Ecological Economics 228 (2025) 108424

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

The welfare properties of climate targets

Léo Coppens [a,*], Frank Venmans [b,*]

[a] Warocqué School of Business and Economics, University of Mons, Place Warocqué 17, 7000 Mons, Belgium
[b] Grantham Research Institute on the Environment and Climate Change London School of Economics, Houghton Street, London, UK

ARTICLE INFO

Keywords:
Climate change mitigation
Targets formulation
Integrated assessment models
Optimal abatement path
Cost–benefit
Cost-effectiveness
Welfare
Negative emissions

ABSTRACT

Two approaches are predominant in climate models: cost–benefit and cost-effectiveness analysis. Cost–benefit analysis maximizes welfare, finding a trade-off between climate damages and emission abatement costs. By contrast, cost-effectiveness analysis minimizes abatement costs, omits damages but adds a climate constraint, such as a radiative forcing constraint, a temperature constraint or a cumulative emissions constraint. 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. For scenarios reaching 1.5 °C in 2100, 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 and large net negative emissions later on, leading to a substantial welfare loss of $23 Trillion. 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. We show that large negative emissions at the end of the century are never optimal and an artefact of constraints with overshoot.

1. Introduction

Within the framework of the Paris Agreement, the "below 2 °C" target is widely accepted as the shared goal for climate policy, alongside the aim to "pursue efforts" to limit the temperature rise to 1.5 °C (United Nations (2015)). Two main approaches are commonly used in the literature to analyse the optimal emissions pathways needed to achieve these climate objectives.

Firstly, cost–benefit (CB) analysis maximizes welfare by considering both abatement costs and climate damages. Peak temperature is endogenous and balances 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.[1] 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. (2018a)). 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 constraints 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, in line with the Paris agreement.

* Corresponding authors.
E-mail addresses: leo.coppens@umons.ac.be (L. Coppens), f.venmans1@lse.ac.uk (F. Venmans).

[1] 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 from of a particular gas is identical to an atmospheric concentration constraint of that gas. However, as there are many greenhouse gases, a constraint on forcing leaves flexibility on how different gases contribute to forcing. By contrast, a constraint on concentrations requires a constraint on each greenhouse gas separately.

https://doi.org/10.1016/j.ecolecon.2024.108424
Received 3 May 2024; Received in revised form 13 October 2024; Accepted 15 October 2024
Available online 8 November 2024

The optimal peak warming depends on uncertain parameters (climate sensitivity, damages, abatement costs) as well as ethical preferences (time preferences and inequality aversion). As a result, some CB studies find optimal warming around 1,5 °C and 2 °C (Glanemann et al. (2020), Hänsel et al. (2020), Dietz et al. (2018)), whereas other studies find higher optimal temperatures (Nordhaus (2019), Tol (2023)). We do not take a stance on what the optimal warming should be, we focus on the difference between CE and CB for any given temperature target, assuming that any target that is chosen for CE is in the end justified by a trade-off between climate damages and abatement costs.

We also do not take a stance on how the optimal warming should be established. For example, some scholars argue that given the deep uncertainty and immense risks related to climate change, we should focus on earth sciences, apply a *guardrail* approach (Stern et al. (2022)) and define a safe operating space for human development (Steffen et al. (2015)). Our essential point is that even if a target is set exogenously, the welfare-maximizing emission pathway to reach that target should take into account not only the timing of abatement costs, but also the timing of damages. Because even if climate policy is optimal, damages will not be zero. And even if damages are related to tipping points, the uncertainty of these tipping points will lead to gradually increasing damages in expected value.

In general, CE analysis reaches an exogenous environmental target at lowest cost. In the case of a flow pollutant such as noise, CE analysis will give the welfare-maximizing outcome, conditional on choosing the optimal target. However, in the case of a stock pollutant such as climate change, the problem is dynamic and CE is no longer welfare maximizing. In other words, the same climate target can be reached with a larger difference between total abatement costs and total climate damages. In most cases, CE analysis will abate too late, because the timing of the damages is ignored. Only costs are discounted, not the damages. However, CE analysis is very 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 give guidance on how to improve its welfare properties and we 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 ask why CB analysis is a good reference scenario, since CE was developed as a solution to avoid uncertainty regarding climate damages. Our answer is threefold. Firstly, our approach is agnostic to the true size of the damages. Instead of choosing a damage parameter from the literature, 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 Appendix E that a cubic damage function gives very similar results.[2] Thirdly, we also analyse 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 have investigated the effect of different CE constraints by comparing the total abatement costs to reach a climate target (e.g., Johansson et al. (2020), Lemoine and Rudik (2017)). We show that such an abatement cost ranking gives confusing results, because the constraint with the lowest cost will also have earlier damages and will not give the highest welfare.

Given our focus on dynamics, we need a realistic representation of the dynamic properties of marginal abatement costs in our model. To do so, we develop a model with both abatement inertia and endogenous technological change, fitted on the main IAMs (Integrated Assessment Models) in the literature. Transition costs depend not only on the level of abatement but also the speed of abatement, 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. (2024).

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 of 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 leads to an increase in forcing which diminishes over time while the marginal temperature increase provoked by this extra tonne of CO_2 remains stable for a long time, due to thermal inertia[3] (Matthews et al. (2009), Eyring et al. (2016), Arora et al. (2019)). This dynamic creates a spurious incentive to postpone abatement. The discounted cost of using the radiative forcing constraint instead of cost–benefit is substantial, $23 Trillion spread out over this century. Finally, a temperature target without overshoot performs badly. 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. Besides, 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. Appendices G and H provide sensitivity analysis of our 1.5 °C scenarios results regarding the impacts of the abatement inertia parameter and the assumptions concerning the other (exogenous) radiative forcing, notably highlighting their driving role on the temperature overshoot.

[2] Most CB analysis assumes that damages are a function of temperature. However, not only temperature but also the speed at which the temperature changes matters, because rapid warming makes adaptation harder. For example, species may migrate under slow warming, but get extinct under fast warming. Since temperature is proportional to cumulative emissions, the speed of warming is proportional to emissions. Since on an optimal path emissions are decreasing, the fastest warming happens at the start. Therefore, this type of damages will create an even stronger incentive to abate early and widen the difference between CE and CB. In that sense, our damage function is a lower bound on the estimated welfare cost of targets (Taconet (2020)).

Note that there is also a third type of damages, such as ice melting, which depends on 'cumulative warming', i.e. the integral of warming over time. This cumulative warming creates again an incentive to care about warming before reaching the target and will contribute to a difference between CE and CB.

[3] Note that there is an initial delay between emissions and peak temperature and a slow temperature decrease afterwards (both mechanisms are represented in our climate module available in Appendix B). The constant long-term warming effect contributes to the almost-linear relationship between cumulative emissions and 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 (2017) 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.[4] This is because all CE scenarios have insufficient abatement early on. If that is computationally 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 (IAMs), 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 IAMs (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 5GtCO_2/y).[5] 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 without overshoot leads to lower discounted abatement costs compared to a forcing constraint without overshoot. Their analysis highlights the advantage of postponing abatement costs. However, we demonstrate that the advantage of delayed abatement costs 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. (2018a), Gidden et al. (2019)).

We now describe the main features of the economic model, which is based on Coppens et al. (2024). We model an endowment economy where exogenous, labour-augmenting technical change improves labour productivity, leading to BAU consumption growth of rate g.[6] In addition to this exogenous growth parameter, per capita consumption is also driven by the following dynamics : abatement costs (taking into account endogenous technological change), inertia costs (i.e., a penalty on the speed of abatement) and climate damages decrease consumption.

Concerning the abatement costs, we firstly define abatement a as the difference between emissions E and business-as-usual emissions E_{BAU}. Cumulative abatement A is the sum of all past aggregate abatement ($\dot{A} = a$). The Marginal Abatement Cost (MAC) function is linear in abatement for fixed technology and consumption[7]

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

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%. There is wide empirical evidence for learning curves with a constant elasticity χ (Way et al. (2022)). We also fit a quadratic static MAC curve to our database but the coefficient on the quadratic term is both statistically and economically insignificant.

