Climate impacts have been underestimated: a new climate damage function for an optimal climate policy

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Abstract

Latest empirical estimates reveal a heavy underestimation of the economic damages from climate change, comprehending extreme events and persistence of impacts on the economy. To ensure a just transition towards a net-zero target that keeps global warming below 2°C, we aim to introduce a novel damage function in the Nested-Inequalities Climate Economy (NICE) model, a derivative of the RICE model that accounts for within-country and between-country inequalities. We begin with a detailed examination of the model and the limitations associated with traditional Integrated Assessment Model damage functions. Following this, we suggest conceptual and formal enhancements to the standard quadratic damage function. These modifications will be subjected to forthcoming evaluations through sensitivity analyses to identify the optimal calibration according to current knowledge, allowing us to analyze the effects of the chosen damage function on temperature trajectories, inequalities, and the cost of implementing a uniform or differentiated carbon tax.

Keywords : Climate Change, IAM, Damage Function, Inequality, Climate Policy

Résumé

Les estimations empiriques les plus récentes, en incluant les événements extrêmes et la persistance des impacts sur l'économie, révèlent une sous-estimation significative des dommages économiques liés au changement climatique. Afin d'assurer une transition juste vers un objectif de zéro émission nette qui maintienne le réchauffement mondial en dessous de 2°C, nous visons à introduire une nouvelle fonction de dommages dans le modèle Nested-Inequalities Climate Economy (NICE), une adaptation du modèle RICE prenant en compte les inégalités intra- et inter-pays. Pour ce faire, nous présentons extensivement le modèle et les limitations propres aux fonctions de dommages traditionnelles des Integrated Assessment Models, avant de proposer des améliorations formelles et conceptuelles à apporter à notre fonction de dommage quadratique. Ces nouveaux apports feront dans un second temps l'objet d'analyses de sensibilité afin de déterminer le meilleur calibrage au regard des connaissances actuelles, et nous observerons les effets de la fonction sélectionnée sur les trajectoires de températures, les inégalités et le prix d'une taxe carbone uniforme ou différenciée.

Mots-clefs : Changement climatique, IAM, Fonction de dommages, Inégalités, Politique climatique

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Contribution statement

Contributors: Thomas Da Costa, Marc Fleurbaey, Fabrice Murtin.

- Defining the scientific investigation: Marc Fleurbaey, Fabrice Murtin
- Selecting the bibliography: Marc Fleurbaey, Thomas Da Costa
- Choosing a specific methodology: Thomas Da Costa, Marc Fleurbaey
- Providing the coefficients for the damage function: Fabrice Murtin
- Updating the model : Thomas Da Costa
- Writing the thesis, producing tables or figures : Thomas Da Costa

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List of Acronyms

CBA Cost-Benefit Analysis

DICE Dynamic Integrated model of Climate and the Economy

EDEC Equally Distributed Equivalent Consumption

EU European Union

FAIR Finite Amplitude Impulse Response

FUND Framework for Uncertainty, Negotiation, and Distribution

GHG Greenhouse Gas

GRP Gross Regional Product

IAM Integrated Assessment Model

IRF Impulse Response Function

LLMICs Low and Low-Middle Income Countries

NICE Nested-Inequalities Climate Economy

PAGE Policy Analysis of the Greenhouse Effect

pcGDP per capita Gross Domestic Product

RCPs Representative Concentration Pathways

RICE Regional Integrated model of Climate and the Economy

SCC Social Cost of Carbon

SSPs Shared Socioeconomic Pathways

TFP Total Factor Productivity

USA United States of America

WPP World Population Prospects

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1
Introduction

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I don't want to set the world on fire,

I just want to start a flame in your heart

The Ink Spots

1.1 Climate change and its damages

Regardless of The Ink Spots intentions, the anthropogenic origin of climate change is well and truly established [1]. It even predates them: for instance, there is evidence of a relationship between the cooling during the Little Ice Age and the genocide of indigenous peoples during the colonization of the Americas, the abandonment of cleared land having significantly increased carbon sequestration on the land surface [2]. Nowadays, human actions leave global impacts on the Earth system, such that global surface temperature has increased by 1.09 [0.95 to 1.20]°C above pre-industrial levels (1850-1900) in the decade 2011-2020 [3]. This warming affects, among other things, yields in agriculture [4] (even though agriculture itself is responsible for at least 15% of total Greenhouse Gas (GHG) emissions [5], [6]), human and non-human health [7]–[9], or economic growth [10].

Two recent studies, while having different methodologies, converge on the same striking conclusion: the macroeconomic damages from climate change are six times larger than previously thought [11], [12]. We could be facing a permanent reduction in average global income by 19% [11-29] by 2050, regardless of our future choices concerning GHG emissions. Then, the costs of mitigation to limit global warming to 2 °C would be six times lower than the costs of climate change [11].

These results bear huge implications for future just-transition policies, as the 2024 G20 Rio de Janeiro summit plans to tackle ”energy transition and sustainable development in its social, economic and environmental aspects” and the European Union (EU) is working on its 2050 carbon-neutral policy.

To evaluate the future impact of climate change and associated public policies on welfare, we will use a very standard approach, relying on a Cost-Benefit Analysis (CBA) using an Integrated Assessment Model (IAM). We will seek to introduce an updated damage function in line with the most recent results, and pay particular attention to the way in which climate change damages and inequalities interact.

