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Léo Coppens and Frank Venmans

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The welfare properties of climate targets

Coppens Léo[*], Venmans Frank[†]

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Abstract

Two approaches are predominant in climate models: cost-benefit and cost-effectiveness analysis. On the one hand, cost-benefit analysis maximises welfare, finding a trade-off between climate damages and emission abatement costs. On the other hand, cost-effectiveness analysis minimises abatement costs, omits damages but adds a climate constraint, such as a radiative forcing constraint, a temperature constraint or a cumulative emissions constraint. These constraints can be applied from today onwards or only from 2100 onwards, allowing to overshoot the target before 2100. We analyse the impacts of these different constraints on optimal carbon prices, emissions and welfare. To do so, we fit a model with abatement costs, capital repurposing costs (stranded assets) and technological change on IPCC and NGFS scenarios. The welfare-maximizing scenario reaching 1.5°C in 2100 has almost no net negative emissions at the end of the century (-2GtCO_2/y). A constraint on cumulative emissions has the best welfare properties, followed by a temperature constraint with overshoot. A forcing constraint with overshoot has insufficient early abatement, leading to a substantial welfare loss of $29 Trillion, spread out over the century. As to the paths reaching 2°C, all cost-effectiveness analysis abate too late, but the welfare impact of this dynamic inefficiency is milder. Again, a forcing constraint with overshoot scores worst.

Keywords: climate change mitigation, targets formulation, integrated assessment models, optimal abatement path, cost-benefit, cost-effectiveness, welfare, negative emissions

1 Introduction

There are two common approaches in the literature on optimal emission scenarios. Cost-benefit (CB) analysis maximizes welfare by considering both abatement costs and climate damages. Peak temperature is endogenous and balances

[*]Department of Finance, Warocqué School of Business and Economics, University of Mons, Place Warocqué 17, 7000 Mons, Belgium, leo.coppens@umons.ac.be

[†]Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science, UK, f.venmans1@lse.ac.uk

costs and benefits from emission abatement. In contrast, cost-effectiveness (CE) analysis only considers abatement costs while imposing a climate constraint (for example, less than 2°C of warming). CE analysis does not specify a damage function and therefore abstracts from the timing of damages. As a result, it tends to abate later than a CB analysis with the same peak temperature. This article evaluates the welfare cost of this delay and investigates the implications of different types of constraints.

We investigate the three most popular constraints in CE analysis: a temperature constraint, a cumulative emissions constraint and a radiative forcing constraint. Radiative forcing is the extra incoming energy flow (in W/m^2) that results from a higher atmospheric concentration of greenhouse gases (GHG). Since forcing is a monotonic function of GHG concentrations, a forcing constraint is identical to an atmospheric concentration constraint. Each constraint can be applied with or without overshoot before 2100. In the past, the most popular constraint was a radiative forcing target as it was used in the IPCC scenarios, which were grouped in different Representative Concentration Pathways (RCP). Each RCP was named after its radiative forcing in 2100 (Van Vuuren et al. [2014], Riahi et al. [2017]). Other model comparisons also use the radiative forcing constraints from the RCP's (Rogelj et al. [2018]). However, temperature targets (e.g., Nordhaus [2018], Shukla et al. [2022]) and cumulative emissions targets (e.g., Luderer et al. [2018]) have become more popular in recent years, including in the most recent IPCC report (Rogelj et al. [2019], Riahi et al. [2020], Johansson et al. [2020], IPCC [2022]).

We assess the implications of these three forms of constraint with and without overshoot and compare them against a CB approach. This allows us to rank the welfare performance of different types of constraints. We calibrate constraints and damage functions such that all models reach 1.5°C or 2°C by 2100.

While CB analysis is conceptually the gold standard, CE analysis is popular because it avoids the need for a damage function, which is notoriously difficult to estimate, and because international climate agreements such as the Paris agreement set a maximum temperature. CE is also computationally simpler, which is important for models with many sectors, countries and/or technologies. Therefore, we do not argue against the use of CE analysis, but show that some constraints are better than others.

We rank the constraints by comparing them to a CB welfare maximization, which requires an estimate of marginal damages. One could argue that CB analysis is not a good reference scenario, since CE was developed as a solution to avoid uncertainty regarding climate damages. We have three arguments why a CB scenario with damages is the most appropriate reference scenario. Firstly, our approach is agnostic to the true size of the damages. Instead of choosing an exogenous damage parameter, we adjust our damage parameter such that both approaches (CE and CB) obtain the same optimal temperature in 2100. Secondly, we use a quadratic damage function in the main analysis and show in the appendix that a cubic damage function gives very similar results. Thirdly, we also analyze a CB case with lower damages, combined with a temperature constraint. This corresponds to the case where the temperature target is considered as a political constraint due to the Paris Agreement. As long as a social planner believes that damages are not zero, it makes sense to consider the timing of these damages. We show that considering even low climate damages improves the welfare properties of CE analysis. Other studies investigating the effect of different constraints have compared the total abatement costs of different scenarios (e.g., Johansson et al. [2020], Lemoine and Rudik [2017]). We show that including the timing of damages can change the relative ranking of constraints.

Optimal emissions depend on the dynamic properties of marginal abatement costs. Not only the level of abatement but also the speed of abatement matters, since capital adjustment costs, stranded assets, and bottlenecks in rapidly expanding green sectors will make very fast abatement more costly. The resulting emissions inertia will increase initial emissions in all models and reduce the differences between them. Another important dynamic property of abatement costs is the pace of endogenous technological change, driven by learning by doing, economies of scale, network effects, and demand-induced R&D. We develop a statistical method to obtain consensus estimates for a dynamic abatement cost structure. More specifically, we use Generalized Method of Moments (GMM) to fit a stylized dynamic abatement cost function on the climate scenarios database of both the IPCC's Special Report on 1.5 degrees and the NGFS, as in Coppens et al. [2022].

Our results are as follows. We start by comparing models reaching 1.5°C in 2100. The welfare-maximizing path (CB) has an optimal peak temperature of 1.60°C and almost no net negative emissions. The CE scenario with a cumulative emission constraint scores second-best. Its emission and temperature trajectory are extremely close to a welfare-maximizing approach (peak temperature 1.61°C). Third-best is the scenario with a temperature constraint allowing overshoot, reaching a peak temperature of 1.70°C. This overshoot can be decreased to 1.65°C by adding modest climate damages to the model. A radiative forcing target with overshoot is worst, showing the largest welfare loss, the highest temperature overshoot (1.73°C) and substantial net negative emissions. This is because an extra tonne of CO_2 emitted today leads to a constant increase in temperature , while the increase on forcing diminishes over time. The diminishing impact on forcing creates an incentive to postpone abatement and increases the discrepancy with CB analysis. The discounted cost of using the radiative forcing constraint instead of cost-benefit is substantial, $29 Trillion spread out over this century. Finally, a temperature target without overshoot performs almost as badly, in welfare terms, as the radiative forcing target with overshoot. This is because the current warming is already 1.2°C with another 0.2°C locked in due to inertia in the climate system, causing a temperature target without overshoot to produce extremely high stranding and repurposing costs. Note that a constraint on radiative forcing without overshoot is physically impossible because keeping the current CO_2 concentration constant leads to more than 1.5°C warming.