[4] Adding mild damages to a CE scenario is mathematically identical to adding a constraint to a CB analysis.

[5] We refer mainly to their 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).

[6] To see how our endowment model maps into a very similar model with a production function and capital, see Dietz and Venmans (2019) and Campiglio et al. (2022).

[7] We assume that, all else equal, abatement costs increase with the size of the economy, because the natural resources used for abatement are finite. In a larger economy, land for biofuels, advantageous locations for wind farms, carbon sinks in soils and forests, olivines for mineral weathering and geological space for carbon storage will become scarcer. Also, higher consumption in hard-to-abate sectors such as meat and aviation will increase the need for negative emissions technologies. Note that these increasing scarcity effects can be offset by technical change.

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. (Campiglio et al. (2022), Rezai and Van Der Ploeg (2017), van der Ploeg and Rezai (2016), Baldwin et al. (2020)). This is modelled 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)).

Our dynamic abatement cost function is fitted with GMM on both the total abatement cost and marginal abatement cost of 109 scenarios of the IPCC 1.5 special report and NGFS scenarios (Rogelj et al. (2018b), Huppmann et al. (2019), NGFS (2021)). By using a flexible abatement cost function (dependent on abatement, cumulative abatement and abatement speed), and by fitting both marginal abatement costs and total abatement costs for all parameters at once, we aim to obtain a 'consensus fit' of the dynamic properties of the main bottom-up IAMs, even if our functional form deviates from the large variety of modelling approaches and functional forms in bottom-up IAMs.

We assume that climate damages are quadratic in temperature T and proportional to consumption, as in DICE and Dietz and Venmans (2019).[8] Bringing all the pieces together, we obtain the following function for consumption per capita

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

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.

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

4. Results

4.1. Theoretical insights

Appendix A shows that the welfare-maximizing marginal abatement cost (MAC) has the following growth rate

$$\frac{\dot{MAC}}{MAC} = r - \frac{Marg\ Damage}{MAC} - \frac{Endog\ Gain\ of\ TC}{MAC} \tag{4}$$

where the MAC (a.k.a. the carbon price) includes both the standard marginal abatement costs and the abatement inertia costs (Eq. (16)).[9] The term r corresponds to the consumption discount rate and is the only term in the case of a standard CE analysis with a cumulative emission constraint (Dietz and Venmans (2019)). This is known as the Hotelling rule.[10] Both damages and endogenous technological change (TC) reduce the optimal growth rate of the carbon price, and lead to a higher carbon price at the start. Damages appear in this equation because greenhouse gases are a stock pollutant, and affect future periods. The insensitivity of CE analysis to the timing of damages is at the origin of its welfare loss.

A temperature target will have similar dynamics compared to a cumulative emissions constraint (leading to a Hotelling rule) unless there are short term dynamics involved (see 1.5 °C scenario).

In the case of a constraint on radiative forcing, former work has shown that the Hotelling rule is augmented by the decay rate of the atmospheric CO_2 concentration Lemoine and Rudik (2017). This increases the welfare cost, because the decay rate further increases the growth rate of the carbon price path, with an even lower initial carbon price.

Analysing the second term "Marg Damage/MAC" gives three further insights. First, a proportional increase of both marginal damages and MAC will merely affect the difference between CB and CE analysis. Second, a higher discount rate will lead to a larger difference between CB and CE analysis, because for a given temperature target, a higher discount rate is associated with a lower MAC or larger damages.[11] Third, for a higher optimal temperature target, say 2.5 °C rather than 2 °C, the difference between CE and CB becomes smaller, because a larger peak temperature is associated with higher MAC or lower damages.

4.2. 1.5 °C scenarios

Fig. 1 plots the emissions and temperature paths of the 6 scenarios reaching 1.5 °C. Table 1 presents the associated net negative emissions and welfare impacts. A scenario with 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.

Appendices G and H provide sensitivity analysis of our 1.5 °C scenarios results. They highlight respectively the impacts of the abatement inertia parameter and the assumptions concerning the other (exogenous) radiative forcing.

4.2.1. Cost–benefit

The CB scenario [CB15] leads to the maximum total welfare by design. The peak temperature is 1.60 °C. This result concerning the temperature overshoot is in line with Hänsel et al. (2020) study[12] and with the IPCC AR6 report in which the family of most ambitious climate scenarios reaches 1.5 °C with a modest overshoot IPCC (2022). However, note that this temperature overshoot is notably driven by our assumptions concerning other radiative forcing and by our abatement inertia parameter (refer to Appendices G and H for the sensitivity analysis). Emissions reach zero around 2075 and there are almost no net negative emissions thereafter ($-2GtCO_2$-eq in 2100).[13] 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

[8] In the damage function, we use the simplifying condition that temperature is proportional to cumulative emissions $T = \zeta S$, with ζ the Transient Climate Response to cumulative carbon Emissions or TCRE.

[9] In the CB analysis, this is equal to the social cost of carbon (discounted sum of marginal damages) plus the social gain of endogenous technological change (discounted sum of marginal technological change gains), see Eq. (18).

[10] Endogenous TC does also decrease the growth rate in CE analysis, but most IAM's ignore this incentive (Coppens et al. (2024)) .

[11] To shed further light on this matter, Appendix I analyses the impact of a higher discount rate on our 2 °C scenarios.

[12] Using an updated version of the DICE model, Hänsel et al. (2020) obtain a range of CB scenarios reaching around 1.5 °C in 2100 (with different discount rates) which all include a temperature overshoot. In Figure 2 of Hänsel et al. (2020), the grey-shaded area corresponds to the 95th percentile ranges in terms of intergenerational fairness (i.e., different discounting parameters) for emissions, SCC (social cost of carbon) and temperature trajectories. Even though the authors show that the assumptions about the discounting parameters can have a substantial impact on those trajectories, all the grey-shaded area concerning the temperature trajectory includes an overshoot of the 1.5 °C target, in line with our results.

[13] Note that large scale carbon removals start well before 2075 to compensate for emissions in hard-to-abate sectors.

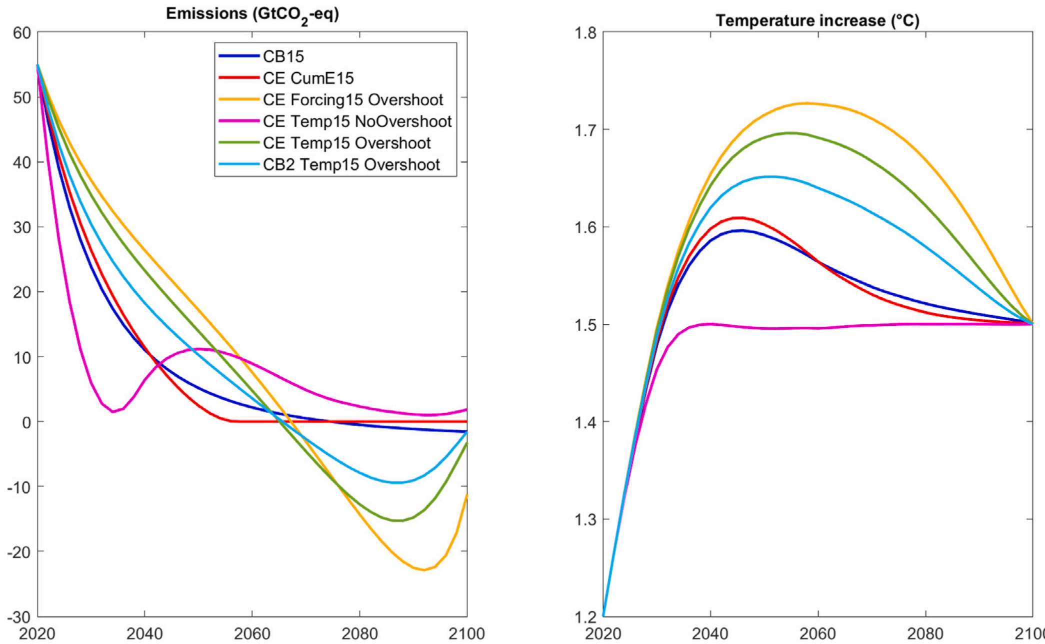

Fig. 1. Emissions and temperature trajectories meeting 1.5 °C. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
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.