After outlining the general functioning of IAMs, we will provide a detailed overview of the Nested-Inequalities Climate Economy (NICE) model, then focus on the potential modifications to its damage function. As our work is still ongoing, our preliminary results will be presented and discussed at a later time, during a conference and subsequently in a working paper.

1.2 Integrated Assessment Models

IAMs are climate-economy models designed to evaluate the interactions between human activities and natural processes, specifically climate change, with the aim of informing policy decisions related to the costs and benefits of climate change mitigation and adaptation. They are useful to estimate the Social Cost of Carbon (SCC), *i.e.* the cost (in current dollars) of the impacts of climate change caused by the emission of an additional ton of CO_2e emissions. They includes at least the following modules:

- a tool projecting the path for GHG emissions;
- a model mapping GHG emissions into climatic change;
- a damage component that calculates the economic costs of climatic change;
- a social welfare function for aggregating damages over time and across space.

The primary objective of IAMs is to maximize the social welfare function, balancing the tradeoff between immediate mitigation efforts (resulting in a reduction in current well-being) and future climate damages (leading to a loss in well-being over a more distant timeframe) [13].

In order to find the optimal path of economic activity and carbon emissions over time, climate-economy models calculate social welfare under the assumption of Total Utilitarianism, *i.e.* as the sum of the welfare of all individuals (as opposed to Average Utilitarianism, which calculates an average social welfare across all existing individuals). It should be noted that, all else being equal, this implies that the existence of additional people is regarded as a social benefit [13]. The social welfare function then takes the following form:

$$W(cpc(t)) = \sum_t \frac{l(t)}{(1+\rho)^t} \frac{cpc(t)^{1-\eta}}{1-\eta} \tag{1.1}$$

With:

- W : social welfare
- $cpc(t)$: per capita consumption over the time period t
- $l(t)$: population over the time period t
- η : inequality aversion (marginal utility elasticity)
- ρ : rate of pure time preference

The three most widely used models to date are the Dynamic Integrated model of Climate and the Economy (DICE), Framework for Uncertainty, Negotiation, and Distribution (FUND), and Policy Analysis of the Greenhouse Effect (PAGE) models, which are employed, for example, by the U.S. Environmental Protection Agency. DICE is an IAM with a Ramsey-type of optimal economic growth model. Under a certainty-equivalent approach, it seeks to optimally allocate consumption and investment over time to maximize the present value of utility [14], [15]. FUND focuses its ambition on equitable climate policies by including detailed damage functions that estimate the economic impacts of climate change on various sectors, including agriculture, health, and infrastructure. It uses 16 regions with different outputs, emissions and damages [16]. Note that a version of DICE, Regional Integrated model of Climate and the Economy (RICE), also provides regional disaggregation across 12 regions. PAGE incorporates a probabilistic approach to account for uncertainties in climate sensitivity, damage functions, and economic impacts, alongside its regional and sector-specific impacts framework [17]. Unlike DICE, FUND and PAGE assume that GDP growth is exogenous [18].

1.3 Nested-Inequalities Climate Economy (NICE) model: a conceptual description

The NICE model is an IAM that builds upon Nordhaus's RICE model but offers much greater granularity. The 12 regions are disaggregated into 179 countries[1] and within-country inequalities are introduced on the the basis of consumption quantiles. They are then reflected through damages, mitigation costs, and carbon tax burdens. This model embodies the idea that the distribution of damages within regions can cause some members of future generations to be less affluent than their current counterparts. Consequently, future poors might bear more than their proportional share of the damage, even with a growth assumption and an optimal policy computed by aggregate models. Optimal mitigation efforts thus depend on the rate of pure time preference ρ and the inequality aversion η [19].

NICE also allows to account for between-country inequalities: in their paper, Dennig *et al.* (2015) [20] show that the disaggregation from RICE to NICE increases the Gini coefficient by 10 percentage points (0.55 to 0.65 respectively).

In the following, we will use the latest version of NICE [21] enhanced by the contributions of Young-Brun *et al.* (2024) [22], which includes distribution, damages and mitigation at the country level, revenue recycling scenarios at the country and global levels (allowing to encompass the effects of different policy designs on a +2 °C target, whether with a global carbon tax or optimally differentiated taxes) and various degrees of redistribution. On top of the existing model, we also included a net-zero 2050 scenario in order to determine the necessary carbon tax pathways required to achieve the EU's goal.

[1] 183 countries as inputs but Somalia, Venezuela, New Caledonia and Trinidad and Tobago were removed due to data limitations.

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Materials and Methods

Contents

2.1 Nested-Inequalities Climate Economy (NICE) model: a technical description

The NICE model is structurally similar to DICE [14], and a comprehensive description of its functioning has been made by Young-Brun *et al.* (2024, [22]). All indices, parameters, and variables are listed in Appendix A.

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2.1.1 General structure

We employ the Mimi framework, specifically the MimiFAIRv2 module developed by Errickson *et al.* (2022) [23]. This module, based on the Finite Amplitude Impulse Response (FAIR) model, computes the global climate system's response to GHG emissions, effectively capturing non-linearities in the carbon cycle while maintaining a low level of complexity and run-time [24].

