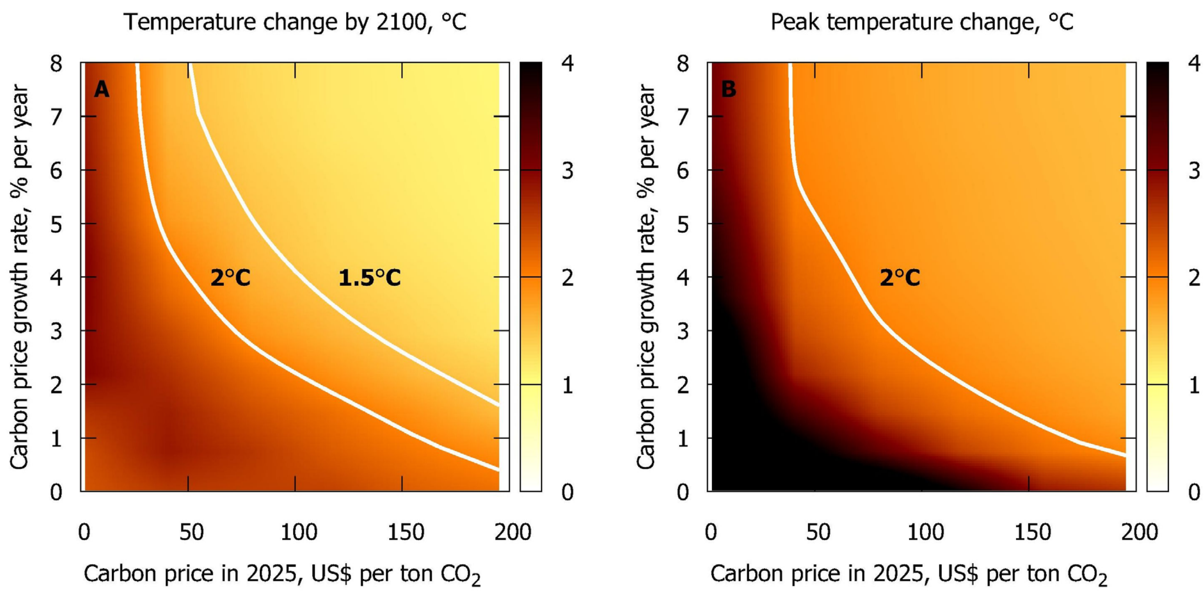

Figure 2 | Climate policy choices and temperature outcomes. Panel **A** shows a heatmap of global average temperature increase by 2100 and Panel **B** for peak temperature increase for various combinations of initial carbon prices in 2025 and annual carbon price growth rates. The temperature color scale is shown on the right. Contours that indicate carbon price paths that lead to UN global temperature targets are denoted by white lines. All prices are in constant 2010 dollars. See Appendix B for a description of methods**.**

3. Uncertainty in Climate Policy Curves

Uncertainty is a central issue for the design and assessment of climate policy. Despite much climate science and climate economics research, substantial uncertainty remains about the key climate-economy interactions (e.g., Gillingham et al., 2018; Nordhaus, 2018). In particular, the CPC's causal chain from carbon prices to global temperatures is subject to *socio-economic uncertainties* in the link from carbon prices to emissions and *climate uncertainties* in the link from emissions to global temperatures. Monte Carlo simulations across probability distributions for model parameters have been used to evaluate the sensitivity of IAM implications (e.g., Nordhaus, 2008; Nordhaus, 2018). However, scientific knowledge about the relevant probability distributions for many model parameters is severely limited. In addition, the multidimensional nature of the calculation of CPCs makes Monte Carlo simulations impractical. Instead, we use an intuitive approach to illustrate how uncertainty affects the CPC climate policy tradeoffs: We vary several important model parameters in turn from their baseline "best guess" estimate to potential high and low plausible boundaries. Plotting CPCs for these values demonstrates how changes in specific parameters affect policy tradeoffs. The resulting curve shifts reveal the magnitude of CPC changes—in level and shape—in response to changes in a specific parameter, and whether the range of parameter choices have symmetric or asymmetric effects on CPCs.

In Figure 1, the shaded regions reflect uncertainty about the equilibrium climate sensitivity (ECS), which measures the temperature change from a doubling of atmospheric carbon. The ECS plays an important role in determining the sensitivity of global temperatures to carbon prices. To shift the CPCs in Figure 1, we vary ECS within the 'likely' range of 2.5°C to 4°C with a baseline estimate of 3°C—consistent with the IPCC's Sixth Assessment report (AR6) (cf. Sherwood et al., 2020). The higher level of the ECS results in a higher temperature—of about 0.4°C—at any given initial carbon price, which makes the Paris goals notably more difficult to achieve.

In Figure 3, six other sources of parameter uncertainty are considered that affect the slope and shape of the CPCs. In contrast to the ECS, there is little guidance in the literature about the appropriate empirical probability distributions for these six parameters. We have considered some plausible alternatives, but our CPC analysis using these parameter variations is more exploratory. Table 1 provides details on the alternative parameterizations we consider and supporting sources, and see the Appendix C for further description.

Panels A, B, and C of Figure 3 consider three curve shifters that could potentially be managed relatively quickly by appropriate policy choices. These are alternative parameterizations for the availability of negative emissions technologies (e.g., direct air capture), the cost of carbon abatement technologies, and the emissions of greenhouse gasses other than CO_2.