Name of scenario	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) 2020–2100	Welfare difference (Trillion) 2020–2050	Welfare difference (Trillion) 2050–2100
[CE Forcing15 NoOvershoot]	CE	Radiative forcing 1.5 °C	no		Impossible	Impossible	Impossible	Impossible	Impossible	Impossible
[CE Forcing15 Overshoot]	CE	Radiative forcing 1.5 °C	yes		−471 $GtCO_2$	1.73 °C	−0.4%	−22.8	44.4	−67.2
[CE CumE15]	CE	Cumulative emissions 1.5 °C	no		0 $GtCO_2$	1.61 °C	0.0%	−0.7	3.0	−3.7
[CE Temp15 NoOvershoot]	CE	Temperature 1.5 °C	no		0 $GtCO_2$	1.5 °C	−0.4%	−23.1	−54.9	31.8
[CE Temp15 Overshoot]	CE	Temperature 1.5 °C	yes		−344 $GtCO_2$	1.70 °C	−0.2%	−12.7	37.2	−49.9
[CB15]	CB	No constraint		1.5 °C optimal temperature in 2100	−22 $GtCO_2$	1.60 °C	0.0%	0.0	0.0	0.0
[CB2 Temp15 Overshoot]	CB	Temperature 1.5 °C	yes	2 °C optimal temperature in 2100	−209 $GtCO_2$	1.65 °C	−0.1%	−4.0	23.8	−27.8

temperature exceeding the long term optimum. Since abatement in the later decades comes 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 22$GtCO_2$-eq over the period 2075–2100. This will generally be the case unless we would start the optimization in 2030 at a temperature of 1.5 °C.

Table 2 reports the growth rate of the carbon price. The Hotelling rule, which is very popular in CE analysis, prescribes that the carbon price should grow at the discount rate (3.3%) . The welfare-maximizing growth rate of the carbon price is 2.1% lower than the Hotelling rule in 2020 and 1.1% lower in 2050. The initial carbon price is $264/$tCO_2$.

We now analyse the CE scenarios from the most ambitious (lowest overshoot) to the least ambitious (highest overshoot).

4.2.2. Temperature constraint without overshoot

This is the scenario with the most rapid fall in emissions ([CE Temp15 NoOvershoot] in Fig. 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 (Matthews et al. (2009), MacDougall et al. (2020)). 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.

4.2.3. Cumulative emissions constraint

The scenario with the cumulative emissions constraint [CE CumE15] has a very similar emissions path compared to the CB scenario [CB15]. 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. Note that our budget constraint applies during the whole temporal horizon. Appendix J shows that if the constraint only binds from 2100, the emissions and temperature trajectories closely resemble the CE scenario with a temperature constraint allowing overshoot [CE Temp15 Overshoot].

4.2.4. Constrained cost–benefit

We also run a CB scenario [CB2 Temp15 Overshoot] with a mild damage function (calibrated to reach 2 °C) while adding a 1.5 °C temperature 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 (in scenario [CB2 Temp15 Overshoot]) is in between the pure CB analysis [CB15] and the CE scenario with a temperature target allowing overshoot [CE Temp15 Overshoot], with a peak temperature of 1.65 °C. In welfare terms, this constrained CB scenario [CB2 Temp15 Overshoot] ranks third, provided that one considers the damage function resulting in 1.5 °C as the true damage function. Finally, it leads to 209 $GtCO_2$-eq cumulative net negative emissions.

4.2.5. Temperature constraint with overshoot

This scenario [CE Temp15 Overshoot] 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.

4.2.6. Forcing constraint with overshoot

This scenario [CE Forcing15 Overshoot] 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 results in the least attractive scenario from a welfare perspective. The welfare loss, compared to the cost–benefit scenario [CB15], is equivalent to a constant loss of 0.4% of consumption and corresponds to a loss with a net present value of $23 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 $GtCO_2$.[14]

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. Large net negative emissions are not optimal from a welfare perspective. The last 2 columns of Table 1 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).

4.3. 2 °C scenarios

An overview of scenarios is shown in Table 3 and Fig. 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 an approximate likelihood of 50%.[15]

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.

4.3.1. Cost–benefit

The CB scenario [CB2] 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 2 shows that the growth rate of the carbon price is 1.7% lower than the Hotelling rule in 2020 and 0.7% lower in 2050. The lower growth rate of the CB analysis implies a higher initial carbon price, at $152/$tCO_2$.

4.3.2. 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 (in scenario [CE Forcing2 NoOvershoot]) 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

[14] 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.

[15] 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.

Table 2
Continuous growth rates of carbon prices for CB scenarios.

	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	1.6%	1.9%	2.4%	2.6%	2.7%	2.7%	2.7%	2.7%	2.7%

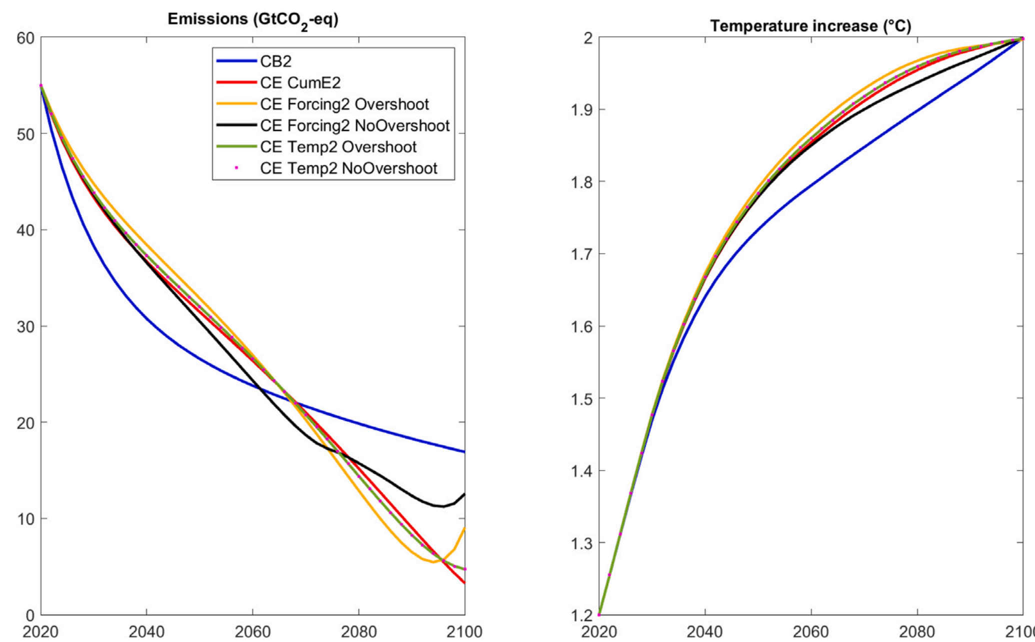

Fig. 2. Emissions and temperature trajectories meeting 2 °C. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

Name of scenario	CE/CB	Type of constraint	Over-shoot	Damage function	Welfare difference as equivalent variation 2020–2100	Welfare effect difference (Trillion) 2020–2100	Welfare difference (Trillion) 2020–2050	Welfare difference (Trillion) 2050–2100
[CE Forcing2 NoOvershoot]	CE	Radiative forcing 2 °C*	no		0.0%	−2.5	11.6	−14.1
[CE Forcing2 Overshoot]	CE	Radiative forcing 2 °C*	yes		−0.1%	−6.3	14.6	−20.9
[CE Temp2 Overshoot], [CE Temp2 NoOvershoot]	CE	Tempera-ture 2 °C	non-binding		−0.1%	−4.9	12.8	−17.7
[CE CumE2]	CE	Cumulative emissions 2 °C	non-binding		−0.1%	−4.5	11.8	−16.3
[CB2]	CB	No constraint		2 °C optimal temperature in 2100	0.0%	0.0	0.0	0.0

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.