At first, the initial concentrations of emissions, along with the radiative response and radiative forcing of aerosols, are updated. This update also applies to methane (CH_4), carbon dioxide (CO_2), fluorinated gases, substances regulated by the Montreal Protocol, and nitrous oxide (N_2O). Finally, the initial temperature is defined.

The emissions and radiative forcing scenario are defined according to SSP2-45[2], between 2020 and 2300. There are 10 quantiles in each of the 179 countries, that can be aggregated into the 12 RICE regions (["US", "EU", "Japan", "Russia", "Eurasia", "China", "India", "MidEast", "Africa", "LatAm", "OHI", "OthAsia"]), 13 regions ("EU" from RICE is splitted into "EU27", designating the EU, and "OthEU", designating the rest of Europe), or 20 regions from the World Population Prospects (WPP).

Abatement and gross output components are added before the FAIR carbon cycle, which is subsequently coupled with local damages, net production (*i.e.* after mitigation costs and damages), tax revenues recycling, distribution of costs across different quantiles of the population and welfare valuation components.

2.1.2 Gross economy

NICE is a classical one-sector model relying on a Cobb-Douglas production function. The capital $K[t, c]$ in each country c at time t is initialized as $k_0[c]$ and updated by taking into account the previous year's capital depreciation $depk$ and the previous year's investment I, multiplied by 5 (representing a 5-year period), *s.t.*:

$$K[t, c] = (1 - depk[t, c])^5 \cdot K[t-1, c] + I[t-1, c] \cdot 5 \tag{2.1}$$

We can inject the calculated value into the production function in capital $K[t, c]$ and labor $l[t, c]$ (exogenous and equal to the country population) to obtain the gross output $YGROSS[t, c]$:

$$YGROSS[t, c] = tfp[t, c] \cdot K[t, c]^{share} \cdot l[t, c]^{(1-share)} \tag{2.2}$$

Total factor productivity ($tfp[t, c]$) is also exogenous, and the share of income allocated to capital ($share$) is set to 0.3.

[2]The definition of Shared Socioeconomic Pathways (SSPs) and their key characteristics can be found in the appendix B.

2.1.3 Abatement

The abatement cost function takes the same form as in Barrage and Nordhaus (2024) [14]: a polynomial function of the emissions mitigation rate μ with an intercept θ_1 representing the necessary fraction of output to bring emissions to zero.

$$ABATEFRAC[t,c] = \theta_1[t,c] \cdot \mu^{\theta_2}[t,c] \tag{2.3}$$

With $\theta_2 = 2.6$. As for it, the abatement cost is calculated as:

$$ABATECOST[t,c] = YGROSS[t,c] \cdot ABATEFRAC[t,c] \tag{2.4}$$

Let us write $C(\mu)$ the cost of abatement in dollars per unit of emissions.

$$C(\mu) = ABATEFRAC(\mu) \cdot \frac{Y}{E} = \frac{\theta_1[t,c] \cdot \mu^{\theta_2}[t,c]}{\sigma[t,c]} \tag{2.5}$$

σ[t,c] represents the emissions output ratio (in unit of emissions per dollars) that models emissions intensity as a function of economic activity for each country c at each period t. It is an exogenous parameter calibrated on emissions projections of the REMIND project [25].

To make the function country-specific, we calibrate θ_1 using the global backstop price (515 2019US$ per tCO2 in 2050) estimated in Barrage and Nordhaus (2024) [14] from the ENGAGE study [26]. We establish that the backstop price decreases by 1%/year betwen 2020 and 2050, and by 0.01%/year afterwards.

As a reminder, a backstop technology is a set of technologies such that at its cost, the economy achieves net-zero carbon emissions. It leads to the assumption that the marginal cost of abatement at a 100% mitigation rate ($\mu = 1$) per unit of emission ($\frac{\partial C(\mu=1)}{\partial \mu}$) is equal to the global backstop price (*pbacktime*) in every country. Therefore, based on equation (2.5), we have:

$$\frac{\partial C(\mu=1)}{\partial \mu} = pbacktime[t] \tag{2.6}$$

$$\frac{\theta_1[t,c]\theta 2}{\sigma[t,c]} = pbacktime[t] \tag{2.7}$$

$$\theta_1[t,c] = pbacktime[t]\frac{\sigma[t,c]}{\theta 2} \tag{2.8}$$

Eventually, $\mu[t,c]$ can be expressed as:

$$\mu[t,c] = \left(\frac{C'(\mu)}{pbacktime[t]}\right)^{\frac{1}{\theta_2 - 1}} = \left(\frac{\text{country\_carbon\_tax[t,c]}}{pbacktime[t]}\right)^{\frac{1}{\theta_2 - 1}} \tag{2.9}$$

In the NICE model, we bound the values of μ between 0 and 1 to prevent negative emissions ($\mu > 1$). The calculation of the country carbon tax depends on the chosen mitigation control regime: whether we opt for a global carbon tax ($country\_carbon\_tax[t,c] = global\_carbon\_tax[t]$), a differentiated tax by

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country ($country\_carbon\_tax[t,c] \propto reference\_carbon\_tax[t]$), or a given mitigation rate per country (where $\mu[t,c]$ is given, $\mu = \mu_{input}$, and $country\_carbon\_tax[t,c] = pbacktime[t] \cdot (\mu_{input}[t,c])^{\theta_2 - 1}$).