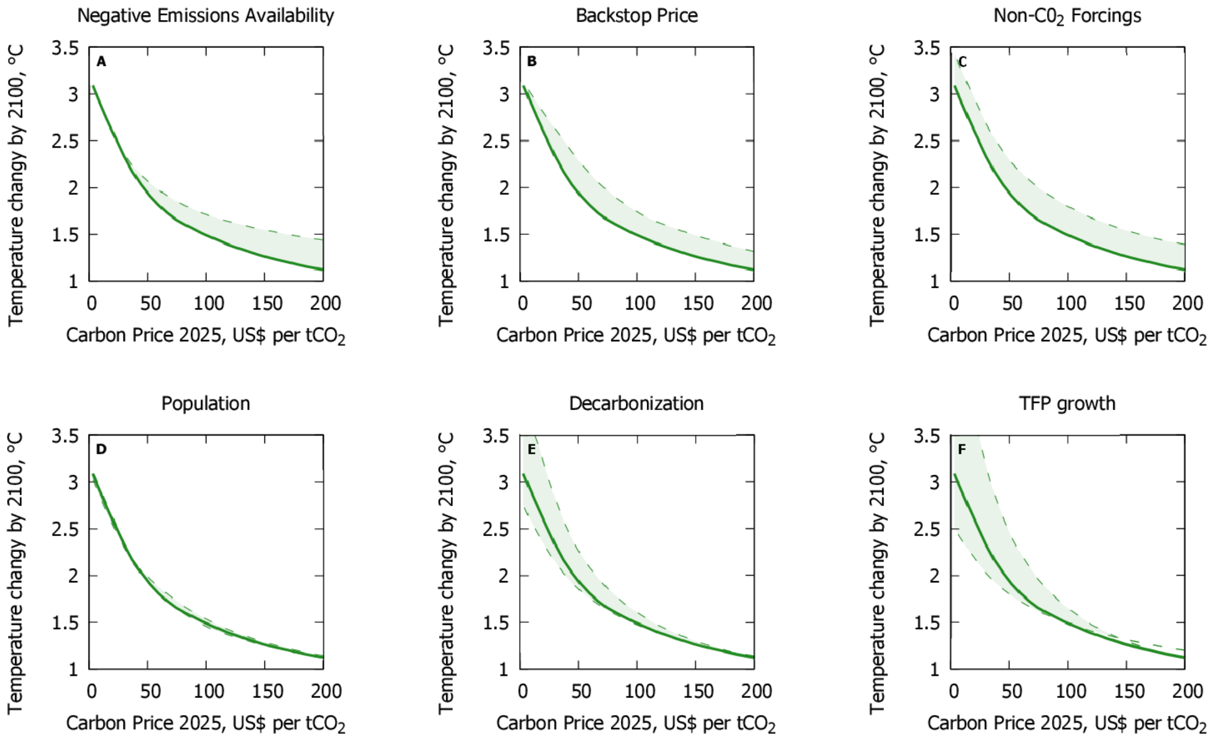

Figure 3 | Climate policy curve shifters. CPCs for a 4% carbon price growth rate: baseline (green solid lines) and under alternative model parameterizations (green shaded areas with dashed lines denoting the upper and lower bounds). Panel **A** shows the effect of making negative emissions technologies available in 2050 and 2100 (green solid and dashed lines respectively). Panel **B** shows the effect of different assumptions on the price of a backstop technology in 2050. Panel **C** shows the effect of higher non-CO_2 forcings—the green dashed line corresponds to the non-CO_2 forcing in Nordhaus (2018). Panel **D** shows the effect of alternative global population projections for 2050. Panel **E** shows the effect of different assumptions on the rate of decarbonisation. Panel **F** shows the effect of different assumption on the growth rate of total factor productivity (TFP). All prices are in constant 2010 dollars. See Appendix C for a description of methods.

The availability of negative emission technologies (Panel 3A) is a critical element for meeting the UN climate targets (IPCC, 2018; Fuss et al., 2018). Most IPCC scenarios assume availability at scale by around 2050, and we adopt this timing for our baseline estimate (Hänsel et al., 2020). As an alternative, we also estimate CPCs assuming negative emission technologies only become available in 2100, which is closer to the assumption in the DICE model. Panel 3A shows that the later availability of negative emission technologies would shift the CPC upward, notably for medium to high carbon prices. This suggests the importance of climate policies that can incentivize the timely uptake of these technologies.

Model attributes that underlie estimation of CPC	**Baseline estimate**	**Range, high end**	**Range, low end**	**Supporting references**
ECS, °C	3	4	2.5	IPCC AR6
Availability of negative emissions technologies at scale, year	2050	2100	2050	IPCC SP1.5; Nordhaus 2018
Backstop price in 2050, 2015 US$ per ton CO_2	461	687	461	Nordhaus 2018; IPCC AR6
Non-CO_2 forcing in 2100, W/m^2	0.33	1	0.33	REMIND SSP2 2.6; Nordhaus 2018
Decarbonization, % per year	-1.52	-0.88	-2.16	Nordhaus 2018
Initial TFP growth, % per year	1.48	2.35	0.57	Nordhaus 2018, Gillingham et al. 2018
Population in 2050, millions	9,791	9,400	10,000	Nordhaus 2018, United Nations 2022

Tab. 1 | Summary of parametrization for CPC shifters.

The costs of emission abatement (Panel 3B) are a major source of uncertainty for CPCs. The DICE model includes a generic backstop technology with an exogenous price path that is calibrated such that the marginal cost of abatement, i.e. the carbon price, is equal to the backstop price at the time of zero emissions. We vary the exogenous time path for the backstop price to account for the uncertainty in abatement costs, similar to Dietz et al. (2018). Specifically, we recalibrate the initial backstop price and its yearly decline rate to the interquartile range of pathways of emissions and carbon prices of the IPCC AR6 model runs that have at least a 67% probability of staying below 2°C. Since the lower IPCC range almost coincides with the DICE specification in Nordhaus (2018), Panel 3B considers only the upper end of the IPCC range as a curve shifter. The panel shows that uncertainty with respect to abatement costs is relevant for the whole range of carbon prices.

The extent to which non-CO_2 emissions (Panel 3C), such as methane emissions from agriculture, will be managed in line with the UN climate targets represent another source of uncertainty. Our baseline estimate of non-CO_2 emissions is aligned with climate scenarios compatible with the UN climate targets (Hänsel et al., 2020). Specifically, the exogenous path for non-CO_2 forcing is calibrated to peak at 0.59 W/m^2 in 2055 and decrease to 0.33 W/m^2 by 2100. We also consider an alternative DICE assumption, which implies a linear increase in non-CO_2 forcing to 1 W/m^2 by 2100. Panel 2C shows that management of non-CO2 emissions is an important determinant of level of the CPC, which highlights the significant potential of non-CO_2 mitigation policies to influence climate outcomes.

The lower three panels of Figure 3 consider variation in growth rates of population, decarbonization, and total factor productivity (TFP). Our baseline assumption for global population growth follows Nordhaus (2018), but as an alternative, we assume exogenous population dynamics in line with updated UN projections (United Nations 2022). However, Panel 3D shows that the effect of different assumptions about population dynamics on CPCs is negligible.

The DICE model we use does not distinguish between dirty and clean sectors, so the exogenous rate of decarbonization follows the decoupling of economic output and CO_2 emissions. Our baseline estimate is -1.5% per year, but as alternative assumptions for the CPC, we consider the range from -0.88% to -2.16% (Nordhaus, 2018). Panel 3E shows that the speed of decoupling matters for the shape of the CPC especially at initial carbon prices below $100. In particular, at the high end of the range (slower decarbonization), low to medium initial carbon prices would result in higher temperatures in 2100 than under our baseline.