Regarding the models reaching 2°C in 2100, the ranking of constraints is slightly different. The largest difference is between CB on the one hand, and all the CE scenarios on the other hand. The CB scenario has lower emissions until 2060. None of the scenarios have a temperature overshoot and none have net negative emissions. A radiative forcing constraint without overshoot, criticized in Lemoine and Rudik (2018) for having earlier abatement than a temperature constraint, is actually the second-best from a welfare perspective. A cumulative emissions constraint is third best, closely followed by a temperature constraint. Again, a forcing constraint with overshoot scores worst. Overall, our advice for 2°C scenarios is to add damages to the optimization problem.[1] This is because all CE have insufficient abatement early on. If that is impossible, we provide a deviation from the Hotelling rule for the carbon price path as a second-best solution.

The paper is organized as follows. Section 2 discusses the related literature. Section 3 introduces the model and the methodology used to assess the different scenarios. Section 4 presents the results: optimal abatement paths, their ranking and their net negative emissions. Section 5 concludes and gives practical recommendations.

2 Literature

Our work is situated within the literature on top-down integrated assessment models (IAM's), focussing on optimal timing of emissions and carbon prices (Grubb et al. [2020, 2021] Campiglio et al. [2022] Vogt-Schilb et al. [2018]), and provides insights on optimal dynamics for more detailed bottom-up IAM's (Shukla et al. [2022], Weyant [2017] , Nikas et al. [2019]). We contribute to a relatively new body of literature that compares the effect of constraints in CE analysis. Our study presents the first comprehensive overview of the effect of 6 different types of constraints, while also ranking their welfare properties.

For example, Johansson et al. [2020] compare two constraints, a radiative forcing constraint with overshoot and a temperature constraint without overshoot. They show that large net negative emissions are the result of a forcing constraint with overshoot, and that in the case of a temperature constraint without overshoot negative emissions are mild (not exceeding $5\text{GtCO}_2/\text{y}$).[2] Expanding their approach, we demonstrate that even under a temperature target with overshoot, net negative emissions are very low and that constraints leading to large negative emissions result in lower welfare.

Taking welfare effects into consideration can lead to opposite conclusions. Lemoine and Rudik [2017] show that a temperature constraint leads to lower discounted abatement costs compared to a forcing constraint (both without overshoot). Their analysis highlights the advantage of postponing abatement costs. However, we demonstrate that the advantage of delayed abatement costs

[1] Adding mild damages to a CE scenario is technically identical as adding a constraint to a CB analysis.

[2] We refer mainly to the results with the GET-Climate model (Azar et al. [2006, 2013]), which has emissions inertia, whereas their results based on a modified version of DICE has no abatement inertia (and hence no negative emissions).

is outweighed by the earlier damages incurred. This reverses their result. For a scenario reaching 2°C by 2100, the constraint on forcing achieves a higher welfare score due to its earlier abatement.

The role of climate inertia depends on the level of ambition of the scenarios. Mattauch et al. [2020] show that a cumulative emissions target and 2°C temperature target exhibit very similar emissions trajectories. We confirm this result for a 2°C target, but show that for a 1.5°C scenario, a cumulative emissions constraint differs from a temperature constraint without overshoot. This difference is driven by the large emissions over the last decade which reach their peak warming effect with a delay of 10 years and lead to a temperature overshoot in the case of a cumulative emissions constraint.

Abatement inertia is important when comparing CB and CE analysis. Dietz and Venmans [2019] show that compared to a CE approach, CB analysis leads to much earlier abatement. Dietz et al. [2021] show similar results for DICE. We obtain a smaller difference between both approaches, due to abatement inertia, in line with the results of Campiglio et al. [2022] and Emmerling et al. [2019]. To solve the problem of insufficient early abatement ambition in CE, Emmerling et al. [2019] suggest using a lower discount rate and show that under this condition net negative emissions are never large.

There is a wider debate on the merits of CE (Stern et al. [2022]) and CB analysis (Aldy et al. [2021]), including ethical, legal, prudential and political arguments, that exceeds the scope of this paper. We provide guidance on how to improve the welfare properties of CE analysis, acknowledging that CE analysis is widely applied for several reasons, including computational constraints.

3 Methods

Our climate module uses the mean CMIP5 model parameters of Joos et al. [2013] for carbon absorption and Geoffroy et al. [2013] for thermal inertia. This results in a calibration which is very close to FAIR (FAIR adds saturation of carbon sinks, which has a minor effect below 2°C). For other greenhouse gases, we add RCP1.9 or RCP2.6 exogenous forcings for our 1.5°C and 2°C models respectively (Riahi et al. [2017], Rogelj et al. [2018], Gidden et al. [2019]).

We now describe the main features of the economic model. Define abatement $a = E_{BAU} - E$, with emissions E (in $GtCO_2$-eq) and business-as-usual emissions E_{BAU}. Cumulative abatement A is the sum of all past aggregate abatement ($\dot{A} = a$). We assume a linear marginal abatement cost function proportional to consumption c, as in Dietz and Venmans [2019]

$$MAC_t = \varphi \left(\frac{A_t}{A_0} \right)^{-\chi} a_t c_t. \tag{1}$$

Parameter φ is the slope of the marginal abatement cost function at time zero. The factor $\left(\frac{A_t}{A_0}\right)^{-\chi}$ represents endogenous technological change, which reduces green technology costs as cumulative abatement increases over time.

Parameter χ is the elasticity of the MAC with respect to cumulative abatement. Each increase of cumulative abatement by 1% reduces the MAC curve by χ%. We also fit a quadratic static MAC curve to our database but the coefficient on the quadratic term is both statistically and economically insignificant.

The model also includes abatement inertia, which adds extra costs when emissions decrease rapidly due to stranding costs, capital repurposing costs, bottlenecks in innovation, adjustments in labour and financial markets etc. This is modeled as a quadratic penalty for abatement speed $v = \dot{a}$, reducing consumption by a factor $\exp\left(\frac{\theta}{2}v^2\right)$. Adding technological change and economic inertia is important since those dynamics have a large effect in ambitious scenarios Grubb et al. [2020].

We assume that climate damages are quadratic in temperature T and proportional to consumption, as in DICE and Dietz and Venmans [2019]. Exogenous labour-augmenting technology improves labour productivity, leading to a BAU consumption growth rate of rate g. Bringing all the pieces together, we obtain the following consumption per capita function

$$c_t = c_0 e^{\left(gt - \frac{\varphi}{2}a_t^2\left(\frac{A_t}{A_0}\right)^{-\chi} - \frac{\theta}{2}v_t^2 - \frac{\gamma}{2}T_t^2\right)}. \tag{2}$$

Our dynamic abatement cost function is fitted on both the total abatement cost and marginal abatement cost of 109 scenarios of the IPCC 1.5 special report and NGFS scenarios (Rogelj, J. et al. [2018], Huppmann, D. et al. [2019], NGFS [2021]) using GMM.