2.1.4 Emissions

In their most recent paper, Barrage and Nordhaus enhance their emissions calculation system by allowing all GHGs to be abatable, not just CO_2. Our model retains the previous version of the calculation, determining CO_2 emissions as follows:

$$E_{\text{gtco2}}[t,c] = YGROSS[t,c] \cdot \sigma[t,c] \cdot (1 - \mu[t,c]) \tag{2.10}$$

2.1.5 Temperature

From the global temperature increase given by the FAIR model, we derive the country-specific temperature anomalies with scaling coefficients (β_temp) according to the Coupled Model Intercomparison Project (CMIP) Phase 6 projections [27]:

$$\text{local\_temp\_anomaly}[t,c] = \beta\_temp[c] \cdot global\_temperature[t] \tag{2.11}$$

2.1.6 Damages

The climate damages function of NICE, prior to modification, is inspired by that provided by Kalkuhl and Wenz (2020, Supplementary Materials, 4.2) [28]. It is a standard quadratic function where damages ($LOCAL\_DAMFRAC\_KW$) are expressed as a share of GDP. However, it differs from traditional approaches by accounting for local temperature increases ($local\_temp\_anomaly$) rather than global warming. Thus, it takes the following form:

$$\begin{aligned} LOCAL\_DAMFRAC\_KW[t,c] = {} & \beta1\_KW[c] \cdot local\_temp\_anomaly[t,c] \\ & + \beta2\_KW[c] \cdot local\_temp\_anomaly^2[t,c] \end{aligned} \tag{2.12}$$

with $\beta1\_KW[c] = \alpha + 2\beta T_0[c]$ and $\beta2\_KW[c] = \beta$ (and $\alpha = -0.01128$, $\beta = 0.00092$), being country-specific parameters that are calibrated to represent a general relationship between temperature increase and climate damages, as predicted in the econometric analysis by Kalkuhl and Wenz (2020) [28]. Using a cross-sectional model, they find that an increase of 1 °C reduces Gross Regional Product (GRP) by 2-4%. With an annual panel model in their prefered econometric specification, they estimate that an increase of 1 °C in a hot region ($T = 25$ °C) decreases the output by about 3.5%, and that +1 °C in a cold region ($T = 10$ °C) decreases the output by 0.8%.

These results are implemented to calibrate the parameters α and β in the NICE model, and $\beta 1\_KW[c]$ is then determined by setting the preindustrial local temperature $T_0[c]$ after the data provided by Dell *et al.* (2012) [10] on the average annual temperature in countries for the period 1900-1909.

It should be noted that $LOCAL\_DAMFRAC\_KW$ represents the proportion of GDP lost. In the last version of DICE, the net output after damages is calculated as $Y = \delta(\Delta T[t,c])YGROSS$, where $\delta(\Delta T[t,c]) = (1 - \Omega(\Delta T))$ and $\Omega(\Delta T)$ is a standard quadratic function in ΔT [14]. In NICE, the functional form of climate damages $\delta_{\mathrm{NICE}}(\Delta T[t,c])$ matches the ones used in previous RICE or DICE models [29], [30]:

$$\delta_{\mathrm{NICE}}(\Delta T[t,c]) = \frac{1}{1 + LOCAL\_DAMFRAC\_KW[t,c]} \tag{2.13}$$

2.1.7 Net economy

The output net of damages and abatement costs Y is easily calculated as:

$$Y[t,c] = \delta_{\mathrm{NICE}}(\Delta T[t,c]) \cdot (1 - ABATEFRAC[t,c]) \cdot YGROSS[t,c] \tag{2.14}$$

We define the investment (I) as a fraction (s, the saving rates) of net output (Y) and the consumption (C) as the difference between net output and investment:

$$I[t,c] = s[t,c] \cdot Y[t,c] \tag{2.15}$$

$$C[t,c] = Y[t,c] - I[t,c] = (1 - s[t,c]) \cdot Y[t,c] \tag{2.16}$$

Consumption per capita (CPC) and net output per capita (Y_pc) are then calculated as the ratio of the respective variables to the population, scaled if necessary to match the right units:

$$CPC[t,c] = \frac{C[t,c]}{l[t,c]} \tag{2.17}$$

$$Y\_pc[t,c] = \frac{Y[t,c]}{l[t,c]} \cdot 10^3 \tag{2.18}$$

2.1.8 Carbon tax trajectories

The following sections are specific to NICE and are partially described in Budolfson *et al.* (2021) [21] and Young-Brun *et al.* (2024) [22].

To determine the value of the carbon tax ($global\_carbon\_tax$ or $reference\_carbon\_tax$, depending on the selected option) for each time period ($year\_step$), we apply an exponential growth carbon tax trajectory. This approach assumes a carbon tax of \$0 in the initial period ($year\_tax\_start$), followed by an immediate increase to tax_start_value, after which the tax increases exponentially at a specified rate

(g_rate) until the end of the designated period ($year\_tax\_end$). Its value remains constant until the model's last period ($year\_model\_end$). Thus, for $t \in [year\_tax\_start + 1 : year\_step : year\_tax\_end]$:

$$tax\_values[t] = tax\_start\_value * (1 + g\_rate)^{(t-(year\_tax\_start+1))} \tag{2.19}$$

$$full\_tax\_path = [0; \text{tax\_values}; fill(\text{tax\_values[end], year\_model\_end - year\_tax\_end})] \tag{2.20}$$

2 °C scenario

By default, NICE runs under the 2 °C scenario. To achieve the optimal scenario, we simulated a large number of global carbon tax trajectories and retained the one which maximized total welfare from 2020 to 2100 (using a discount rate ρ of 0.015) while keeping the temperature increase below 2 °C from 2020 to 2120. By varying the initial value from 80 to 120 and the growth rate from 0.025 to 0.035, we obtained $tax\_start\_value_{optimal} = 114$ and $g\_rate_{optimal} = 0.03$.