Panel 3F shows that total factor productivity (TFP) growth is also an important determinant of the CPC. Faster productivity growth boosts economic output, which in turn increases CO_2 emissions and temperature. Around our baseline estimate of 1.48% per year, we consider the 66-percentile range of 0.55 - 2.41% in Nordhaus (2018) and Gillingham et al. (2018). The different TPF growth scenarios affect the steepness of the CPC especially for initial carbon prices below US$100. Higher productivity growth translates into higher temperature increases on its own. However, a more nuanced view recognizes that decarbonization (Panel 3E) and TFP growth (Panel 3F) are intimately related aspects of technological progress. Namely, TFP growth will exacerbate climate change unless it is part of an offsetting transformation towards cleaner production.

4. Implications for Policy and Model Evaluation

Climate policies come in many forms, including carbon prices and emissions trading systems as well as many policies without an explicit price per ton of CO_2, such as efficiency standards, clean-energy subsidies, and pledges to achieve net zero emissions. CPCs can be a useful policy tool by enabling a comparison of various policies, quantifying the climate outcomes of such policies, and elucidating the uncertainty in obtaining those outcomes.

For example, CPCs can crystalize the importance of comparing climate policy today with its future path. Different combinations of these two components can lead to similar climate outcomes: An initial effective carbon price of US$50 that grows at 6% each year and an initial price of US$160 that grows at 2% both appear likely to limit the global temperature increase in 2100 to below 2°C. These different carbon price paths starkly illustrate the choice of climate mitigation burden-sharing across generations: the tradeoff between today's climate policy setting and the burden on future generations. Accordingly, CPCs can help frame and navigate the difficult choices between near-term ambition and procrastination. In addition, CPCs can highlight the fundamental role of uncertainty in these choices as shown in Figures 1 and 3.

CPCs can also serve as a useful summary metric for IAM evaluation and comparison. In particular, contrasting the CPCs obtained from different types and calibrations of IAMs can provide a straightforward means to compare the key implications of these models and to highlight differences in climate policy implications. Along these lines, CPCs can serve as a useful model diagnostic tool that illuminates important policy tradeoffs in model comparison exercises (see, e.g., Harmsen et al., 2021; Kriegler et al., 2015). As an example, Figure 4 plots each of the different model simulations from the IPCC AR6 (Byers et al., 2022) as grey dots in the carbon price and temperature space. The black line fits a power function to these data and provides the composite "AR6-CPC" that is implicit in the diverse AR6 model runs, which feature a wide variety of modelling choices and carbon price paths. For a range of 2025 carbon prices between US$35 and US$95, the AR6-CPC settles between our CPCs based on the updated DICE model with constant carbon price growth rates of 4% and 6% (the green and blue lines). While the AR6-CPC suggests that carbon prices below US$35 are more effective in reducing temperatures as compared to the 6%-CPC; however, above US$95, the AR6-CPC is rather insensitive suggesting that a carbon price is less effective than the 4%-CPC.

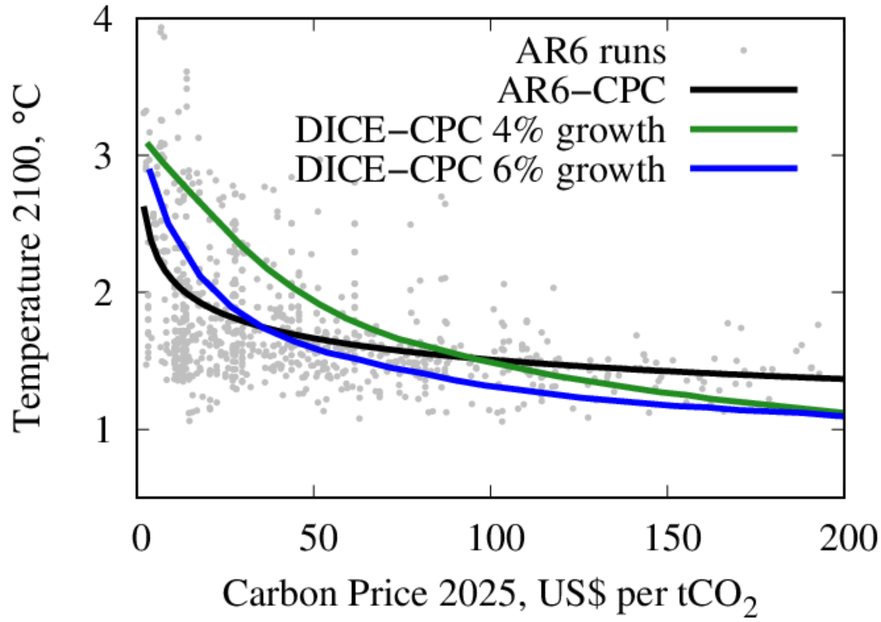

Figure 4 | AR6-CPC. Comparison of DICE-based CPCs with a CPC fitted to AR6 model simulations. The grey dots represent AR6 data on the 2025 carbon price and the global-mean surface air temperature (GSAT), and the black line fits a power function to these data. The green and the blue line are the CPCs based on an updated DICE model with 4% and 6% carbon price growth rates. See Appendix D for a description of methods.

By focusing on the essential mapping from climate policy to climate outcomes, CPCs can assist in understanding complex climate-economy interactions. They provide a novel and powerful summary of climate policy that can help calibrate, assess, and communicate that policy. The broad range of CPCs we have considered underscore that while policy-makers can, to some degree, trade-off initial policy ambition with mitigation burden delayed on future generations, attaining the UN climate targets will require setting in place sizable carbon prices, or their regulatory equivalents, in the near future.

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Appendix

We calculate *climate policy curves* (CPCs) using the DICE 2016R2 model (Nordhaus 2018) as updated by Hänsel et al. (2020). The DICE model updates provide a more accurate calibration of the carbon cycle and energy balance model, improved climate damage estimates, an updated timing of the availability of negative emissions technologies, and updated projections of non-industrial emissions.[2]

A. Methods for Figure 1: Climate policy curves

To calculate the CPCs implied by the model, we use the optimality condition for the carbon price paths that would result in a first-best setting. Accordingly, the first-best optimal carbon price $p^*_{CO_2}$ must be equal to the marginal cost of emission, which in DICE (cf. Nordhaus 2018) is:

$$p^*_{CO_2}(t) = p_{back}(t)\, \mu(t)^{\theta_2 - 1}. \qquad (1)$$

Note that time t is measured in increments of five years with $t \in [0; 100]$, and $t = 0$ corresponds to the year 2015. All prices are in 2010 US$ (purchasing power parity corrected). The optimal carbon price path $p^*_{CO_2}(t)$ is modelled to depend on the time path of the price of a generic backstop technology, $p_{back}(t)$; a technology, like wind energy or solar PV, that is expected to be capable of replacing CO_2 –intensive energy production by 100% at some future date. In the baseline parametrization, the price of the backstop is assumed to be $550 per tonne of CO_2 in 2020, and to decline by an exogenously given rate of half a percent per year. Furthermore, the carbon price depends on the emissions control rate $\mu(t)$ capturing the fraction of industrial CO_2 emissions that

[2] The model is written in the AMPL programming language and solved with the Knitro optimization solver (version 12.4).

is abated in each period. Finally, the calibration parameter $\theta_2 = 2.6$ reflects the convexity of the marginal abatement cost function, i.e., that the marginal cost of emission abatement increases the more emissions are already abated.