We use a standard utility function with constant elasticity of marginal utility and utility discount rate δ. Population is growing at rate n and standardized at 1 at time zero. This results in the following welfare maximization problem

$$max \int_0^\infty e^{-(\delta-n)t}\frac{c^{(1-\eta)}}{1-\eta}dt. \tag{3}$$

The damage coefficient is chosen such that the optimal temperature path reaches either 1.5°C or 2°C in 2100. For our CE analysis, we set damages to zero ($\gamma = 0$) and add a constraint which is again designed to reach 1.5°C or 2°C in 2100. A constraint with overshoot implies that the constraint is only binding from 2100 onwards. We also develop a CB scenario with a lower damage function and a temperature constraint.

Appendixes A, B and C describe the details of the economic model, the climate module and GMM estimation respectively.

4 Results

4.1 1.5°C scenarios

Figure 1 plots the emissions and temperature paths of the 6 scenarios reaching 1.5°C. Table 2 presents the associated net negative emissions and welfare

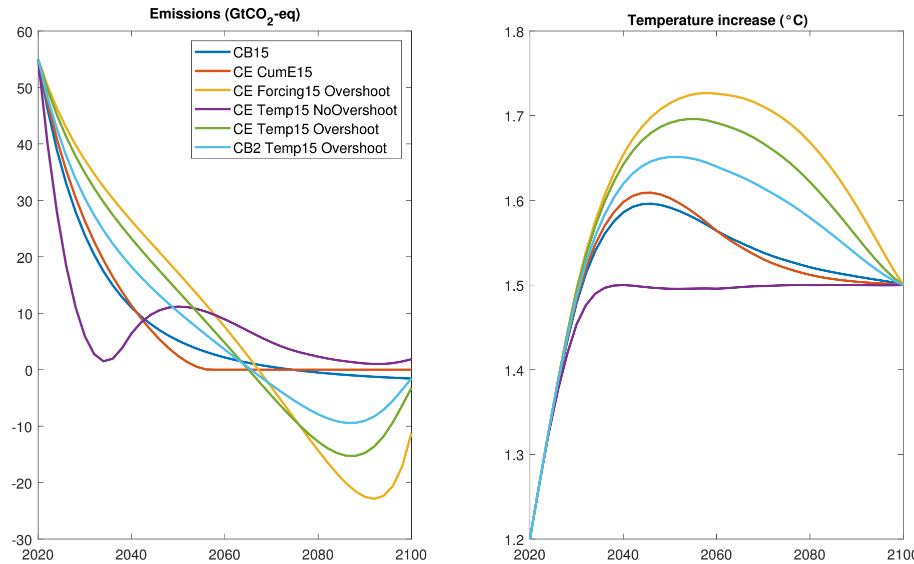

Figure 1: Emissions and temperature trajectories meeting 1.5°C

impacts. A radiative forcing constraint without overshoot is infeasible (as in Johansson et al. [2020]) because keeping radiative forcing constant at the current level will give a temperature that exceeds 1.5°C.

4.1.1 Cost-benefit

The CB scenario leads to the maximum total welfare by design. The peak temperature is 1.60°C. Emissions reach zero around 2075 and there are almost no net negative emissions thereafter (-2GtCO_2-eq in 2100). Note that large scale negative emissions start well before 2075 to compensate for emissions in hard-to-abate sectors. It is worth reflecting on the logic of net negative emissions. In a CB analysis, net negative emissions are driven by two factors. First, high economic inertia costs lead to high emissions during the first decade and a temperature exceeding the long term optimum. Since abatement in the later decades come with less inertia costs, negative emissions may become optimal. This effect is negligible in our model because emissions reach net zero in 2075, when inertia costs have become negligible. The second driver of net negative emissions is technological change after peak warming. Since negative emissions technologies become cheaper over time, it becomes optimal to deploy them at a larger scale. This effect is again small in our analysis as by 2075 most of the learning gains, economies of scale and network effects will have been obtained. As a result, the optimal path has only very modest net negative emissions of 22GtCO_2-eq over the period 2075-2100. This will generally be the case unless we would start the optimisation in 2030 at a temperature of 1.5°C.

Table 1 reports the growth rate of the carbon price. The Hotelling rule

	2020	2030	2040	2050	2060	2070	2080	2090	2100
1.5°C scenario	1.2%	1.4%	1.9%	2.2%	2.3%	2.3%	2.4%	2.4%	2.4%
2°C scenario	1.7%	2.2%	2.5%	2.6%	2.6%	2.6%	2.6%	2.6%	2.6%

Table 1: Continuous growth rates of carbon prices for CB scenarios.

prescribes that the carbon price should grow at the discount rate (2.76%) in the period before the constraint binds and is very popular in CE analysis. The welfare-maximizing carbon price is 1.5% (0.5%) lower than the Hotelling rule in 2020 (2050). The initial carbon price is \$210/tCO_2.

We now analyse the CE scenarios from the lowest to the highest overshoot.

4.1.2 Temperature constraint without overshoot

This is the scenario with the most rapid fall in emissions (Figure 1). Emissions need to drop drastically to 5.9 GtCO_2-eq in 2030. This is due to the very large past emissions between 2010 and 2020 which have their peak warming effect a decade later. Since emissions decrease so rapidly after 2020, an increase in emissions is allowed in 2040. This early dip in emissions is the direct consequence of not allowing overshoot. The sharp drop by 2030 leads to very high inertia costs and lower welfare. In other words, the window of opportunity to stay below 1.5°C without overshoot is behind us. It is neither politically feasible, nor desirable from a welfare perspective.

4.1.3 Cumulative emissions constraint

The scenario with the cumulative emissions constraint has a very similar emissions path compared to the CB scenario. In the first decades, emissions are largely driven by inertia costs and are very close to the CB trajectory, leading to a very similar peak temperature of 1.61°C. Zero emissions are reached earlier (in 2058) and by the nature of the constraint, there are no net negative emissions. This makes the emission path close to the CB solution in the second half of the century. The welfare outcome is almost indistinguishable from the CB analysis.

4.1.4 Constrained cost-benefit

We also run a CB scenario with a mild damage function (calibrated to reach 2°C) while adding a 1.5°C constraint with overshoot. We frame this as an elegant solution to improve the welfare properties of models that are traditionally running CE scenarios and are designed to inform target-based policy such as the Paris agreement. As expected, the emission trajectory is in between the pure CB analysis and the unconstrained temperature target with overshoot, with a peak temperature of 1.65°C. In welfare terms, this scenario ranks third, provided that one considers the damage function resulting in 1.5°C as the true damage function. This constrained CB scenario leads to 209 $GtCO_2$-eq cumulative net negative emissions.

4.1.5 Temperature constraint with overshoot

This scenario reaches net zero in 2065 and has a peak temperature of 1.70°C and peak net negative emissions of 14 $GtCO_2$-eq at the end of the century.Since a temperature overshoot is allowed the model is insensitive to warming before 2100. Since discounting shrinks future costs, it becomes optimal to do more net negative emissions in the far future, which are expensive in current prices, but cheap in present value terms. This leads to large cumulative net negative emissions of 344$GtCO_2$-eq. Net negative emissions peak in 2090, since their cooling effect comes with a delay of approximately 10 years. However, negative emissions in 2100 are still needed to keep warming below 1.5°C after 2100.