To find optimally differentiated carbon tax trajectories, we rely on the method given by Young-Brun *et al.* (2024) [22]. We maximize the sum of all utilities from consumption (before climate damages and taxes) under an emission budget constraint expressed by $\sum_c (1 - \mu[t, c])E[t, c] < E[t]$. It gives us a relationship between the carbon tax value in any country c and the carbon tax value in a country of reference, that we set as the United States of America (USA). Because we are now looking for the optimal carbon tax trajectory which maximizes welfare in the USA, we have to perform new simulations of various trajectories. By varying the initial value from 275 to 325 and the growth rate from 0.025 to 0.04, we obtain $differentiated\_tax\_start\_value_{optimal} = 277$ and $g\_rate_{optimal} = 0.035$.

Net-zero 2050 scenario

To determine the optimal trajectory of the global carbon tax under the EU's net-zero 2050 target, we added a new constraint to the optimization described for the 2 °C target (section 2.1.8): only the trajectories that result in zero emissions from the EU before 2050 are retained. We conducted various tests to observe the effect of bounds definition for tax_start_value and g_rate, the characteristics of which are presented in Table 2.2.

The last four rows of the table correspond to the same test. We examined every trajectory that met the net-zero target before 2050 to assess the significance of welfare differences across the trajectories and years. Given the less-than-0.5% difference in global welfare over the entire carbon tax period between the net-zero 2050 target and the optimal value (net-zero 2038), we chose to set $(tax\_start\_value_{optimal}; g\_rate_{optimal}) = (114; 0.052)$, which achieve net-zero by 2050. Similar to section 2.1.8, we aimed to identify the trajectory that maximizes welfare in the USA over the period 2020-2100. To achieve this, we varied the initial value from 275 to 450 and the growth rate from 0.035 to 0.1.

From (tax_start;rate)	To (tax_start;rate)	Optimal parameters (tax_start;rate)	Maximal welfare value	EU27 net-zero goal achievement
(100; 0.04)	(800; 0.1)	(300; 0.04)	- 3.07793533 e8	2038
(80; 0.025)	(120; 0.070)	(120; 0.07)	- 3.08241602 e8	2043
(110; 0.05)	(120; 0.06)	(120; 0.06)	- 3.08335754 e8	2046
(110; 0.045)	(114; 0.055)	(114; 0.055)	- 3.08465239 e8	2049
(110; 0.045)	(114; 0.055)	(113; 0.0545)	- 3.08484631 e8	2049/50
(110; 0.045)	(114; 0.055)	(111; 0.055)	- 3.08501604 e8	2049/50
(110; 0.045)	(114; 0.055)	(114; 0.052)	- 3.08511639 e8	2050

Table 2.2: Various trajectories achieving EU net-zero before 2050, along with the associated global welfare.

By doing so, we obtained $differentiated\_tax\_start\_value_{optimal} = 280$ and $g\_rate_{optimal} = 0.065$, which translate in a similar initial tax value than the 2 °C scenario, but a faster growth towards the backstop price.

2.1.9 Revenue recycling

The carbon tax revenue calculation is quite simple: it corresponds to the product of a country's emissions ($E_{gtCO2[t,c]}$) and its carbon tax ($country\_carbon\_tax[t,c]$), calculated in corresponding units, ajusted by any potential revenue loss ($lost\_revenue\_share$, which is set to a default zero, meaning that the entire tax revenue is available for recycling).

$$\text{tax\_revenue}[t,c] = \left(E\_gtco2[t,c] \times \text{country\_carbon\_tax}[t,c] \times 10^9\right) \times (1 - \text{lost\_revenue\_share}) \quad (2.21)$$

Young-Brun *et al.* (2024) [22] explored multiple methods for distributing carbon tax revenues. These configurations are of significant importance, as each reflects a distinct potential public policy strategy for implementing a carbon tax. These strategies can be compared both with one another and against a baseline model without any CO2 mitigation policy. First, the uniform global tax and differentiated carbon taxes can be distributionnally neutral (a "no recycling" scenario), where carbon tax revenues are refunded within each country to exactly offset the carbon tax payment, making it possible to isolate the carbon tax effects on emissions without the potential offsetting effects of income redistribution. We can also configure the model to allow for full revenue recycling at the national level, where revenues are redistributed as equal per capita payments within each country.