4.3.3. Temperature and cumulative emissions constraint

The temperature constraint is not binding before 2100, so the scenario which allows overshoot [CE Temp2 Overshoot] and the one which does not [CE Temp2 NoOvershoot] are identical. Temperature and cumulative emissions constraints have very similar impacts and have almost the same welfare ranking. The scenario with a cumulative emissions constraint [CE CumE2] scores slightly better and leads to more abatement in the first decades. In the first periods, the CE scenario with a cumulative emissions constraint [CE CumE2] 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 the CB scenario [CB2]. The scenarios with a temperature constraint ([CE Temp2 Overshoot] and [CE Temp2 NoOvershoot]) show 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.

4.3.4. 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 [CE Forcing2 Overshoot] has the highest early emissions, deviates most from the CB scenario [CB2] and scores worst on welfare. For instance, emissions in 2040 are 38.4GtCO_2-eq (in scenario [CE Forcing2 Overshoot]), slightly higher than the 36.5GTCO_2-eq for a cumulative emissions constraint [CE CumE2] and much higher than the 30.7 GtCO_2-eq in the CB analysis [CB2]. It also 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.

4.3.5. CE is worse for longer time horizons and for methane

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 most popular 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 and the welfare cost of using CE rather than CB analysis can be up to $23 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,[16] the welfare-maximizing carbon price starts higher and increases at a slower rate. In fact, damages and endogenous TC create an incentive to abate earlier, reducing the optimal carbon price growth rate by 1.7%, 1.4% and 0.7% 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. In our central CB scenario, a modest overshoot of 1.6 °C has become desirable from a welfare point of view (note that we highlight the effect of the abatement inertia parameter and the other radiative forcing assumptions on this overshoot in Appendices G and H). Our central CB scenarios has a substantial starting marginal abatement cost (carbon price) of $264/t$CO_2$. Concerning the constraints that can be applied in CE analysis, a cumulative emissions 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 $23 Trillion for the 1.5 °C and $6 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-eq 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 *net* negative emissions. Instead, respecting the Paris agreement at the lowest welfare cost requires radical worldwide reductions in emissions by 2040.

CRediT authorship contribution statement

Léo Coppens: Writing – original draft, Software, Conceptualization. **Frank Venmans:** Writing – original draft, Methodology, Conceptualization.

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

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are grateful for comments on the EAERE conference (2023 Limassol), the BEED conference (2023 Brussels) and Ph.D. thesis defense of Léo Coppens (2023 Mons). Frank Venmans acknowledges financial support from the Grantham Research Institute on Climate Change and the Environment, at the London School of Economics, the ESRC Centre for Climate Change Economics and Policy (CCCEP) (ref. ES/R009708/1) and the BIOADD NERC grant (ref. NE/X002292/1). Léo Coppens acknowledges financial support from the University of Mons, in partnership with ICEDD ASBL (via an awarded doctoral scholarship).

Appendix A. 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,

$$a = E_{BAU} - E \tag{5}$$

Cumulative abatement A equals cumulative BAU emissions minus cumulative emissions,

$$A_t = A_0 + \int_0^t E_{BAU}\, d\tau - S_t + S_0. \tag{6}$$

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

We use an endowment model for our business-as-usual consumption (as the fruit tree model in 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,

$$MAC \overset{def}{=} -\frac{\partial c}{\partial a} = \varphi \left(A/A_0\right)^{-\chi} ac. \tag{7}$$

Parameter φ is the slope of the MAC curve. The factor $\left(A/A_0\right)^{-\chi}$ represents endogenous TC, with elasticity χ, such that for every percentage increase in cumulative abatement, the marginal abatement cost, decreases by χ%. 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 $-\frac{\partial c}{\partial v} = \theta v c$.

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

$$c = c_0 e^{\left(gt - \frac{\varphi}{2}\left(A/A_0\right)^{-\chi} a^2 - \frac{\theta_2}{2} v^2 - \frac{\gamma}{2} T^2\right)}, \tag{8}$$

where c_0 is a constant, representing initial consumption in the absence of climate damages and abatement costs and g is an exogenous total factor productivity 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.[17] In the CB setting, the social planner maximizes discounted utility and solves the following problem

$$max_{\{a\}} \int_0^\infty e^{-(\delta - n_t)t} u(c) dt, \tag{9}$$

subject to

$$T_t = f(\{E_{\tau<t}\}); \dot{A} = a; S_0\ given; A_0\ given. \tag{10}$$

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 $T = \zeta S$.

The present value Hamiltonian is

$$H^{PV} = e^{(-\delta + n_t)t} u(c) - \lambda^S (E_{BAU} - a) + \lambda^a v. \tag{11}$$

Optimality conditions include

$$\lambda^a = e^{(-\delta+n_t)t} u_c c \theta v, \tag{12}$$

$$\dot{\lambda^a} = e^{(-\delta+n_t)t} u_c c \varphi_t a \left(A/A_0\right)^{-\chi} - \lambda^S, \tag{13}$$

$$\dot{\lambda^S} = e^{(-\delta+n_t)t} u_c c_S. \tag{14}$$

with c_S the sum of marginal damages and foregone gains from technical change (an extra unit of cumulative emissions implies less cumulative abatement $A_S = -1$) : $c_S = -c\gamma\zeta^2 S - \frac{\chi\varphi_\tau}{2A_\tau} a_\tau^2 \left(A_\tau/A_0\right)^{-\chi}$. Take the time derivative of Eq. (12)

$$\dot{\lambda^a} = e^{(-\delta+n_t)t} u_c c \theta v \left[-\delta + n_t + \dot{n}t - \eta\frac{\dot{c}}{c} + \frac{\dot{c}}{c} + \frac{\dot{v}}{v}\right] \tag{15}$$

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[18]

$$\underbrace{p = \frac{\lambda^S e^{-(\delta - n_t)t}}{u_c}}_{Carbon\ Price} = \underbrace{c\varphi a \left(A/A_0\right)^{-\chi}}_{\partial c/\partial a\ standard\ MAC} + \underbrace{c\theta\,[rv - \dot{v}]}_{Abatement\ speed\ costs\ (pos)}, \tag{16}$$

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

Eqs. (14) and (16) can be combined as follows

$$\dot{p_\tau} = r_\tau p_\tau - \underbrace{c\gamma\zeta^2 S_\tau}_{Marginal\ damages} - \underbrace{\frac{\chi\varphi_\tau}{2A_\tau} a_\tau^2 \left(A_\tau/A_0\right)^{-\chi}}_{endogenous\ TC\ gain}. \tag{17}$$

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 Eq. (17), shows that the carbon price is also the sum of both the SCC and the future gains from technological change

$$p_t = \int_t^\infty \underbrace{e^{e^{-\delta(\tau - t) + (n_\tau \tau - n_t t) - \eta \int_t^\tau \frac{\dot{c}}{c} ds}}}_{Discount\ factor} c_\tau \left(\underbrace{-c_{S_\tau}}_{Marginal\ damages} + \underbrace{\frac{\chi\varphi_\tau}{2A_\tau} a_\tau^2 \left(A_\tau/A_0\right)^{-\chi}}_{endogenous\ TC\ gain} \right) d\tau. \tag{18}$$

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

[18] Appendix K illustrates quantitatively this theoretical result for our central CB scenario reaching 1.5 °C in 2100.