4.1.6 Forcing constraint with overshoot

This scenario has the largest temperature overshoot (1.73°C) and a substantial amount of negative emissions (22 $GtCO_2$-eq in 2090). Although still very popular in the literature, the radiative forcing constraint with overshoot is least attractive from a welfare perspective. The welfare loss, compared to the cost-benefit scenario, is equivalent to a constant loss of 0.4% of consumption and corresponds to a loss with a net present value of $29.0 Trillion.

The logic of a constraint on forcing is somewhat different from a temperature constraint. Forcing is a function of atmospheric GHG concentrations, so the dynamics of atmospheric CO_2 absorption will drive the model. An extra tonne of CO_2 emitted today will be absorbed at approximately 50% in 2100 when the constraint starts. By contrast, a tonne of CO_2 emitted in 2100 will not yet be absorbed at all in 2100. This creates an extra incentive to emit earlier when compared to a temperature target (the temperature impact response function is more or less constant after 15 years). Therefore, total net negative emissions are highest at 471 $GtCO_2$. Note that from 2095 onwards emissions increase again. A model without abatement inertia would give decreasing emissions until 2100 and slightly positive emissions from 2100 onwards. Since our model has abatement inertia (it would be costly to abandon all infrastructure for negative emissions), the model smooths emissions in the decade before and after 2100. This artificial switch is an undesirable artefact of a forcing constraint, which is unrelated to damages.

To sum up, we obtain the following ranking in welfare terms: cost-benefit (by design), cumulative emissions, temperature constraint with overshoot and with low damages, temperature constraint with overshoot, a forcing constraint with overshoot and a temperature constraint without overshoot. Note that the commonly used radiative forcing constraint leads to the same level of welfare losses as the unrealistic 1.5°C temperature constraint without overshoot, even though there is a 0.23°C difference in terms of peak temperature between the 2 cases. Large net negative emissions are not optimal from a welfare perspective.

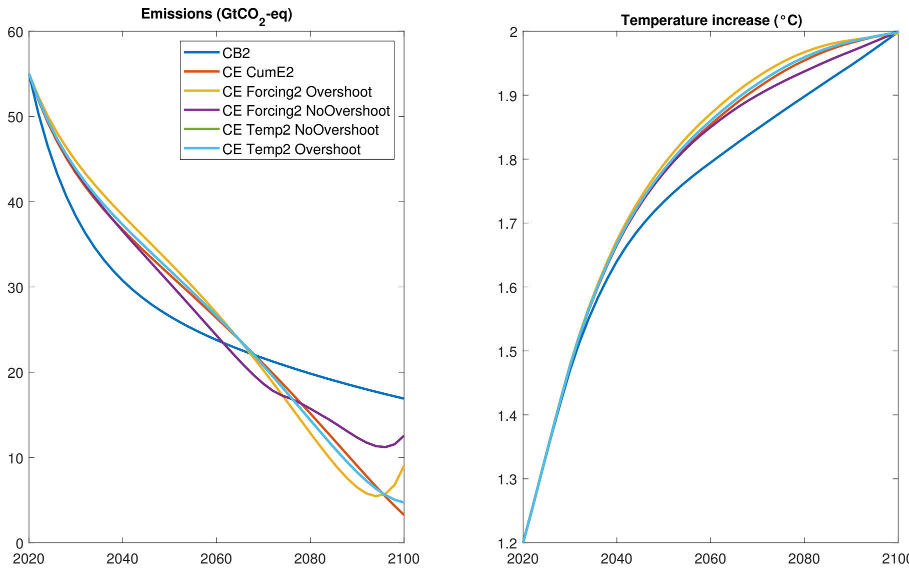

Figure 2: Emissions and temperature trajectories meeting 2°C.

The last 2 columns of Table (2) shows how welfare differences are distributed between the early period (2020-2050) and the later one (2050-2100).,The less ambitious scenarios (the CE scenarios with overshoot for instance) have welfare gains compared to the optimal scenario in the first period because of delayed action. However, those gains are exceeded by the welfare losses incurred in the second period due to larger climate damages and higher costs of net negative emissions. As to the case with the temperature constraint without overshoot, the opposite is happening: there are early welfare losses due to large inertia in abatement (stranded assets).

4.2 2°C scenarios

An overview of scenarios is shown in Table 3 and Figure 2. Note that we do not model climate uncertainty. This means that although our emission scenarios reach 2°C as a best estimate, they will exceed 2°C with a likelihood of 50%.[3]

Compared to the 1.5° scenarios, the emission paths are logically less steep. The scenarios do not reach net zero in this century, there are no net negative emissions and none of them overshoot the temperature target. Consequently, the two scenarios with the temperature constraint (with or without overshoot) have the same trajectory. We will again discuss scenarios with earliest abatement first.

[3]In 2100, the IPCC SSP1-RCP2.6 scenario results in 1.8°C warming as the median estimate, with a very likely range of 1.30°C to 2.4°C (Table SPM.1). This scenario is often interpreted as in line with a 2°C constraint, yet it is actually in between our model of 1.5°C and 2°C.

CE/CB	Type of constraint	Over-shoot	Damage function	Net negative emissions 2020-2100	Peak temperature	Welfare difference as equivalent variation 2020-2100	Welfare difference (Trillion $ of 2020) 2020-2100	Welfare difference (Trillion $ of 2020) 2020-2050	Welfare difference (Trillion $ of 2020) 2050-2100
CE	Radiative forcing 1.5°C	no		Impossible	Impossible	Impossible	Impossible	Impossible	Impossible
CE	Radiative forcing 1.5°C	yes		-471 $GtCO_2$	1.73°C	-0.4%	-29.0	56.4	-85.4
CE	Cumulative emissions 1.5°C	no		0 $GtCO_2$	1.61°C	0.0%	-0.9	3.8	-4.7
CE	Temperature 1.5°C	no		0 $GtCO_2$	1.5°C	-0.4%	-29.4	-69.7	40.4
CE	Temperature 1.5°C	yes		-344 $GtCO_2$	1.70°C	-0.2%	-16.1	47.2	-63.4
CB	No constraint		1.5°C optimal temperature in 2100	-22 $GtCO_2$	1.60°C	0.0%	0.0	0.0	0.0
CB	Temperature 1.5°C	yes	2°C optimal temperature in 2100	-209 $GtCO_2$	1.65°C	-0.1%	-5.0	30.3	-35.3

Table 2: Net negative emissions, peak temperature and welfare comparison for 1.5°C scenarios. The welfare difference expressed as equivalent variation is the permanent reduction in consumption (in %) on the unconstrained CB scenario which gives the same total discounted welfare as the CE scenario. The welfare difference expressed in Trillion $ of 2020 is the welfare difference, divided by the marginal utility of 2020 (using $133 Trillion World GNP in 2020 (in PPP) from the World Bank).