Subsequently, we test a uniform global carbon tax with total per capita revenue recycling at the global level, assuming the feasibility of significant international transfers between countries: the rate of shares recycled is 100% ($global\_recycle\_share = 1$). Aware of the limitations of this assumption, we also simulate a "Loss and Damage" fund, financed by transfers from developed countries to LLMICs (as defined by the World Bank and listed in Appendix C). It takes the form of a global uniform carbon tax, recycled at a rate ($global\_recycle\_share$) of 5% to households in LLMICs, the remaining carbon tax revenues($1 - global\_recycle\_share$) being redistributed within countries on an equal per capita basis. Three criteria are then considered for redistribution:

- as a ratio to relative damages weighted by population in LLMICs (computed with $TRANSFRAC\_dam\_rel\_llmic$)
- as a ratio to absolute damage (in dollars per capita) in LLMICs (computed with $TRANSFRAC\_dam\_abs\_llmic$)
- as a ratio to a risk index ($list\_risk\_index$) weighted by population in LLMICs (computed with $TRANSFRAC\_risk\_llmic$)

In the first time step, each redistribution fraction for LLMICs is initialised as the inverse of their total number:

$$\left.\begin{array}{l} TRANSFRAC\_dam\_rel\_llmic[t=1,c] \\ TRANSFRAC\_dam\_abs\_llmic[t=1,c] \\ TRANSFRAC\_risk\_llmic[t=1,c] \end{array}\right\} = \frac{1}{\text{Number of LLMICs}} \tag{2.22}$$

Then, the redistribution fractions are updated at each time step according to the following formula:

$$TRANSFRAC\_dam\_rel\_llmic[t,c] = \frac{\max\Big(LOCAL\_DAMFRAC\_KW[t,c],0\Big)\cdot l[t,c]}{\sum_{c\in LLMIC}\max\Big(LOCAL\_DAMFRAC\_KW[t,c],0\Big)\cdot l[t,c]} \tag{2.23}$$

$$TRANSFRAC\_dam\_abs\_llmic[t,c] = \frac{\max\Big(LOCAL\_DAMFRAC\_KW[t,c],0\Big)\cdot Y[t,c]}{\sum_{c\in LLMIC}\max\Big(LOCAL\_DAMFRAC\_KW[t,c],0\Big)\cdot Y[t,c]} \tag{2.24}$$

$$TRANSFRAC\_risk\_llmic[t,c] = \frac{list\_risk\_index[c]\cdot l[t,c]}{\sum_{c\in LLMIC} list\_risk\_index[c]\cdot l[t,c]} \tag{2.25}$$

The risk index is an adapted version of the INFORM Index for Risk Management [31], modified to account solely for climate-related natural risks in the Hazards & Exposure sub-index, namely flood, tropical cyclone, and drought. We then combine them with the INFORM country indices for Vulnerability and Lack of Coping Capacity, based on the latest data available [32]. The risk index allows to account for extreme events in the recycling process, but it doesn't take into account other climate threats (*e.g.* sea-level rise, ocean acidification, etc.). Note that it is negatively correlated with GDP.

In the program, the recycling options are controlled using boolean variables: $switch\_recycle = 0$ deactivate revenue recycling, while $switch\_scope\_recycle = 1$ act on the level of recycling, either national (0) or global (1).

If activated, the $switch\_global\_pc\_recycle$ variable entails the recycling of carbon tax revenues globally on an equal per capita basis. $switch\_dam\_rel\_llmic\_recycle$, $switch\_dam\_abs\_llmic\_recycle$, and $switch\_risk\_llmic\_recycle$ are used to select the recycling criterion for the "Loss and Damage" fund policy. Here is how domestic and global dividends are calculated based on the activated boolean variables:

`switch_recycle = 0` No income recycling implies no dividends.

$$\left.\begin{aligned} &country\_pc\_dividend\_domestic\_transfers[t,c] \\ &country\_pc\_dividend\_global\_transfers[t,c] \end{aligned}\right\} = 0 \tag{2.26}$$

`switch_recycle==1, switch_scope_recycle==0` Revenues from the carbon tax are recycled at a national level:

$$country\_pc\_dividend\_domestic\_transfers[t,c] = \frac{tax\_revenue[t,c]}{l[t,c] \times 10^6} \tag{2.27}$$

$$country\_pc\_dividend\_global\_transfers[t,c] = 0 \tag{2.28}$$

`switch_recycle==1, switch_scope_recycle==1` Carbon tax revenues are recycled at a global level:

$$country\_pc\_dividend\_domestic\_transfers[t,c] = (1 - global\_recycle\_share[c]) \times \frac{tax\_revenue[t,c]}{l[t,c] \times 10^6} \tag{2.29}$$

$$revenue\_recycled\_global\_level[t] = \sum_c (tax\_revenue[t,c] \times global\_recycle\_share[c]) \times 10^{-3} \tag{2.30}$$

- `switch_pc_global_recycle = 1`; Carbon tax revenues are recycled globally on an equal per capita basis ($global\_recycle\_share = 1$).

$$country\_pc\_dividend\_global\_transfers[t,c] = \frac{revenue\_recycled\_global\_level[t]}{\sum_c (l[t,c]) \times 10^3} \tag{2.31}$$