In order to compute the CPC as a mapping of a current *given* non-optimal carbon price to the future level of global temperature, we proceed in three steps.

First, we solve the carbon price equation (1) for the emission control rate $\mu(t)$, which we require to be bounded above by 1 (maximal 100% emission control) until the last period N before negative emissions technologies are available, and 1.2 thereafter (c.f. Nordhaus, 2018). For the baseline (best) estimate we set $N = 6$, i.e., negative emission technologies are available from 2050 onwards following recent IPCC reports and Hänsel et al. (2020).

$$\mu(t) = \begin{cases} \min\left[1.0,\ \left(\frac{p_{CO_2}(t)}{p_{back}(t)}\right)^{\frac{1}{\theta_2 - 1}}\right], if\ t \leq N \\ \min\left[1.2,\ \left(\frac{p_{CO_2}(t)}{p_{back}(t)}\right)^{\frac{1}{\theta_2 - 1}}\right], if\ t > N \end{cases} \tag{2}$$

Second, we assume an exogenous carbon price path that grows exponentially, until it hits the backstop price, at the per-period rate g:

$$p_{CO_2}(t) = p_{CO_2}(0)\ e^{gt}. \tag{3}$$

For a given initial carbon price, $p_{CO_2}(0)$, and carbon price growth rate, g, equations (2) and (3) together determine an exogenous non-optimal path for the emissions control rate. The non-optimal time path of the emissions control rate reflects the abatement of industrial emissions that is incentivized by a particular exogenously given carbon price path and thereby determines the dynamics of global temperature increases.

Third, we solve the updated DICE model as in Hänsel et al. (2020) subject to the pre-specified exogenous path for the emission control rate according to equation (2) and (3) and calculate the resulting global temperature increases. All other model equations including social welfare remain unaffected and calibrated according to the main specification in Hänsel et al. (2020).[3]

[3] Specifically, we use the central estimate for welfare parameters in Hänsel et. al (2020) implying a rate of pure time preference of 0.5% per year and a unit value for the elasticity of marginal utility (cf. Drupp et al., 2018).

In our CPC analysis we use $p_{CO_2}(2)$, i.e., the carbon price in 2025, as our independent variable, which is the next possible planning step. As the outcome variable, we plot either (a) the change of the atmospheric temperature in 2100, or (b) the peak atmospheric temperature change over the whole time horizon from 2010-2510, in both cases relative to the 1850-1900 pre-industrial level. These two alternative outcome variables are both useful for policy analysis in their own right, as we discuss in the main text.

The uncertainty ranges in Figure 1 are based on varying the equilibrium climate sensitivity (ECS), i.e., the temperature resulting from a doubling of atmospheric carbon. The ECS represents a key source of uncertainty with respect to carbon price sensitivity, and its quantification has been the subject of extensive prior research. In our simulations, we vary ECS within the range considered in the latest ECS assessment (Sherwood et al., 2020) and IPCC's Sixth Assessment report. This includes a 'likely' range of 2.5°C-4°C and best estimate of 3°C.

B. Methods for Figure 2: Climate policy choices and the UN climate targets

Figure 1 in the main paper presents CPCs for three illustrative carbon price growth rates. In order to depict a more comprehensive possibility space for the link between climate policy and climate outcomes, we calculate and plot heatmaps. Using color codes, these heatmaps show in two dimensions the temperature increases in 2100 and their peaks that result from a broad combination of initial carbon prices and growth rates. To obtain these, we solve the updated DICE model 8600 times, while for each run we (i) draw $p_{CO_2}(0)$ from a uniform distribution on the interval [\$2, \$200] and (ii) vary the yearly carbon price growth rate in 0.1% steps on the interval [0%, 8%].

We use the heatmaps to illustrate the combinations of initial carbon prices and growth rates that are in line with the 1.5°C and 2°C UN temperature targets. To calculate these contour lines within the depicted two-dimensional space of prices and growth rates we use the algorithm implied by the "dgrid3d" option of gnuplot version 5.2 that converts the plotting data into a suitable grid data format. Specifically, we use a grid of size 12 by 12 and a norm value of 4. The norm parameter is used to inversely weight each data point by its distance from the grid raised to the norm power.

C. Methods for Figure 3: Climate policy curve uncertainty

Figure 3 of the main text shows the effect of six sources of parameter uncertainty on the estimated slope and shape of the CPCs. We consider alternative parameterizations for the availability of negative emissions technologies (e.g., direct air capture), the cost of carbon abatement technologies, the emissions of greenhouse gasses other than CO_2, and the growth rates of population, decarbonization, and total factor productivity (TFP). There is little guidance in the literature about the appropriate empirical probability distributions for these six parameters, so our CPC uncertainty analysis using these parameter variations is more exploratory.

Negative emissions availability

In the DICE model, the dynamics of industrial emissions $E_{Ind}(t)$ is given by

$$E_{Ind}(t) = \sigma(t)\, Q(t) \left(1 - \mu(t)\right), \tag{4}$$

where $Q(t)$ is global output, $\sigma(t)$ the CO_2-intensity of output and $\mu(t)$ is the emissions control rate. The availability of negative emissions technologies (NETs) is then simply modelled by an upper bound for the emissions control rate $\mu(t)$ at a particular point in time t. In equation (3), we denote by N the last time period t with a maximal emissions control rate of $\mu(t) = 1$ (maximal 100% emission control), i.e. the last period before NETs are available. As in Nordhaus (2018), $\mu(t)$ is bounded above by $\mu(t) = 1.2$ thereafter, i.e. NETs allow for a maximum of 20% of industrial emissions to be taken out of the atmosphere for each period t. For the baseline (best) estimate, we set $N = 6$, i.e., NETs are available from 2050 onwards following recent IPCC reports and Hänsel et al. (2020). As a curve shifter, we explore the implications of a 50 year later availability by 2100 corresponding to $N = 16$. Figure C1 depicts the dynamics of industrial CO_2 emissions for different initial carbon prices $p_{CO_2}(0)$ (assuming the same 4% carbon price growth rate) and different time horizons for the availability of NETs. The figure shows that for low initial carbon prices, like \$10, the time path of industrial emissions is independent from the availability of NETs. For medium to high(er) initial carbon prices, here \$50-\$100, the time horizon until NETs are available affect the emissions time path and thereby the increase in global temperatures.