CE/CB	Type of constraint	Over-shoot	Damage function	Welfare difference as equivalent variation 2020-2100	Welfare effect difference (Trillion \$ of 2020) 2020-2100	Welfare difference (Trillion \$ of 2020) 2020-2050	Welfare difference (Trillion \$ of 2020) 2050-2100
CE	Radiative forcing 2°C*	no		0.0%	-3.2	14.7	-17.9
CE	Radiative forcing 2°C*	yes		-0.1%	-8.0	18.6	-26.6
CE	Temperature 2°C	non-binding		-0.1%	-6.2	16.3	-22.5
CE	Cumulative emissions 2°C	non-binding		-0.1%	-6.2	16.3	-22.5
CB	No constraint		2°C optimal temperature in 2100	0.0%	0.0	15.0	0.0 0.0

Table 3: Welfare comparison for 2°C scenarios. The welfare difference expressed as equivalent variation is the permanent reduction in consumption (in %) on the unconstrained CB scenario which gives the same total discounted welfare as the CE scenario. The welfare difference expressed in Trillion \$ of 2020 is the welfare difference, divided by the marginal utility of 2020 (using \$133 Trillion World GNP in 2020 (in PPP) from the World Bank).

4.2.1 Cost-benefit

The CB scenario is significantly different from all the CE scenarios: it leads to much earlier abatement and a slower temperature increase. For example, there are 30.7 $GtCO_2$-eq annual emissions in 2040 and a temperature increase of 1.73°C in 2050. In the 2°C analysis, the largest differences are not caused by the different ways to constrain the scenarios but they appear between CB on the one hand, and all the CE scenarios on the other hand. Table 1 shows that the growth rate of the carbon price is 1% (0.3%) lower in 2020 (2050) than the Hotelling rule. The lower growth rate of the CB analysis implies a higher initial carbon price, at \$121/tCO_2.

4.2.2 Forcing constraint without overshoot

Due to thermal inertia, a constant level of forcing leads to a slowly increasing temperature for several centuries. Therefore, the forcing constraint becomes binding around 2070 at a temperature of only 1.9°C, since constant forcing from 2070 onwards will increase temperature from 1.9°C to 2°C. As the forcing constraint without overshoot imposes earlier abatement, especially after 2040, it scores slightly better on welfare than the other CE scenarios. Remember that this constraint was not explored in the 1.5°C analysis as it was infeasible i.e. constant current radiative forcing leads to warming above 1.5°C in 2100.

However, the binding constraint on forcing is not attractive from a theoretical perspective for three reasons. Firstly, forcing does not drive damages, temperature does. Secondly, when combined with a higher discount rate or used for warmer temperature constraints, the constraint does not bind before 2100 and the result is the same as the forcing constraint without overshoot, i.e. slightly worse than a temperature constraint. Thirdly, a constant forcing constraint leads to an increasing temperature for centuries. Hence the temperature will increase beyond 2°C after 2100.

4.2.3 Temperature and cumulative emissions constraint

The temperature constraint is not binding before 2100, so the scenarios which allow overshoot and those which do not are identical. Temperature and cumulative emissions constraints have very similar impacts and have almost the same welfare ranking. The cumulative emissions constraint scores slightly better and leads to more abatement in the first decades. In the first periods, the CE scenario with a cumulative emissions constraint is actually the most ambitious CE scenario. Temperature increase is gradual, leading to 1.78°C warming in 2050, compared to 1.73°C for CB. The scenario with a temperature constraint shows a deceleration of abatement after 2095. This is an artefact of the short delay between emissions and warming and is non-desirable from a welfare perspective. A cumulative emissions constraint avoids this disadvantage.

4.2.4 Forcing constraint with overshoot

As mentioned before, the earlier the emissions, the more CO_2 gets absorbed by 2100, creating an incentive to postpone abatement. This is why the forcing with overshoot scenario has the highest early emissions, deviates most from CB and scores worst on welfare. For instance, emissions in 2040 are 38.4GtCO_2-eq, slightly higher than the 36.5GTCO_2-eq for a cumulative emissions constraint and much higher than the 30.7 GtCO_2-eq in the CB analysis. It leads to a slightly faster temperature increase compared to other CE scenarios (1.79°C in 2050). Emissions rise just before 2100 due to the combination of two factors: 1) constant forcing after 2100 is compatible with rising temperatures after 2100 and therefore higher emissions after 2100 and 2) our model includes an abatement speed penalty and anticipates higher emissions after 2100.

Note that we have compared scenarios with the same temperatures in 2100. This is because the IPCC is organized around scenarios until 2100. However, the CB scenarios have a peak warming much later than 2100. If we compare scenarios with identical temperature at a later period, the difference between CE and CB becomes much larger. Appendix F compares 2°C CE scenarios with a CB scenario which reaches 2°C in 2200, the difference between the CE and CB scenarios becomes much larger and the welfare cost of CE becomes substantial.

A second reason why we may underestimate the costs of CE analysis is because methane, the second most important greenhouse gas, has a short atmospheric lifetime. As a result, current methane emissions have very modest warming effect in 2100, therefore the incentive to postpone abatement in CE analysis with overshoot will be even stronger for methane than for CO_2.

5 Conclusion and discussion

Using the climate dynamics from the CMIP5 ensemble, and abatement cost dynamics of the IPCC 1,5°C report and NGFS, we analyse the principle forms of climate constraints used in CE models: a cumulative emissions budget, a temperature target, and a radiative forcing target (all with or without overshoot). We show that the type of constraint matters in terms of emissions trajectory, temperature overshoot and welfare losses. For instance, in order to reach the 1.5°C target in 2100, the emissions level in 2050 ranges from 2 to 17 GtCO_2-eq, depending on the formulation of the target. Total net negative emissions until 2100 ranges from 0 to 471 GtCO_2-eq andthe welfare cost of using CE rather than CB analysis can be up to $29 Trillion. We have five key messages from our findings.

First, for scenarios reaching 2°C in 2100, CB scenarios differ substantially from CE scenarios. In this case, the short term dynamics of warming do not play a large role and all CE constraints give similar results, with insufficient early abatement and approximately 20% excess emissions in 2050. Since CE analysis disregards the timing of climate damages, it misses an incentive for early abatement. One way to improve the dynamics of the trajectory is to add damages to the model. Even if damages would be poorly calibrated or underestimated, they will improve the dynamic properties of the model. Another way to improve the dynamics is to adjust the carbon price path. Whereas the cost-effective carbon price increases at the discount rate[4], the welfare-maximizing carbon price starts higher and increases at a slower rate. Appendix A shows that the welfare-maximizing carbon price dynamic follows $\dot{p} = rp - Marg\ damage - Endog\ TC\ gain$. The term rp corresponds to the Hotelling rule and indicates that discounting of abatement costs creates an incentive to postpone abatement. By contrast, damages and endogenous TC create an incentive to abate earlier, reducing the optimal carbon price growth rate by 1%, 0.5% and 0.3% in 2020, 2030, and 2050 respectively. To improve the welfare properties of their scenarios, modellers can use these percentages to obtain a welfare-corrected Hotelling rule.