Appendix 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

$$\frac{\Delta T_t}{\Delta t} = \xi_1 \left[F_t - \xi_2 T_{t-1} - \xi_3 \left[T_{t-1} - T_{ocean_{t-1}}\right]\right] \tag{19}$$

$$\frac{\Delta T_{ocean_t}}{\Delta t} = \xi_4 \left[T_{t-1} - T_{ocean_{t-1}}\right] \tag{20}$$

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

$$F_t = F_{CO2X} * log(MAT_t/MAT_{eq})/log(2) + F_{oth_t} \tag{21}$$

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. (2018a), 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[19]

$$\frac{dM}{dt} = \frac{0.75}{3.66}\alpha E_{CO2} - \omega M_i \tag{23}$$

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.

Appendix 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 et al. (2018b), Huppmann 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 Eq. (1) and define abatement as $60GtCO_2$-eq minus emissions. Our stylized 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 minimize the sum of the square errors of the two equations, and we do not minimize 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 confidence intervals, please refer to Coppens et al. (2024) for an analysis of the impacts of the uncertainties around the main parameters defining the abatement costs (included in Table 4).[20] The impacts of those changes are highly intuitive. For instance, a faster technological change favours earlier abatement in order to benefit from costs reduction in the future thanks to endogenous TC. Coppens et al. (2024) also include a sensitivity analysis on the discount rate, illustrating the standard result that a lower discount rate would also shift more efforts towards the beginning of the period considered. To shed further light on this matter, Appendix I analyses the impacts of a higher discount rate on our 2 °C scenarios. Concerning the impact of our abatement inertia assumption θ_2, a sensitivity analysis is available in Appendix G.

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.

Variable	Parameters estimates
φ_0	4.74e−05
	3.64e−06
θ_2	.0036
	.000604
χ	.109
	.0452
A_0	100.6
	134.7
N	1848
ll	7121.0
bic	−142112.0
aic	−14234.1

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 summarizes our physical climate parameters. A sensitivity analysis on the other (exogenous) radiative forcing assumptions is available in Appendix H.

Appendix D. Optimization and calibration

We use the fmincon function in Matlab for our optimization. The algorithm maximizes welfare or minimizes 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

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

$$M_{t+2} = \alpha/\omega * (1 - e^{-2\omega})\frac{0.75}{3.66}E_{CO2} + M_t e^{-2\omega} \tag{22}$$

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

[20] The framework is the same but there is a slightly different temperature in 2100.

Table 5
Other parameters for the economic model.

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)
c_{2020}	105 Trillion	GDP average based on the scenarios database (Rogelj et al. (2018b), Huppmann et al. (2019), NGFS (2021))

Table 6
Parameters of the climate module.

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)

last 200 years to avoid increasing emissions at the result of the finite horizon).

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

Appendix 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.

Appendix 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

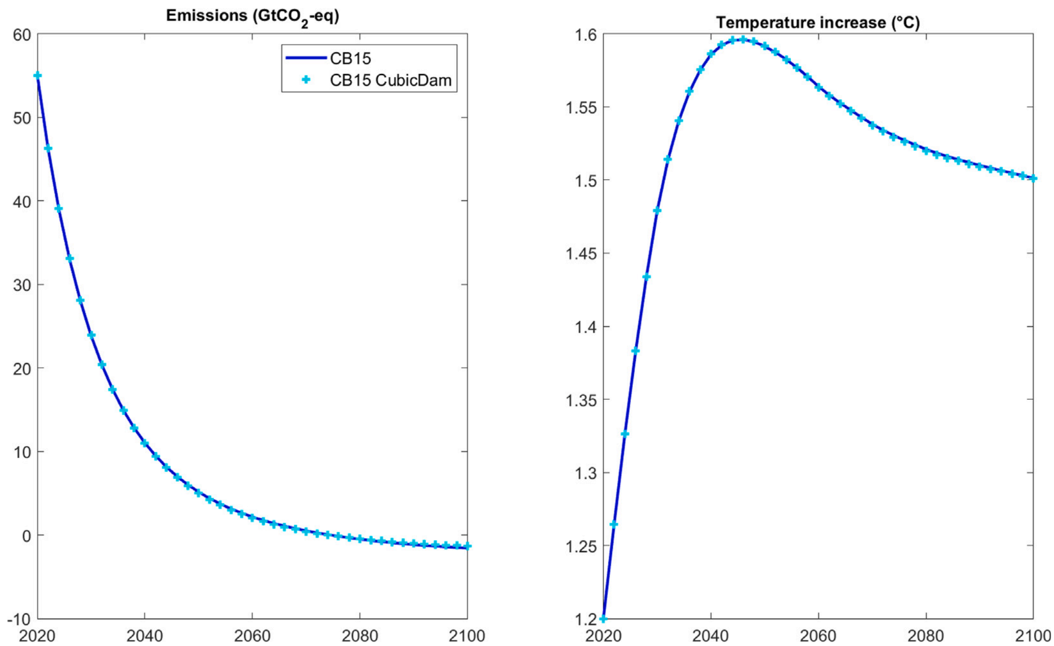

Fig. 3. Emissions and temperature trajectories meeting 1.5 °C: differences between a quadratic and a cubic damages function.

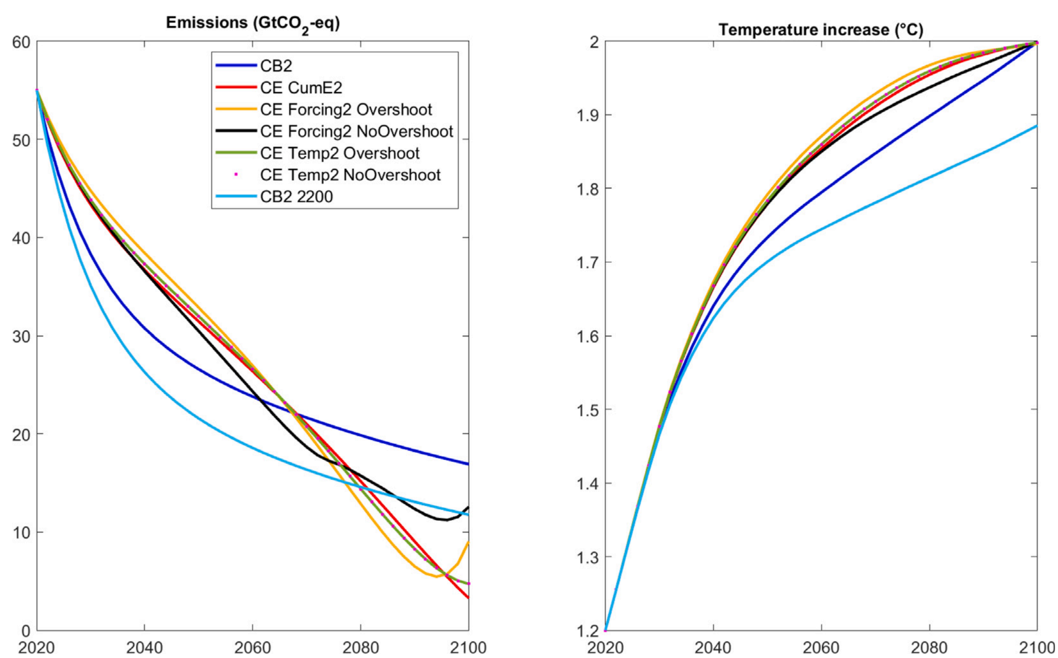

Fig. 4. Emissions and temperature trajectories meeting 2 °C: central scenarios and a CB scenario with a peak warming in 2200. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 [CB2 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 [CB2 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.