Figure C1: Industrial Emissions

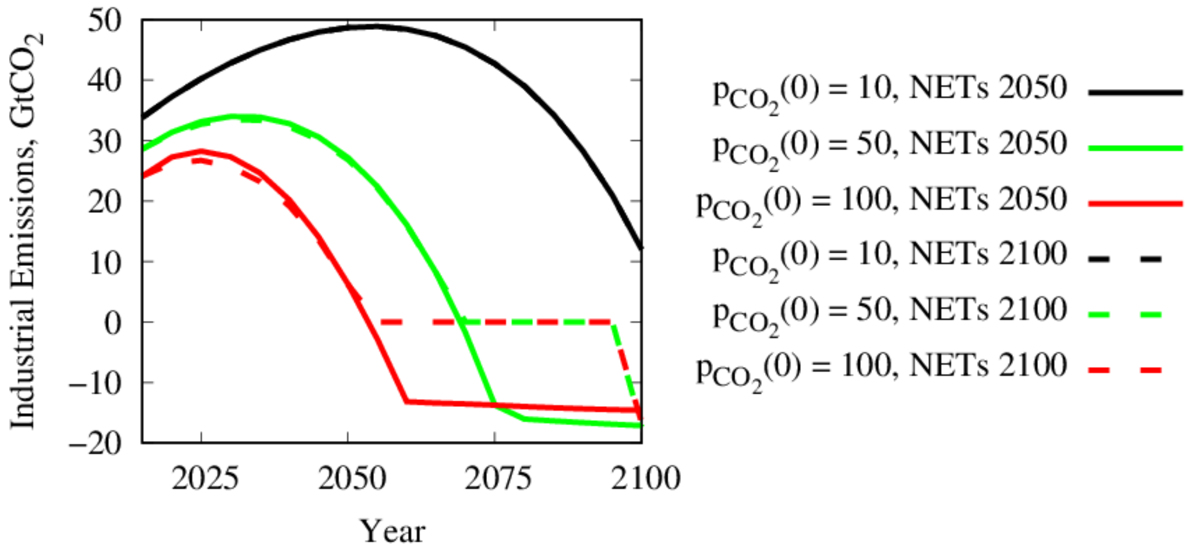

Figure C1 | Industrial Emissions. Dynamics of industrial CO_2 emissions for different initial carbon prices $p_{CO_2}(0)$ with the same 4% growth rate and different time-horizons for the availability of negative emissions technologies.

Backstop price

We use variations of the exogenous time path of the price of the generic backstop technology $p_{back}(t)$ to capture uncertainty about abatement costs. Equation (2) clearly shows that $p_{back}(t)$ is a major determinant of the time path of the emissions control rate $\mu(t)$ that results from a particular carbon price path $p_{CO_2}(t)$. Given the backstop price in the first period $p_{back}(0)$, the exogenous time path of the backstop evolves according to

$$p_{back}(t) = p_{back}(t-1)\,(1 - g_{back}), \tag{5}$$

with $g_{back} = 0.025$ being the per-period decline rate. The initial backstop price $p_{back}(0)$ and its decline rate g_{back} are calibrated such that the marginal abatement costs, i.e. the carbon price, is equal to the backstop price at the time of zero emissions. To calculate how the best-guess CPC shifts as a result of different scenarios on the cost development of the backstop, we recalibrate the initial backstop price and its decline rate to the interquartile range of pathways of emissions and carbon prices of the IPCC AR6 model runs (AR6 Scenario Database 2022) that have at least a 67% probability of staying below 2°C. From this set of model runs, we extract the time of zero emissions within the interquartile range and the corresponding carbon prices in that year. The interquartile range (IQR) for the year of zero emissions ranges from 2080 to post-2100 with carbon prices ranging from \$321-\$637 at the time of zero emissions.[4] In a next step we calibrate $p_{back}(0)$ and g_{back} to best match the IQR from the AR6 modelling data. The calibration for the first quartile and the resulting time path for the backstop almost coincides with the standard DICE 2016R2 parametrization. Thus, we stick to that parametrization as our best-guess while using the parametrization for the third quartile as a curve shifter. Table C1 summarizes the resulting parametrization and Figure C2 plots the resulting trajectories for the backstop price.

	Best-Guess	**Range Up**
$p_{back}(0)$	\$550	\$750
g_{back}	0.025	0.0125
Resulting backstop price in 2050, $p_{back}(7)$	\$461	\$687

Tab.C1 | Summary of parametrization for the backstop technology as a CPC curve shifter.

Figure C2: Backstop Price

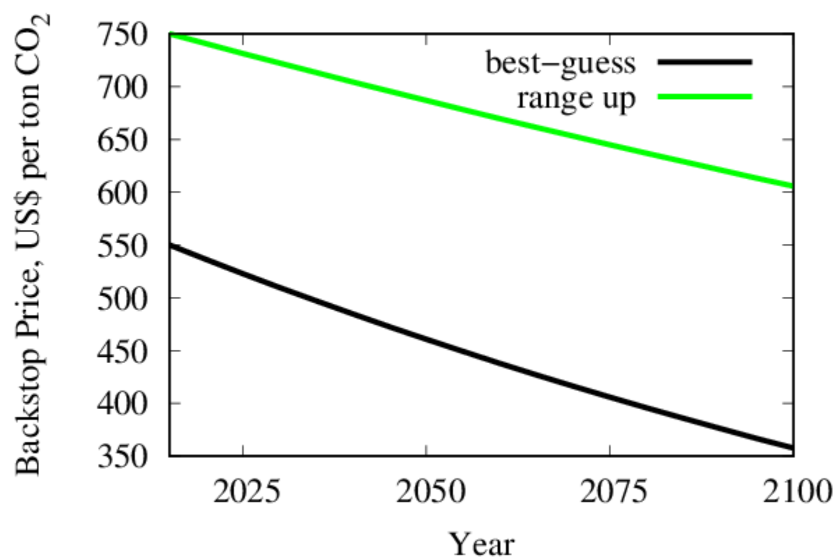

Figure C2 | Backstop Price. Time paths for the exogenous backstop price for two different parametrizations: The best-guess (black line) is the standard Nordhaus (2018) specification and almost coincides with the lower interquartile rate of IPCC AR6 model runs. The upper range (green line) is a parametrization that resembles the upper interquartile range of the AR6 model runs.

[4] The IQR for 2025 carbon prices for that path is \$33-74\$.