Secondly, the overly steep carbon price path of CE is exacerbated by the choice of high discount rates. Gollier [2021] shows that the mean discount rate used in the 767 scenarios of the AR5 IPCC database is 7.0%. Similarly, the US Climate Leadership Council, the French Quinet commission and the UK government have proposed carbon price paths increasing at 5%, 8% and 16% per year respectively Gollier [2021]. These implicit discount rates are very far from economists' consensus discount rates (Drupp et al. [2018]). High discount rates may be chosen because high abatement costs today are deemed politically infeasible. Yet it should be clear that the resulting scenarios are not welfare-maximizing and put an excessive burden on future generations. It should also be clear that this is a risky strategy, because a carbon price increasing at 7% per year can be as politically difficult as a carbon price that starts relatively high. The 'second-best' solution could then lead to a world of 2,5 or 3°C.

Thirdly, when analysing paths leading to 1.5°C in 2100, short term climate dynamics matter. The window of opportunity to stay below 1.5°C is more or less behind us, and modest overshoot of 1.6°C, has become desirable from a welfare point of view. This requires a substiantial worldwide marginal abatement cost (carbon price) of $210/t$CO_2$. A cumulative emission constraint scores best on welfare, followed by a temperature constraint with overshoot.

Fourthly, a radiative forcing target with overshoot, is dynamically the least attractive and should be avoided. It leads to the farthest path from the optimal CB path because the carbon absorption over time creates an incentive to postpone abatement. The discounted extra cost of using this constraint compared to cost-benefit is $29 Trillion for the 1.5°C and $8 Trillion for the 2°C scenario.

Fifthly, for scenarios starting in 2020,large net negative emissions are never optimal. Instead, they tend to be an artefact of the radiative forcing constraint with overshooting (see also Johansson et al. [2020]), sometimes combined with high discount rates. Our welfare-maximizing paths reaching 1,5°C in 2100 does not exceed 2GtCO_2 net negative emissions per year. Carbon removals from the atmosphere are important in optimal climate scenarios, but they should compensate emissions from hard-to-abate sectors and should not lead to large

[4]This is exact for a cumulative emission constraint and approximate for other CE models.

net negative emissions. Instead, respecting the Paris agreement at the lowest welfare cost requires radical worldwide reductions in emissions by 2040.

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A Appendix : Our model

Since our analysis focuses on the transition rather than the long term outcome (all our models have 1.5°C or 2°C in 2100) it is important that we model the dynamics of the abatement cost function in a convincing way. Our model is flexible, yet parsimonious. This has the advantage that we are able to fit our model to a few variables which are available for a large set of model runs of detailed bottom-up models: the time series of total abatement costs, marginal abatement costs, abatement and GDP.

Abatement a equals business-as-usual emissions minus emissions,

$$a = E_{BAU} - E \tag{4}$$

Cumulative abatement A equals cumulative BAU emissions minus cumulative emissions,

$$A_t = A_0 + \int_0^t E_{BAU} d\tau - S_t + S_0. \tag{5}$$

Therefore, all else equal, an extra unit of cumulative emissions implies a unit less of cumulative abatement $A_S = -1$.

We use a non-stochastic fruit tree model for our business-as-usual consumption (Lucas Jr [1978]). Exogenous labour-augmenting TC improves labour productivity, leading to a BAU consumption growth rate of rate g. For a similar model with capital and savings, see Campiglio et al. [2022].

Assume the following linear marginal abatement cost function, proportional to consumption c,

$$MAC \stackrel{def}{=} -\frac{\partial c}{\partial a} = \varphi \left(A/A_0\right)^{-\chi} ac. \tag{6}$$

Parameter φ is the slope of the MAC curve. The factor $(A/A_0)^{-\chi}$ represents endogenous TC, with elasticity χ, such that for every percentage increase in cumulative abatement, the marginal abatement cost, decreases by $\chi\%$. Our main model has a linear MAC curve. We also fit a model with a quadratic MAC curve, but the quadratic term is both economically and statistically insignificant.

We add a penalty on the abatement speed, because very rapid abatement leads to stranded assets, repurposing costs and capital adjustment costs. We define the abatement speed $v = \dot{a}$ and assume a quadratic total speed penalty. This results in a linear marginal abatement speed penalty $-\frac{\partial c}{\partial v} = \theta vc$.

We assume that climate damages are quadratic and proportional to consumption. The climate dynamics are modelled in the next appendix, and define how a given emission trajectory translates into a temperature trajectory. All the above leads to the following expression for consumption per capita

$$c = c_0 e^{\left(gt - \frac{\varphi}{2}(A/A_0)^{-\chi}a^2 - \frac{\theta_2}{2}v^2 - \frac{\gamma}{2}T^2\right)}, \tag{7}$$

where c_0 is a constant, representing initial consumption in the absence of climate damages and abatement costs and g is an exogenous tfp-growth process.

We use a utility function with constant elasticity of marginal utility $u = \frac{c^{1-\eta}}{1-\eta}$, with c consumption per capita and η the elasticity of marginal utility. We standardize population at time zero at 1 and assume that population grows at rate n_t.[5] In the CB setting, the social planner maximises discounted utility and solves the following problem

$$max_{\{a\}} \int_0^{\infty} e^{-(\delta - n_t)t} u(c) dt, \tag{8}$$

subject to

$$T_t = f(\{E_{\tau<t}\}); \dot{A} = a; S_0 \; given; A_0 \; given. \tag{9}$$

We solve the problem as a constrained maximization problem over a finite horizon between 2020 and 2400 and a time step of 2 years.

To give some analytical insight we use optimal control under the simplifying condition that temperature is proportional to cumulative emissions $T = \zeta S$.

[5] In our calibration, we assume that the growth rate is constant, i.e. $\dot{n}_t = 0$.

The present value Hamiltonian is

$$H^{PV} = e^{(-\delta+n_t)t}u(c) - \lambda^S(E_{BAU} - a) + \lambda^a v. \tag{10}$$

Optimality conditions include

$$\begin{aligned}
\lambda^a =& e^{(-\delta+n_t)t}u_c c\theta v, && (11)\\
\dot{\lambda^a} =& e^{(-\delta+n_t)t}u_c c\varphi_t a\,(A/A_0)^{-\chi} - \lambda^S, && (12)\\
\dot{\lambda^S} =& e^{(-\delta+n_t)t}u_c c_S. && (13)
\end{aligned}$$

with marginal damage $c_S = -c\gamma\zeta^2 S$. Take the time derivative of equation 11

$$\dot{\lambda^a} = e^{(-\delta+n_t)t}u_c c\theta v\left[-\delta + n_t + \dot{n}t - \eta\frac{\dot{c}}{c} + \frac{\dot{c}}{c} + \frac{\dot{v}}{v}\right] \tag{14}$$

The shadow price of cumulative emissions expressed in consumption units, a.k.a. the carbon price, corresponds to the marginal abatement cost augmented by extra inertia costs

$$\underbrace{p = \frac{\lambda^S e^{-(\delta-n_t)t}}{u_c}}_{Carbon\ Price} = \underbrace{c\varphi a\,(A/A_0)^{-\chi}}_{\partial c/\partial a\ standard\ MAC} + \underbrace{c\theta\,[rv - \dot{v}]}_{Abatement\ speed\ costs\ (pos)}, \tag{15}$$

with the consumption discount rate $r = \delta - n_t - \dot{n}_t t + (\eta - 1)\frac{\dot{c}}{c}$.