Appendix G. Results for CB and CE scenarios without inertia or with low inertia

Abatement inertia 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 dynamic has a large effect in ambitious scenarios (Grubb et al. (2020)). In this appendix, the sensitivity of our results to the value of our inertia parameter θ_2 (which is modelled as a quadratic penalty for abatement speed) is studied. The link between the inertia parameter and the

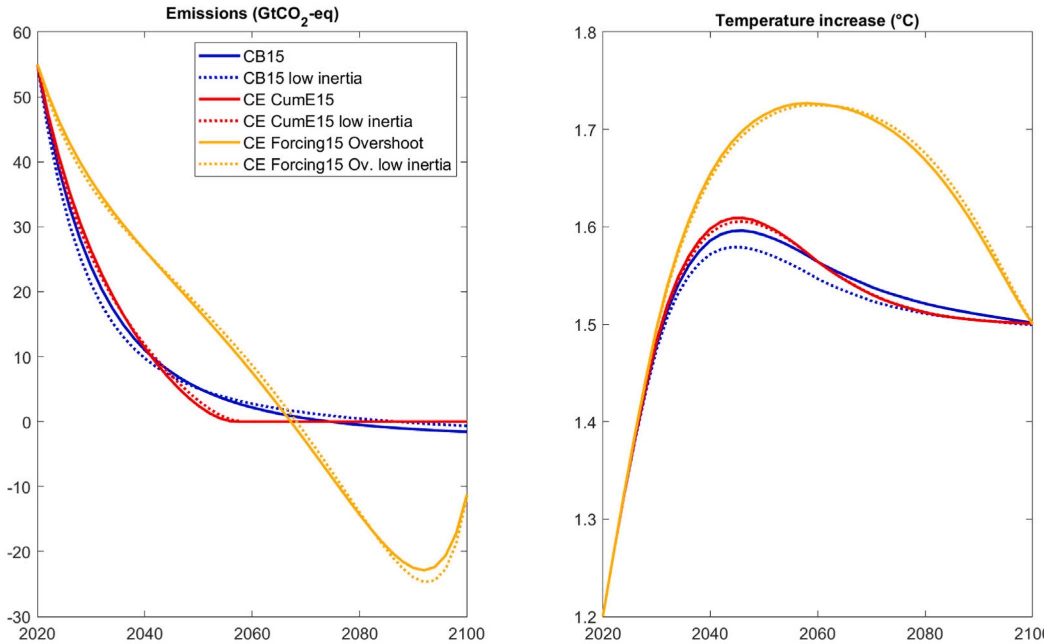

Fig. 5. Emissions and temperature trajectories meeting 1.5 °C, with standard and low inertia. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

temperature overshoot is highlighted. We show that an important overshoot remains even with low inertia (except in the CB case with θ_2=0). Note that is overshoot is also driven by the assumptions concerning other (exogenous) forcing (see Appendix H).

Fig. 5 illustrates the difference between 3 scenarios reaching 1.5 °C with standard inertia and with low inertia: the CB scenario, the CE scenario with a cumulative emissions constraint and the CE scenario with a forcing constraint allowing overshoot.[21] Low inertia corresponds to the central value for θ_2 minus its standard error multiplied by two.[22] Fig. 5 shows that lower inertia only slightly modifies the CE trajectories while the difference between the CB scenarios is more significant (for instance, peak temperature is decreased by less than 0.005 °C in CE scenarios and by 0.02 °C in the CB scenario). This is due to the fact that there is more flexibility to answer the call for earlier abatement in CB analysis (in order to avoid damages, which are not considered in CE analysis). Lower inertia does not modify our conclusions but increases the gap between CB and CE analysis in terms of temperature, emissions trajectories and welfare.

Moreover, in order to explore further the sensitivity of our results, Fig. 6 shows the same scenarios but with and without any abatement inertia (i.e., θ_2=0).[23] In this case, the differences are much clearer. The CB scenario without inertia [CB15 no inertia] nearly meets the target without any overshoot (peak temperature of 1.503 °C). However, the early jump in abatement is highly unrealistic. On the other hand, the CE cases with a cumulative emissions constraint with or without inertia ([CE CumE15] and [CE CumE15 no inertia]) lead to a similar overshoot (peak temperatures of 1.61 °C and 1.58 °C respectively). Thus, the comparison of the CB and CE scenarios without inertia highlights again the fact that the gap between CE and CB results is greater without inertia (or with low inertia as shown in Fig. 5). The flexibility coming from the absence of inertia exacerbates the deviations of the CE scenarios compared to the central CB case. More specifically, the radiative constraint leads to even more net negative emissions at the end of the century.

Appendix H. Results for scenarios with constant other radiative forcing

Other radiative forcing (non-CO_2 forcing) is exogenous in our model. In our central scenarios, we use the IPCC RCP 1.9 other forcing data (or RCP 2.6 for 2 °C trajectories) (Riahi et al. (2017), Rogelj et al. (2018a), Gidden et al. (2019)). In this appendix, we analyse the impact of these assumptions concerning other radiative forcing on the optimal path, highlighting the effect on the temperature overshoot.

In fact, in the CB scenario reaching 1.5 °C [CB15], the overshoot is not only driven by the inertia parameter (see Appendix G), it is also a consequence of our assumptions concerning other radiative forcing. Fig. 7 pictures 3 scenarios reaching 1.5 °C in 2100 with varying and constant other radiative forcing assumptions (either the IPCC RCP 1.9 other forcing data (see Table 7) or a constant exogenous forcing of 0.456 W/m²).

Concerning the temperature overshoot, the impact of a constant other radiative forcing of 0.456 W/m² differs widely depending on the scenarios. First, the peak temperature is 0.04 °C lower in the CB scenario [CB15 cst oth forcing] than in the central scenario [CB15] because the other forcing is now constant and not following the increasing and then decreasing trend coming from RCP 1.9. Second, with this constant other forcing, the cumulative emissions budget is significantly smaller and thus net zero is achieved earlier, leading to the absence of temperature overshoot in the CE scenario with a cumulative emissions constraint [CE CumE15 cst oth forcing]. Third, the temperature overshoot is 0.02 °C higher in the CE scenario with a radiative constraint and constant other forcing [CE Forcing15 Overshoot cst oth forcing] than in the central scenario with the same constraint [CE Forcing15 Overshoot] because the "more ambitious" objective in 2100 (same temperature target, but with higher other radiative forcing at the end

[21] We do not include the CE scenario with a temperature constraint with overshoot in the sensitivity analysis so that Figs. 5 and 6 remain readable. The conclusions of the sensitivity analysis for this specific scenario are the same as for the CE scenario with a radiative forcing constraint.

[22] θ_2=0.0036-2*0.0006=0.0024. Note that lower inertia leads to a lower warming in 2100 in CB analysis. Therefore, the damages parameter is raised to ensure the 1.5 °C target is still achieved.

[23] Concerning the scenario with a radiative forcing constraint, we add a limit on the annual net negative emissions (maximum 30 GtCO$_2$-eq).