Non-CO_2 forcings

In the DICE model, the time path for total radiative forcing is given by

$$F(t) = \kappa \, \frac{\log \frac{MAT(t)}{MAT_E}}{\log 2} + Fex(t), \tag{6}$$

where κ is forcing of equilibrium CO_2 doubling, $MAT(t)$ is atmospheric carbon in period t, MAT_E is the equilibrium (pre-industrial) concentration of atmospheric carbon and $Fex(t)$ are exogenous non-CO_2 forcings. The standard DICE 2016R2 version assumes that $Fex(t)$ linearly increases from 0.5 W/m^2 in 2015 to 1 W/m^2 in 2100 and remains constant thereafter. For our best-guess we follow the updated DICE version (Hänsel et al., 2020) assuming that the management of non-CO_2 forcings is in line with, e.g., the Representative Concentration Pathways (RCP) 2.6 and 4.5 or the Shared Socioeconomic Pathways (SSPs). Specifically, the exogenous path for non-CO_2 forcing is calibrated to match the REMIND integrated assessment model using the SSP2 2.6 scenario peaking at 0.59 W/m^2 in 2055 and decreasing to 0.33 W/m^2 by 2100. Figure C3 compares our best-guess estimate (black line) for non-CO_2 forcings to the standard DICE 2016R2 pathway (green line), which we use as a CPC curve shifter.

Figure C3: Non-CO_2 forcings

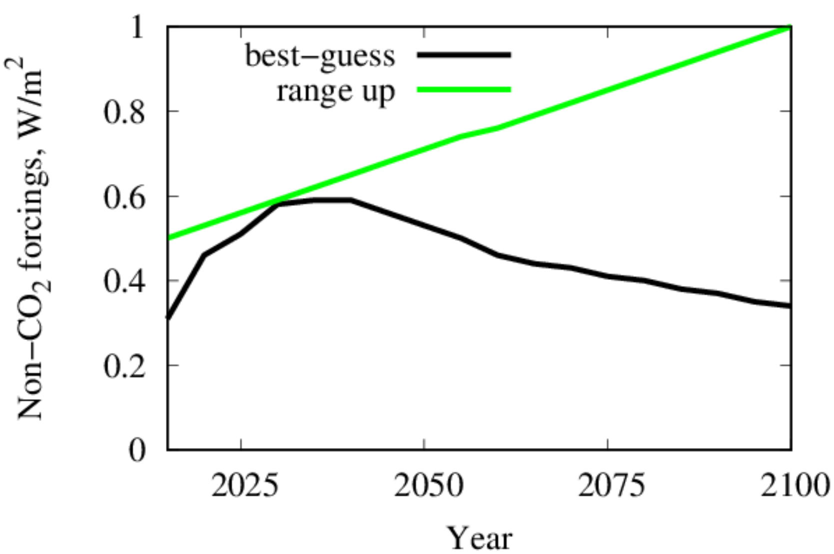

Figure C3 | Non-CO_2 forcings. Time paths for exogenous non-CO_2 forcings for two different parametrizations: The best-guess (black line) is Hänsel et al. (2020) specification taken from the REMIND model that is compatible with the UN climate targets. The upper range (green line) is the Nordhaus (2018) specification.

Population

Given the initial level of global population $L(0)$ the exogenous population development in DICE 2016R2 is given by

$$L(t) = L(t-1)\left(\frac{\bar{L}}{L(t-1)}\right)^{g_L}, \tag{7}$$

where $\bar{L}$ is an assumed asymptotic population size and g_L is the per-period growth rate calibrated to meet UN projections for the size of the global population in 2050. In this paper we recalibrate $\bar{L}$ and g_L in (7) to meet the 95% confidence level of 2050 population projections summarized in the latest 2022 UN report on that matter (United Nations 2022). The report estimates the mean global population to grow to 9400 million people by 2050 with a 95% confidence interval ranging from 9400 to 9700 million people. Despite these new estimates the standard DICE 2016R2 calibration still seems to be a good middle-of-the-road assumption and thus we stick to it for the best-guess estimate. Table C2 summarizes the parametrization and Figure C4 shows the resulting population dynamics until the end of the century.

	Range Up	**Best-Guess**	**Range Low**
$\bar{L}$	14500	11500	10000
g_L	0.08122	0.134	0.2022

Tab. C2 | Summary of parametrization for the backstop technology as a CPC curve shifter.

Figure C4: Population

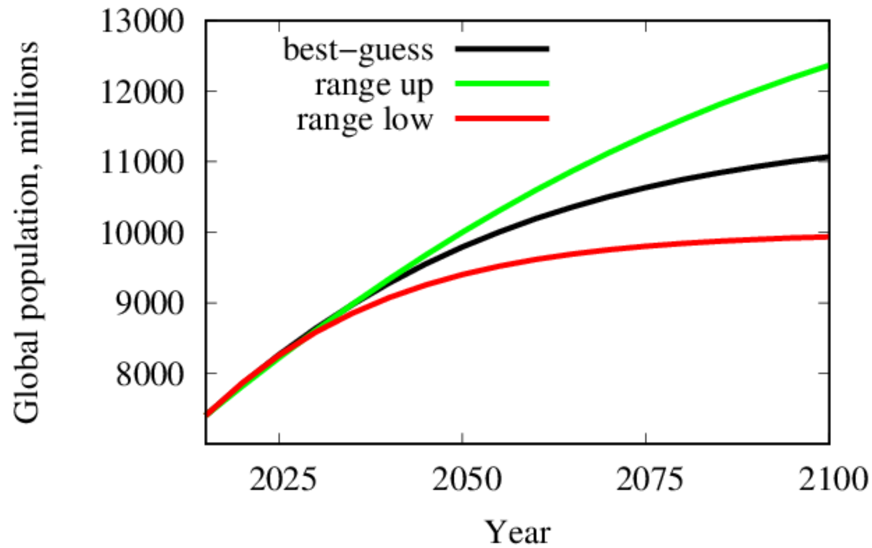

Figure C4 | Population. Time paths for exogenous global population development for three different parametrizations: The best-guess (black line) is the standard DICE 2016R2 assumption while the upper range (green line) and the lower range (red line) correspond to the 95% confidence interval of the 2022 UN population projections.

Decarbonization

Given its initial value in the first period $\sigma(t)$ the time path for the CO_2-intensity of output in DICE 2016R2 reads

$$\sigma(t) = \sigma(t-1)\, e^{5g^{\sigma}(t-1)}, \tag{8}$$

where $g^{\sigma}(t) = g^{\sigma}(t-1)(1+\delta^{\sigma})^5$ and $g^{\sigma}(0)$ given.