Equations 13 and 15 can be combined as follows

$$\dot{p_\tau} = r_\tau p_\tau - \underbrace{(-c_{S_\tau})}_{Marginal\ damages} + \underbrace{\frac{\chi\varphi_\tau}{2A_\tau}a_\tau^2\,(A_\tau/A_0)^{-\chi}}_{endogenous\ TC\ gain}. \tag{16}$$

This shows that the growth rate of the carbon price is lower than the discount rate, both due to the inclusion of climate damages and due to endogenous technological change.

Integrating equation 16, shows that the carbon price is also the sum of both the SCC and the future gains from technological change

$$p_t = \int_t^\infty \underbrace{e^{e^{-\delta(\tau-t)+(n_\tau\tau-n_t t)-\eta\int_t^\tau \frac{\dot{c}}{c}ds}}}_{Discount\ factor} c_\tau \left(\underbrace{-c_{S_\tau}}_{Marginal\ damages} + \underbrace{\frac{\chi\varphi_\tau}{2A_\tau}a_\tau^2\,(A_\tau/A_0)^{-\chi}}_{endogenous\ TC\ gain}\right) d\tau. \tag{17}$$

B The climate module

Concerning the climate module, we use the Joos et al. [2013] carbon cycle and the Geoffroy et al. [2013] thermal inertia model, as done in Dietz et al. [2021].

The temperature dynamics are defined as

$$\frac{\Delta T_t}{\Delta t} = \xi_1 \left[F_t - \xi_2 T_{t-1} - \xi_3 \left[T_{t-1} - T_{ocean_{t-1}} \right] \right] \tag{18}$$

$$\frac{\Delta T_{ocean_t}}{\Delta t} = \xi_4 \left[T_{t-1} - T_{ocean_{t-1}} \right] \tag{19}$$

with T, the warming of the atmosphere; T_{ocean}, warming of lower oceans; Δt is our time step (2 years); ξ_1, the warming delay parameter; ξ_2, the forcing per degree warming; ξ_3, the transfer of heat from ocean to surface; ξ_4, the transfer of heat from surface to ocean.

F_t the radiative forcing function is defined by

$$F_t = F_{CO2X} * log(MAT_t/MAT_{eq})/log(2) + F_{oth_t} \tag{20}$$

with F_{CO2X}, the forcing from CO_2 doubling; MAT_t, carbon concentration in the atmosphere at time t; MAT_{eq}, equilibrium carbon concentration in 1850 (588 GtC); F_{oth_t}, other radiative forcing.

Other forcings are exogenous. We use IPCC RCP 1.9 and 2.6 other forcing data (Riahi et al. [2017], Rogelj et al. [2018], Gidden et al. [2019]), depending on the scenario.

MAT_t (carbon stock in the atmosphere) is actually the sum of 4 different reservoirs or "boxes", denoted by M. Following the approach in Joos et al. [2013], each box is a fraction of atmospheric concentration decaying at a different speed, but those boxes do not represent a physical reality. Each box evolves according to the following differential equation[6]

$$\frac{dM}{dt} = \frac{0.75}{3.66} \alpha E_{CO2} - \omega M_i \tag{22}$$

with M_t,a vector of stocks of carbon in 4 reservoirs or 'boxes'; α is a vector of 4 parameters allocating emissions to each CO_2 reservoir; ω, a vector containing the decay rates of each box. One of the boxes does not decay ($\omega = 0$). E_{CO2} is carbon emissions. When we calibrate the model on the IPCC and NGFS scenarios, we only have abatement costs for total GHG emissions. Therefore, we calibrate abatement costs, assuming that the proportion of CO_2 in these models remains constant at 25%, i.e. $E_{CO_2} = 0.75E$. The factor 3.66 corrects for the fact that emissions are expressed in $GtCO_2$, whereas carbon stocks are in GtC.

[6]We discretize the equation using a time step of 2 years and obtain the following formula (abstracting from the effect of decreasing emissions)

$$M_{t+2} = \alpha/\omega * (1 - e^{-2\omega}) \frac{0.75}{3.66} E_{CO2} + M_t e^{-2\omega} \tag{21}$$

For $\omega = 1$, we have the exact solution $\Delta M_t = \alpha \frac{0.75}{3.66} E_{CO2}$.

C GMM and model parameters

We fit the main parameters of our dynamic marginal abatement cost function to the climate scenarios database of IPCC 1.5°C report and the NGFS (Rogelj, J. et al. [2018], Huppmann, D. et al. [2019], NGFS [2021]). For the calibration, we use the model presented in appendix A, which includes a speed penalty on abatement and endogenous learning. We use equation 1 and define abatement as 60GtCO_2-eq minus emissions. Our stylised model has the advantage that it requires only four variables, which are available for all IPCC and NGFS scenarios: total abatement costs, marginal abatement costs (carbon price), emissions and GDP. We use 109 scenarios of the IPCC and NGFS database which are defined for 17 periods of 5 years (from 2015 to 2100). We assume that each modelling team makes a meaningful estimate of abatement costs in the future. However, those different scenarios are obtained thanks to various modelling tools which use various assumptions. In order to avoid the impact of extreme values, carbon prices are winsorized at the 5% value within each period and total abatement costs are winsorized at the 1% level. We fit both the total abatement cost and marginal abatement cost functions to the dataset, using Generalized Method of Moments and assuming that the errors of the equations are normally distributed. We minimise the sum of the square errors of the two equations, and we do not minimise the product of the errors. We tried different specifications of this fit, giving different relative weights to the two equations. We found that our values of our cost parameters are quite stable for the different weights assumptions (except for the inertia parameter). In the final fit, same weights are assumed for both equations and the inertia parameter is significant and has a meaningful value. Conceptually, we fit a line through different combinations of MAC and abatement of each model. We assume this relationship between MAC and abatement is meaningful, even if the model would have reached that level of abatement via a suboptimal path. Table 4 provides the parameters estimates.

Concerning the other parameters of the economic model $(\delta, n, \eta, g, \zeta, \gamma)$, we use values from the literature, provided in Table 5. Table 6 summarises our physical climate parameters.

D Optimisation and calibration

We use the fmincon function in Matlab for our optimisation. The algorithm maximises welfare or minimises discounted abatement costs by choosing emissions in each period of 2 years. In the objective function, we use the mid-period discount factor and mid-period values for consumption, cumulative emissions and cumulative abatement. Even though we report the trajectories only until 2100, we run the model from 2020 to 2400 (we constrain emissions to be zero or less in the last 200 years to avoid increasing emissions at the result of the finite horizon).

The CE scenarios with a temperature constraint minimises abatement costs subject to a temperature constraint of 1.5°C or 2°C, and has no damages. As

Variable	Parameters estimates
φ_0	4.74e-05
	3.64e-06
θ_2	.00178
	.000302
χ	.109
	.0452
A_0	100.6
	134.7
N	1848
ll	7121.0
bic	-142112.0
aic	-14234.1

Table 4: Parameters of the abatement cost function, fitting total abatement cost and marginal abatement cost functions to 109 scenarios of the IPCC 1.5°C report and the NGFS, using Generalized Methods of Moments.