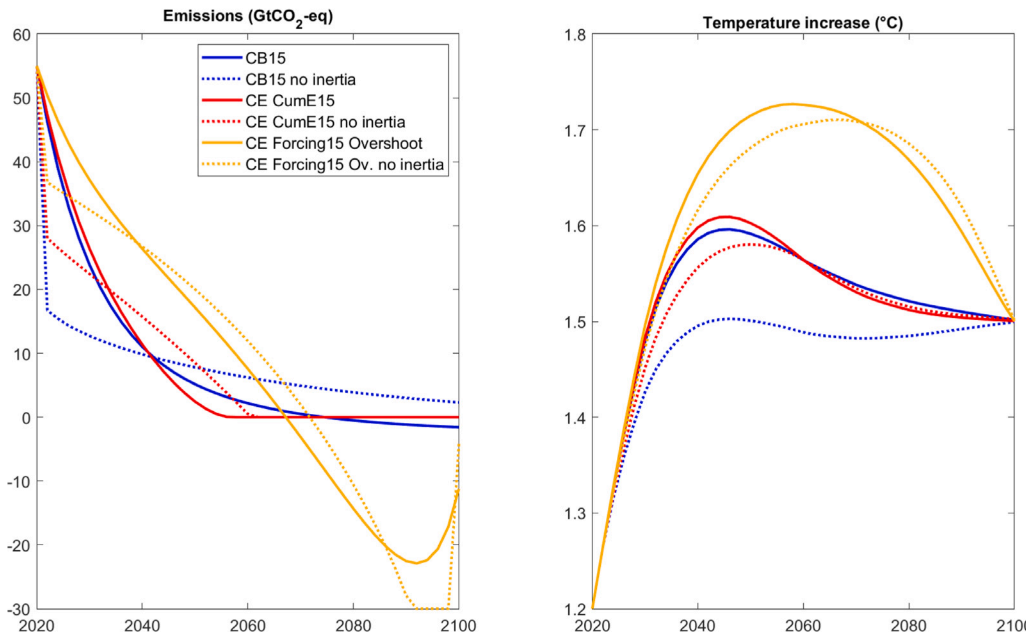

Fig. 6. Emissions and temperature trajectories meeting 1.5 °C, with and without inertia. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

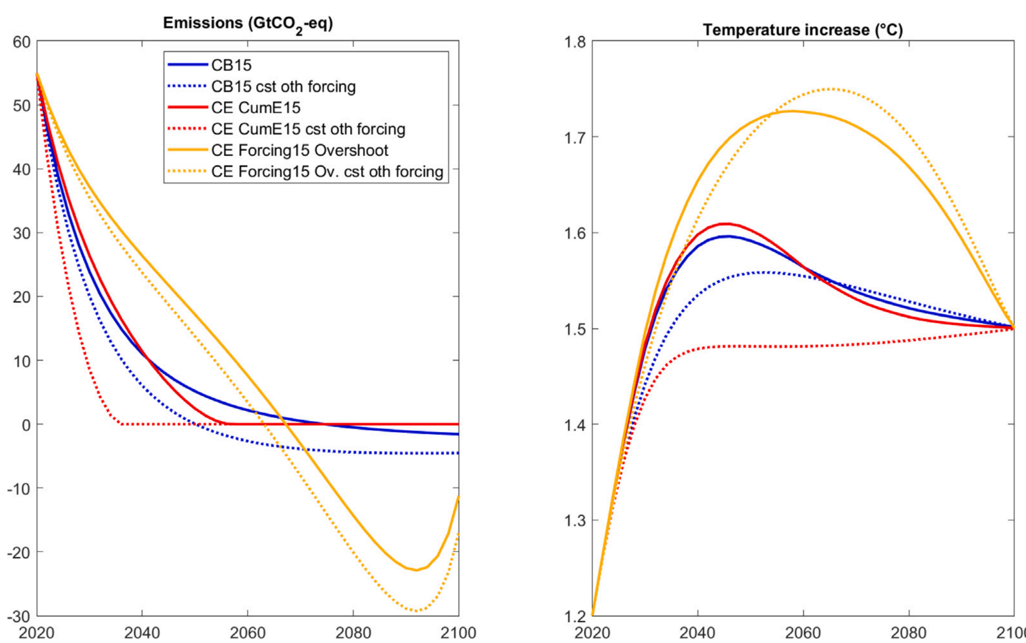

Fig. 7. Emissions and temperature trajectories meeting 1.5 °C, with varying and constant other radiative forcing. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the period) is achieved mainly by higher net negative emissions at the end of the century.

Appendix I. Results considering a high discount rate

What is the effect of a higher discount rate on our scenarios? We know from the theoretical insights (section 4.1) that it increases the difference between CB and CE analysis. Fig. 8 shows to which extent, for 3 scenarios reaching 2 °C in 2100: the CE scenarios with a cumulative emissions constraint and a radiative forcing constraint allowing overshoot as well as the CB scenario. The 3 scenarios are plotted considering the central value for the discount rate and considering a high discount rate (δ=0.02[24] instead of δ=0.011).

[24] 0.02 corresponds to the 75th percentile value of Drupp et al. (2018) study. Note that a higher discount rate leads to a higher warming in 2100 in CB analysis. Therefore, the damages parameter was also modified in this case to ensure the 2 °C target is still achieved.

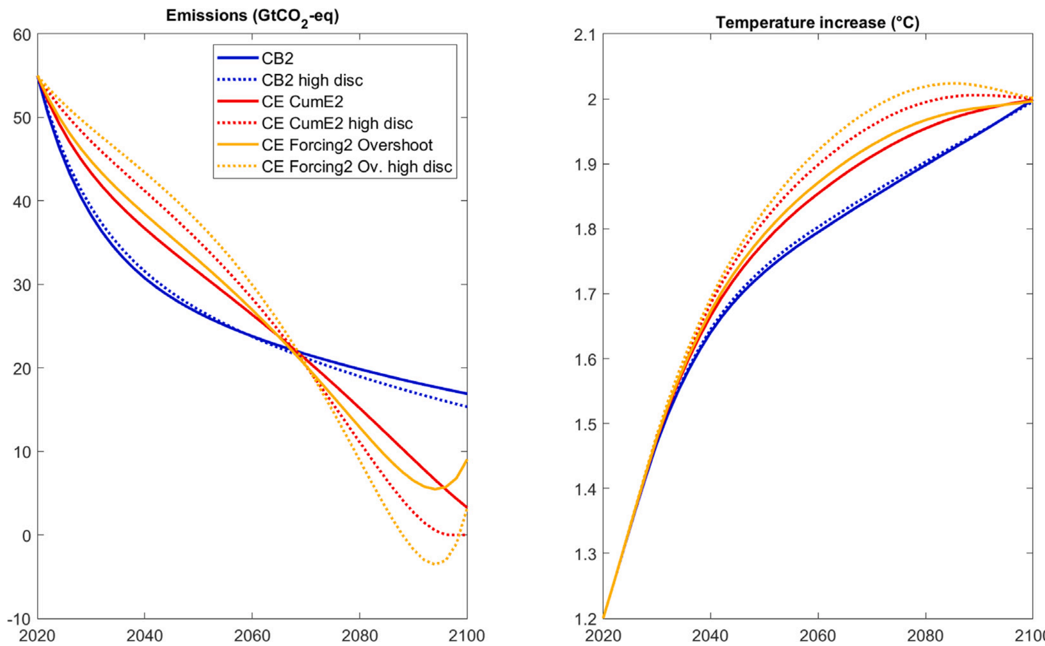

Fig. 8. Impact of a high discount rate on 2 °C scenarios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

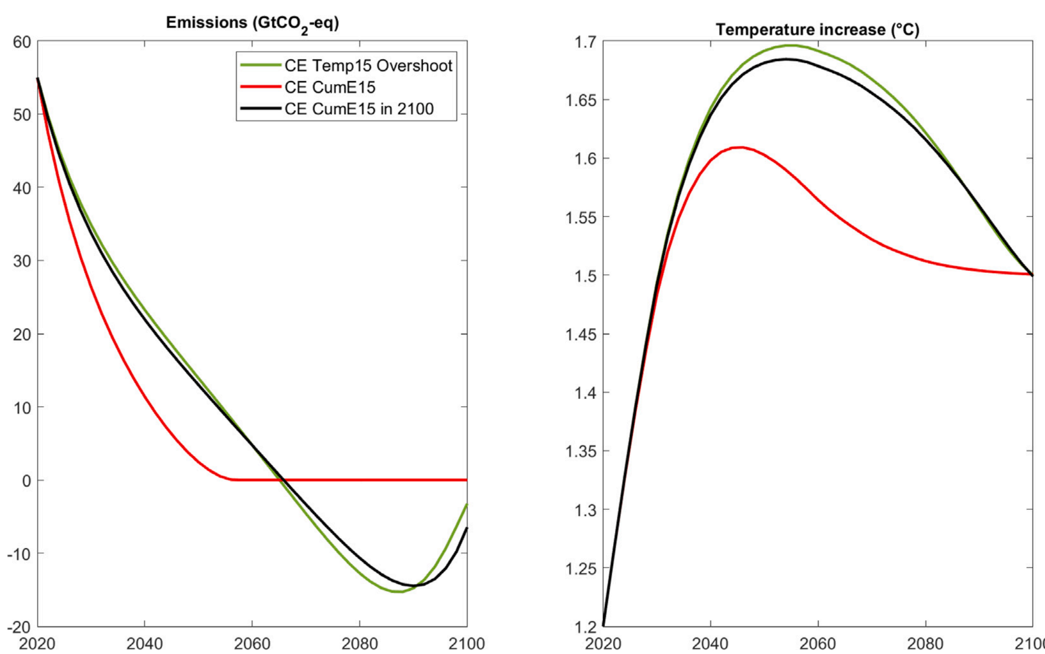

Fig. 9. The effect of a cumulative emissions constraint with overshoot, compared to a cumulative emissions constraint without overshoot and to a temperature constraint with overshoot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Other radiative forcing assumptions in RCP 1.9 (Riahi et al. (2017), Rogelj et al. (2018a), Gidden et al. (2019)).