As curve shifters we consider the 95 percentile range for the initial growth rate $g^{\sigma}(0)$ from Nordhaus (2018) with a mean of -1.5% per year and standard deviation of 0.32% (95 percentile range from -0.88% to -2.16%). The resulting dynamics for $\sigma(t)$ is plotted in Figure C5.

Figure C5: CO_2-intensity output

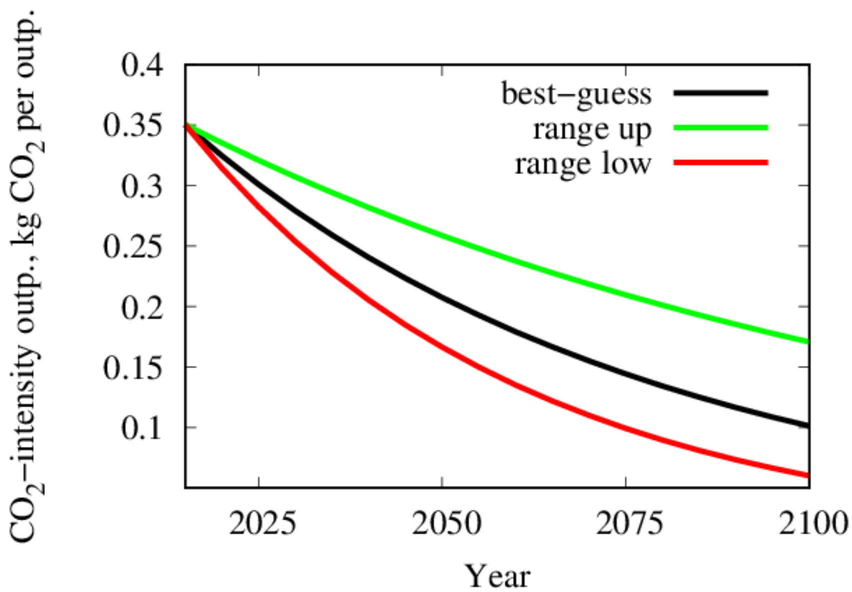

Figure C5 | CO_2-intensity output. Time paths for the exogenous CO_2-intensity of output for three different parametrizations: The best-guess (black line) is the standard DICE 2016R2 assumption while the upper range (green line) and the lower range (red line) correspond to the 95% confidence interval in Nordhaus (2018).

Total factor productivity (TFP) growth

Total factor productivity is exogenous in the DICE 2016R2 model and evolves according to

$$A(t) = \frac{A(t-1)}{1-g^A(t-1)}, \tag{9}$$

where $g^A(t) = g_0^A\ e^{-\delta^A 5t}$ and $A(0)$ is given.

As curve shifters we consider the 66 percentile range for the initial rate of productivity growth g_0^A as used in Nordhaus (2018) and Gillingham et al. (2018). The range has a mean of 1.48% p.a. with a standard deviation of 0.93% leading to a 66 percentile range between 0.55% to 2.41%.

Figure C6: TFP growth

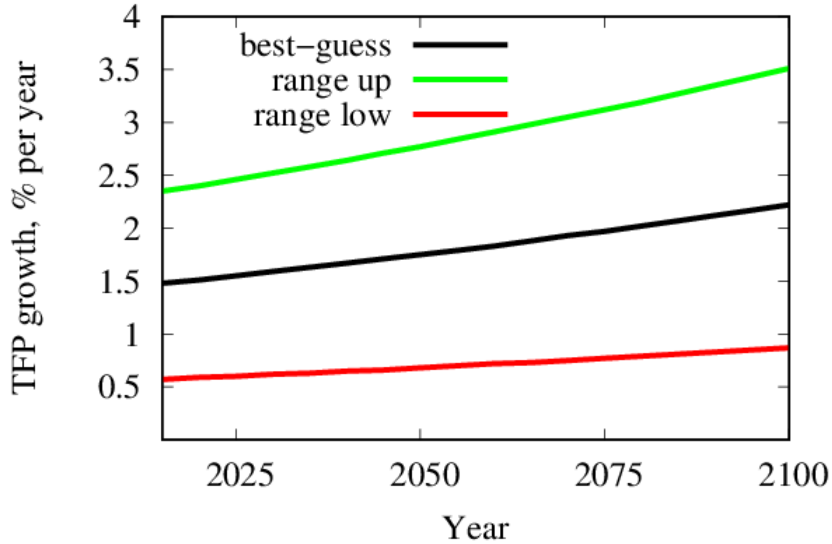

Figure C6 | TFP growth. Time paths for the exogenous rate of total factor productivity growth (TFP) for three different parametrizations: The best-guess (black line) is the standard DICE 2016R2 assumption while the upper range (green line) and the lower range (red line) correspond to the 95% confidence interval in Nordhaus (2018) and Gillingham et al. 2018.

D. Methods for Figure 4: AR6-CPC

So far our analysis has only relied on the DICE 2016R2 integrated assessment model as updated in Hänsel et. al (2020). To explore how the CPCs derived from this modelling framework compare to a more diverse set of models and modelling assumptions we use the IPCC AR6 Scenario Database (2022) to trace out the relationship between carbon pricing and temperature increase across AR6 model runs. From the raw data, we've extracted data on the 50.0th Percentile of Surface Temperature (GSAT) forecast for the year 2100 from the FaIRv1.6.2 model and carbon prices in US$2010/t CO2 for the years 2025, 2030, 2050 and 2100 for 1665 model runs. We excluded runs where temperature in 2100 was not available (N=157), thus leaving 1507 model runs. We inflated all carbon prices to US$2020/t CO2, multiplying by 1.09. We then replaced all non-existent or zero values in specific years – mostly in year 2025 – by a carbon price of 0.01 US$2010/t CO2 to be able to calculate growth rates. Next, we calculated an exponential growth rate of the carbon price from 2025 to 2100. To compute the AR6-CPC equivalent to the ones derived from the updated DICE model, we base the AR6-CPC on all 875 data point pairs of 2025 carbon prices in-between \$2 and \$200 and 2100 temperatures. Specifically we apply the nonlinear least-squares Marquardt-Levenberg algorithm of gnuplot version 5.2 to fit a power function of the form $f(x) = a\, x^b$ to the modelling data.[5] The estimated parameters and summary statistics of the non-linear fitting procedure are summarized in Table D1.

Non-linear fitting statistics for AR6-CPC	
Sum of squares of residuals	143.808
Degrees of freedom	873
Standard deviation of residuals	0.405868
Variance of residuals	0.164729
Final set of parameters	**Asymptotic Standard Error**
a = 2.90217	+/- 0.07751
b = -0.142065	+/- 0.007941

Tab. D1 | Non-linear fitting statistics for AR6-CPC and final set of parameters

Figure 4 in the main text shows the AR6 modelling data and the resulting AR6-CPC and compares them to the CPCs with the constant 4% and 6% growth rates based on the updated DICE model used in this paper. Figure 4 illustrates how the CPCs based on the updated DICE model by Hänsel et al. (2020) with constant growth rates of carbon prices relate to a CPC derived from the diverse set of models and assumption used in the IPCC AR6 report.