Parameter	Value	Source
$\delta - n$	0.011-0.005	Drupp et al. [2018], United Nations [2017]
η	1.35	Drupp et al. [2018]
g	0.02	By assumption
ζ	0.0006	By assumption
γ	0.0102-0.0268	Calibrated to reach the desired temperature outcome
E_{BAU}	60 $GtCO_2$	IPCC AR6 WGIII IPCC [2022]

Table 5: Other parameters for the economic model.

Parameter	Value	Source
ω	1; 1-0.00254; 1-0.0274; 1-0.232342	Joos et al. [2013]
α	0.2173; 0.2240; 0.2824; 0.2763	Joos et al. [2013]
MAT_{eq}	588	Dietz et al. [2021]
initial values of$M$	588+139.1; 90.2; 29.2; 4.2	Dietz et al. [2021]
$TATM_0$	1.2	IPCC [2021]
T_{ocean_0}	0.28	Dietz et al. [2021]
F_{CO2X}	3.503	Geoffroy et al. [2013], Dietz et al. [2021]
ξ_1	0.386	Geoffroy et al. [2013], Dietz et al. [2021]
ξ_2	1.13	Geoffroy et al. [2013], Dietz et al. [2021]
ξ_3	0.73	Geoffroy et al. [2013], Dietz et al. [2021]
ξ_4	0.034	Geoffroy et al. [2013], Dietz et al. [2021]

Table 6: Parameters of the climate module.

to the scenarios with cumulative emissions or radiative forcings constraints, we run the scenarios multiple times in order to find the right constraint in terms of cumulative emissions or radiative forcing which correspond to the desired temperature level in 2100. For the CB analysis, we replace the constraint by climate damages and calibrate the damage parameter with a similar trial and error procedure to reach 1.5°C or 2°C.

E Results for a cubic damage function

We run the model with a cubic damages function (considering T^3 instead of T^2). We call this scenario the "cubic case" ("CB15 CubicDam" in Fig. 3) while we refer to our central scenario with a quadratic damages function as the "quadratic case" ("CB15" in Fig. 3). In the cubic case, we modify the damages coefficient so that 1.5°C remains the welfare-maximizing temperature in 2100. In order to reach 1.5°C, we see that the optimal (unconstrained) CB path is very similar whether one considers a quadratic or a cubic damages function (see Fig. 3). There are almost no visible differences. The peak overshoot actually remains almost the same. However, in the cubic case, emissions decrease slightly faster after peak warming and hence temperature decreases faster as well. In fact, the temporary overshoot is more costly in this scenario because of the more convex shape of the climate damages function. However, the effect is not large since it still needs to reach the same temperature outcome and since the inertia costs play an important role in early decades. Note that following the faster decrease in emissions after peak warming, the abatement rate then decreases (after 2080 there are more emissions in the cubic case than in the quadratic case). As a consequence, there are slightly less end-of-century net negatives emissions in the cubic case.

F Results for a cost-benefit scenario with peak warming of 2°C in 2200

In the main analysis, we compare scenarios with the same temperatures in 2100. However, the CB scenarios have peak warming much later than 2100. If we compare scenarios with identical temperature at a later period, the difference between CE and CB becomes larger. In this appendix, we compare our central 2°C CE scenarios with a CB scenario which reaches 2°C in 2200. The difference between the CE and CB scenarios becomes much larger and the welfare cost of CE becomes substantial.

Fig. 4 illustrates this difference. It is the same as Fig. 2, except that there is one more scenario: a CB scenario with a peak warming of 2°C in 2200. We see that early abatement is much more important when we consider 2°C to be the peak warming in 2200 instead of 2100.

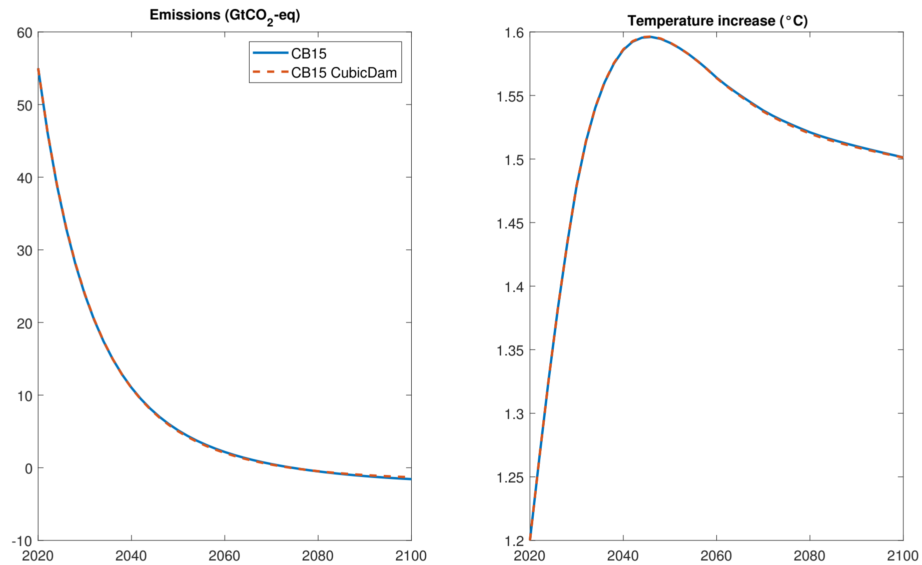

Figure 3: Emissions and temperature trajectories meeting 1.5°C: differences between a quadratic and a cubic damages function.

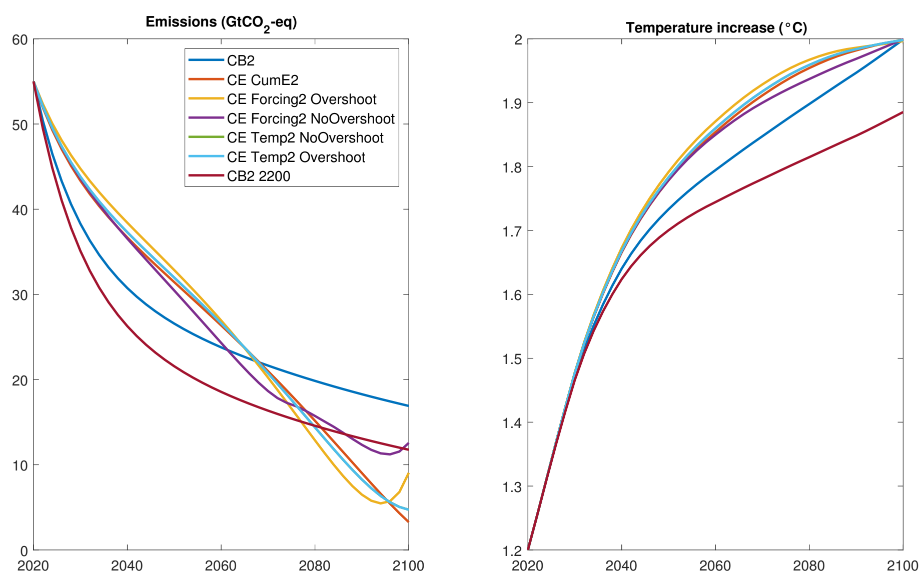

Figure 4: Emissions and temperature trajectories meeting 2°C: central scenarios and a CB scenario with a peak warming in 2200.