- `switch_dam_rel_llmic_recycle = 1`; OR `switch_dam_abs_llmic_recycle = 1`; OR `switch_risk_llmic_recycle = 1`; Carbon tax revenues are recycled to LLMICs based on the selected criterion ($global\_recycle\_share = 0.05$). For $c \in$ LLMICs:

$$country\_pc\_dividend\_global\_transfers[t, c_{\text{LLMICs}}] =$$
$$\frac{revenue\_recycled\_global\_level[t, c_{\text{LLMICs}}]}{l[t, c_{\text{LLMICs}}] \cdot 10^3} \cdot \begin{cases} TRANSFRAC\_dam\_rel\_llmic[t, c_{\text{LLMICs}}] \\ TRANSFRAC\_dam\_abs\_llmic[t, c_{\text{LLMICs}}] \\ TRANSFRAC\_risk\_llmic[t, c_{\text{LLMICs}}] \end{cases} \tag{2.32}$$

Total dividends per person are eventually computed as:

$$country\_pc\_dividend[t, c] = country\_pc\_dividend\_domestic\_transfers[t, c] + country\_pc\_dividend\_global\_transfers[t, c] \tag{2.33}$$

2.1.10 Distribution across deciles

In order to account for within-country inequalities, we divide each country into consumption deciles derivated from income deciles following the approach given by Pinkovskiy and Sala-i Martin (2009) [33]. To find income deciles, we first calibrate baseline deciles ($quantile\_income\_shares[t, c, q]$) using country income Gini projections until 2100 in the SSP2-45 scenario[3], as provided by Rao *et al.* (2019) [34]. We assume that income is distributed across deciles according to a lognormal distribution $LN(\mu[t, c], \sigma[t, c])$. Following Cowell (2011), we calculate σ and μ, taking care to maintain homogeneous units, as:

$$\sigma_{cons}[t, c] = \sqrt{2} \cdot quantile\left(\mathcal{N}(0, 1), \frac{gini\_cons[t, c]/100 + 1}{2}\right) \tag{2.34}$$

$$\mu_{cons}[t, c] = \log(CPC[t, c] \cdot 10^3) - \frac{(\sigma_{cons})^2}{2} \tag{2.35}$$

More details on the Julia quantile function can be found here. From the standard deviations $\sigma_{cons}[t, c]$, we deduce a Lorenz curve for each country and each time step, from which we obtain country income deciles over time, which then give us access to consumption deciles.

Climate damages, mitigation costs and carbon tax burdens are distributed across deciles using consumption elasticities, more precisely an endogenous CO_2-income elasticity ($CO2\_income\_elasticity$) and an exogenous damage elasticity ($damage\_elasticity$). The CO_2-income elasticity is calibrated using the estimation provided in Budolfson *et al.* (2021, Fig. 1) [21], which is coming from a review of the literature on the distribution of the initial burden of a carbon (or gasoline) tax and the resulting relationship with

[3] The definition of SSPs and their key characteristics can be found in the appendix B.

per capita Gross Domestic Product (pcGDP).

$$\text{CO2\_income\_elasticity}[t, c] = \text{elasticity\_intercept} + \text{elasticity\_slope} \cdot log(GDP) \tag{2.36}$$

where :

$$GDP = \begin{cases} pc\_gdp[t, c] & \text{if pc\_gdp[t,c]} \in \text{[min\_study\_gdp, max\_study\_gdp]} \\ min\_study\_gdp & \text{if pc\_gdp[t,c]} < \text{min\_study\_gdp} \\ max\_study\_gdp & \text{if pc\_gdp[t,c]} > \text{max\_study\_gdp} \end{cases} \tag{2.37}$$

The distributions of the shares of the carbon tax burden ($carbon\_tax\_dist$) and mitigation costs ($abatement\_cost\_dist$) across deciles are considered equals and relies on the CO_2-income elasticity.

The estimation of damage elasticity is thoughtfully presented by Budolfson et al. (2017) [19]. Its value depends on the impact of climate change at a sub-regional scale, the vulnerability of economic organization and existing infrastructure, and public policies. While damage elasticity estimation is based on empirical studies and ethical considerations, there are no empirical estimates available across consumption deciles. Its value can be inversely proportional to consumption ($damage\_elasticity = -1$), proportional to consumption ($damage\_elasticity = 1$), evenly distributed ($damage\_elasticity = 0$), more than proportional to consumption ($damage\_elasticity > 1$), etc. However, it is suggested that poorer populations will disproportionately suffer from climate change [35]–[38]. Therefore, we assume that climate damages will be slightly less than proportional to income, by choosing $damage\_elasticity = 0.85$ (as a reminder, all parameters values can be found in Appendix A). Distribution of the share of climate damages ($damage\_dist$) can be then calculated using baseline deciles (the ratio between decile consumption and average consumption) and damage elasticity.

Let us now navigate through the consumption per quantile calculations, from gross consumption to consumption after the redistribution of carbon tax revenues. First, we define a gross consumption per capita (CPC_{GROSS}), such that:

$$CPC_{GROSS}[t, c] = \frac{(1 - s[t, c])YGROSS[t, c]}{l[t, c]} \tag{2.38}$$

Gross consumption per quantile ($qc\_base[t, c, q]$) is expressed as:

$$qc\_base[t, c, q] = nb\_quantile \cdot CPC_{GROSS}[t, c] \cdot quantile\_income\_shares[t, c, q] \tag{2.39}$$

Then, we calculate the consumption per quantile net of climate damages and mitigation costs by subtracting the sum of the products of the consumption affected by the incurred costs (either in damages or mitigation) and the distributions of the shares across deciles from qc_base. In the NICE model, for all forthcoming

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calculations, we ensure that the value of consumption is never negative, maintaining a minimum value of zero.