[5] We have also tested the power function specification against alternative functions of the form $f(x) = a\ln(\mathrm{x}) + \mathrm{b}$ (log-specification) and $f(x) = a\mathrm{x} + \mathrm{b}$ (linear specification). Among these functional forms, the power function specification minimizes the sum of squared residuals, which we used as the relevant criterion.

References

Andersson, J. J. (2019). Carbon taxes and CO 2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy*, 11(4), 1-30.

Bayer, P., & Aklin, M. (2020). The European Union emissions trading system reduced CO2 emissions despite low prices. *Proceedings of the National Academy of Sciences*, 117(16), 8804-8812.

Best, R., Burke, P. J., & Jotzo, F. (2020). Carbon pricing efficacy: Cross-country evidence. *Environmental and Resource Economics*, 77(1), 69-94.

Byers, E. et al. (2022). AR6 Scenarios Database hosted by IIASA. International Institute for Applied Systems Analysis, 2022. doi: 10.5281/zenodo.5886912| url: data.ene.iiasa.ac.at/ar6/

Dietz, S., Gollier, C., & Kessler, L. (2018). The climate beta. *Journal of Environmental Economics and Management*, 87, 258-274.

Dietz, S., & Venmans, F. (2019). Cumulative carbon emissions and economic policy: in search of general principles. *Journal of Environmental Economics and Management*, *96*, 108-129.

Drouet, L., Bosetti, V., Padoan, S.A. et al. Net zero-emission pathways reduce the physical and economic risks of climate change. *Nature Climate Change* 11, 1070–1076 (2021).

Drupp, M.A., Nesje, F., & R.C. Schmidt (2022). Pricing Carbon. *CESifo Working Paper* No 9608.

Drupp, M. A., Freeman, M. C., Groom, B., & Nesje, F. (2018). Discounting disentangled. *American Economic Journal: Economic Policy*, *10*(4), 109-34.

Fuss, S., Lamb, W. F., Callaghan, M. W., Hilaire, J., Creutzig, F., Amann, T., ... & Minx, J. C. (2018). Negative emissions—Part 2: Costs, potentials and side effects. *Environmental Research Letters*, *13*(6), 063002.

Gerlagh, R., & Liski, M. (2018). Carbon prices for the next hundred years. *The Economic Journal*, *128*(609), 728-757.

Gillingham, K., & Stock, J. H. (2018). The cost of reducing greenhouse gas emissions. *Journal of Economic Perspectives*, 32(4), 53-72.

Gillingham, K., Nordhaus, W., Anthoff, D., Blanford, G., Bosetti, V., Christensen, P., ... & Reilly, J. (2018). Modeling uncertainty in integrated assessment of climate change: A multimodel comparison. *Journal of the Association of Environmental and Resource Economists*, 5(4), 791-826.

Gollier, C. (2021). The Cost-Efficiency Carbon Pricing Puzzle (March 1, 2021). *CEPR Discussion Paper* No. DP15919, Available at SSRN: https://ssrn.com/abstract=3805342.

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, *82*(1), 41-88.

Gosnell, G. K., List, J. A., & Metcalfe, R. D. (2020). The impact of management practices on employee productivity: A field experiment with airline captains. *Journal of Political Economy*, 128(4), 1195-1233.

Hänsel, M. C., Drupp, M. A., Johansson, D. J., Nesje, F., Azar, C., Freeman, M. C. & Sterner, T. (2020). Climate economics support for the UN climate targets. *Nature Climate Change*, *10*(8), 781-789.

Harmsen, M., Kriegler, E., Van Vuuren, D. P., van der Wijst, K. I., Luderer, G., Cui, R., ... & Zakeri, B. (2021). Integrated assessment model diagnostics: key indicators and model evolution. *Environmental Research Letters*, 16(5), 054046.

International Monetary Fund, (2021). Proposal for an International Carbon Price Floor Among Large Emitters. *Staff Climate Note* No. 2021/001.

IPCC (2018). Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)].

IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. https://www.ipcc.ch/report/ar6/wg2/.

Kriegler, E., Petermann, N., Krey, V., Schwanitz, V. J., Luderer, G., Ashina, S., ... & Van Vuuren, D. P. (2015). Diagnostic indicators for integrated assessment models of climate policy. *Technological Forecasting and Social Change*, *90*, 45-61.

Leroutier, M. (2022). Carbon pricing and power sector decarbonization: Evidence from the UK. *Journal of Environmental Economics and Management*, 111, 102580.

Nesje, F., Drupp, M.A., Freeman, M., & Groom, B. (2022). Philosophers reinforce economists' support for UN climate targets, but disagree on why. Research Square, https://www.researchsquare.com/article/rs-2136517/v1.

Nordhaus, W. D. (1994) *Managing the Global Commons*, MIT Press, Cambridge.

Nordhaus, W. D. (2008) *A Question of Balance,* Yale University Press.

Nordhaus, W. D. (2018). Projections and uncertainties about climate change in an era of minimal climate policies. *American Economic Journal: Economic Policy*, *10*(3), 333-60.

Pretis, F. (2022). Does a carbon tax reduce CO2 emissions? Evidence from British Columbia. *Environmental and Resource Economics*, 1-30.

Raftery, A., Zimmer, A., Frierson, D., Startz, R. & Liu P. (2017). Less than 2 °C warming by 2100 unlikely. *Nature Climate Change* 7, 637-641. https://doi.org/10.1038/nclimate3352.

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10), 895-900.

Sherwood, S.C., Webb, M.J., Annan, J.D., Armour, K.C., Forster, P.M., Hargreaves, J.C., Hegerl, G., Klein, S.A., Marvel, K.D., Rohling, E.J. and Watanabe, M., 2020. An assessment of

Earth's climate sensitivity using multiple lines of evidence. *Reviews of Geophysics*, *58*(4), p.e2019RG000678.

Traeger, C. (2022). ACE—Analytic Climate Economy. *American Economic Journal: Economic Policy*.

United Nations Department of Economic and Social Affairs, Population Division (2022). *World Population Prospects 2022: Summary of Results*. UN DESA/POP/2022/TR/NO. 3.

Van den Bijgaart, I., Gerlagh, R., & Liski, M. (2016). A simple formula for the social cost of carbon. *Journal of Environmental Economics and Management*, *77*, 75-94.