RCP 1.9	2020	2030	2040	2050	2060	2070	2080	2090	2100
Total forcing (W/m²)	2.582	2.844	2.791	2.635	2.469	2.336	2.208	2.069	1.905
CO_2 forcing (W/m²)	2.126	2.287	2.298	2.234	2.149	2.056	1.948	1.818	1.662
Other forcing (W/m²)	0.456	0.557	0.494	0.401	0.320	0.280	0.260	0.251	0.243

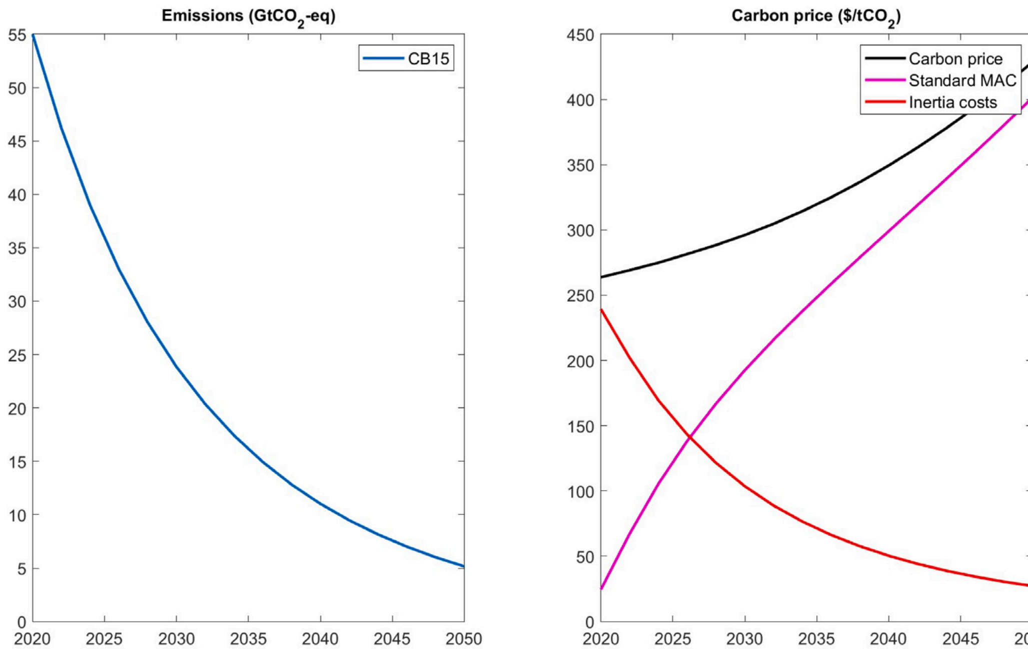

Fig. 10. Carbon price of the central CB scenario reaching 1.5 °C in 2100. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

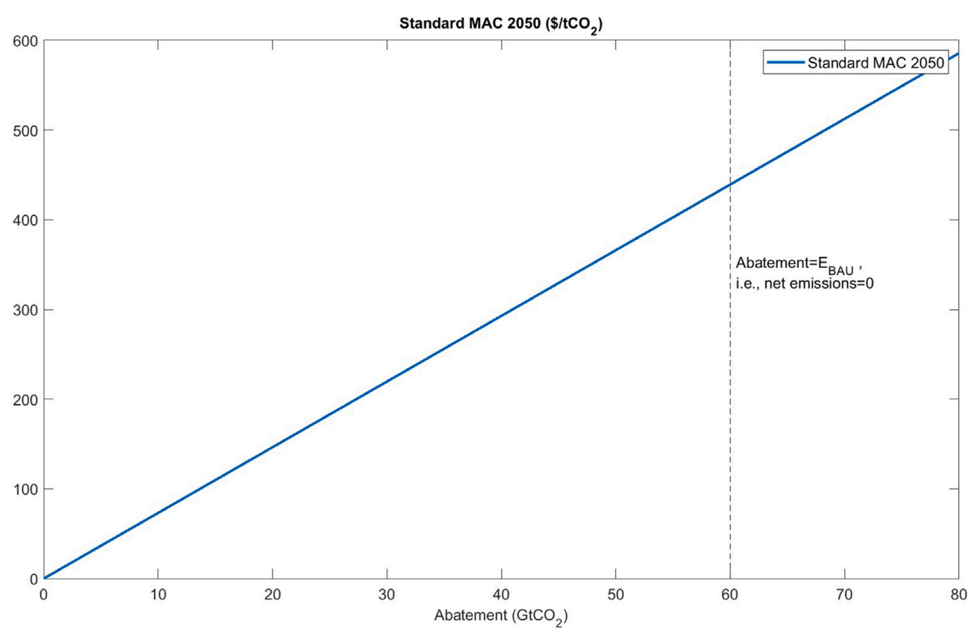

Fig. 11. MAC in 2050 for the central CB scenario reaching 1.5 °C in 2100.

Our quantitative results confirm the theoretical insights: the gap between CB and CE, in terms of emissions, temperature trajectories and welfare, is greater with a higher discount rate. Thanks to the counterbalancing effect of climate damages in the CB scenario, the emissions trajectory remain similar (abatement efforts are only slightly reported towards the end of the century). On the other hand, the shift is considerable in CE cases. For instance, in the CE scenarios with cumulative emissions and radiative forcing constraints, the higher discount rate results in additional emissions of 3.7 and 4.6 $GtCO_2$-eq in 2050, respectively. In contrast, the CB case experiences only a slight increase of 0.4 $GtCO_2$-eq. This delay in abatement efforts in CE scenarios even leads to a small temperature overshoot (peak temperature of 2.005 °C and 2.024 °C in the CE scenarios with a cumulative emissions constraint [CE CumE2 high disc] and a forcing constraint respectively [CE Forcing2 Ov. high disc]) and to net negative emissions at the end of the century in the radiative forcing case [CE Forcing2 Ov. high disc].

Appendix J. The effect of a cumulative emissions constraint with overshoot

In this appendix, we show that if the carbon budget constraint only applies from 2100, the emissions and temperature trajectories (in scenario [CE CumE15 in 2100]) become close to the CE scenario with a temperature constraint allowing overshoot [CE Temp15 Overshoot]. Fig. 9 illustrates this result for the 1.5 °C trajectories.

Appendix K. Carbon price and MAC function

Fig. 10 illustrates the carbon price in our central CB scenario reaching 1.5 °C in 2100 [CB15].

The starting carbon price is $264/t$CO_2$. Following equation 16, we divide the carbon price in two components: the "standard MAC" and the "inertia costs". Fig. 10 highlights the tremendous importance of inertia costs in the early years.

Fig. 11 illustrates the MAC in 2050 (thus, with fixed cumulative abatement and consumption).

Data availability

Data will be made available on request.

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