$$\begin{aligned} qc\_post\_damage\_abatement[t,c,q] = qc\_base[t,c,q] - \\ nb\_quantile \cdot CPC_{GROSS}[t,c] \cdot ABATEFRAC[t,c] \cdot abatement\_cost\_dist[t,c,q] - \\ nb\_quantile \cdot CPC[t,c] \cdot LOCAL\_DAMFRAC\_KW[t,c] \cdot damage\_dist[t,c,q] \end{aligned} \quad (2.40)$$

To obtain consumption by quantile after the tax, we reduce $qc\_post\_damage\_abatement$ by the product of the carbon tax burden ($carbon\_tax\_dist[t,c,q]$) and the carbon tax payment per capita ($tax\_pc\_revenue[t,c]$).

$$\begin{aligned} qc\_post\_tax[t,c,q] = qc\_post\_damage\_abatement[t,c,q] - \\ (nb\_quantile \cdot tax\_pc\_revenue[t,c] \cdot carbon\_tax\_dist[t,c,q]) \end{aligned} \quad (2.41)$$

It should be noted that the initial burden of the carbon tax refers to the sum of mitigation costs and tax payments before tax revenues are recycled and redistributed.

- If the revenues are recycled, then post-tax consumption per quantile ($qc\_post\_recycle$) is increased by the product of the total per capita dividends from the carbon tax ($country\_pc\_dividend$) and the share of its recycling to each decile:

$$\begin{aligned} qc\_post\_recycle[t,c,q] = qc\_post\_tax[t,c,q] + \\ (nb\_quantile \cdot country\_pc\_dividend[t,c] \cdot recycle\_share[c,q]) \end{aligned} \quad (2.42)$$

- If revenues are not recycled, carbon tax revenues are refunded within each country according to the distribution of the initial burden, eliminating the cost of tax payments.

$$\begin{aligned} qc\_post\_recycle[t,c,q] = qc\_post\_tax[t,c,q] + \\ (nb\_quantile \cdot tax\_pc\_revenue[t,c] \cdot carbon\_tax\_dist[t,c,q]) \end{aligned} \quad (2.43)$$

Which is equivalent to $qc\_post\_recycle[t,c,q] = qc\_post\_damage\_abatement[t,c,q]$

We can eventually aggregate those consumption values at country, region or global level, and compute the proportion of per capita quantile consumption (qc_share, in %), as:

$$qc\_share[t,c,q] = \frac{qc\_post\_recycle[t,c,q]}{\sum_q qc\_post\_recycle[t,c,q]} \cdot 100 \quad (2.44)$$

2.1.11 Welfare

We use two methods to calculate welfare: the standard approach and the Equally Distributed Equivalent Consumption (EDEC) approach. It corresponds to the level of consumption that, if given to each member of a population, yields the same level of welfare as the actual distribution of consumption. For each country (c), standard and EDEC welfare are calculated as follows:

$$welfare\_country[t,c] = \left(\frac{l[t,c]}{nb\_quantile}\right)\sum_q \left(\frac{qc\_post\_recycle[t,c,q]^{(1-\eta)}}{(1-\eta)}\right) \tag{2.45}$$

$$welfare\_global[t] = \sum_c (welfare\_country[t,c]) \tag{2.46}$$

$$cons\_EDE\_country[t,c] = \left(\frac{1}{nb\_quantile}\sum_q (qc\_post\_recycle[t,c,q]^{(1-\eta)})\right)^{\frac{1}{(1-\eta)}} \tag{2.47}$$

$$cons\_EDE\_global[t] = \left(\frac{\sum_c (l[t,c]\cdot cons\_EDE\_country[t,c]^{(1-\eta)})}{\sum_c l[t,c]}\right)^{\frac{1}{(1-\eta)}} \tag{2.48}$$

We also have to account for the case where $\eta = 1$. We use a logarithm transformation, which gives:

$$welfare\_country[t,c] = \left(\frac{l[t,c]}{nb\_quantile}\right)\sum_q \log(qc\_post\_recycle[t,c,q]) \tag{2.49}$$

$$welfare\_global[t] = \sum_c (welfare\_country[t,c]) \tag{2.50}$$

$$cons\_EDE\_country[t,c] = \exp\left(\frac{1}{nb\_quantile}\sum_q \log(qc\_post\_recycle[t,c,q])\right) \tag{2.51}$$

$$cons\_EDE\_global[t] = \exp\left(\frac{\sum_c l[t,c]\cdot \log(cons\_ED\_country[t,c])}{\sum_c l[t,c]}\right) \tag{2.52}$$

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3

Towards a new damage function

Contents

3.1 Some issues related to previous damage functions

In 2002, Richard Tol estimated that a 1 °C increase in temperature would result in a 2% positive effect on global GDP [39]. In contrast, 22 years later, Bilal and Känzig [12] assert that a 1 °C temperature shock would lead to substantial and enduring adverse effects on GDP, with a peak decline of -12% occurring six years after the shock. Using a time-series local projection approach, they estimate that global GDP per capita would have been 37% higher in the absence of the 0.75 °C increase from 1960 to 2019. How could such significant discrepancies arise? Is it possible to accurately estimate the effects of future climate change? These last decades, many critics have been made about the damage functions used in IAMs. Howard and Sterner define the damage function as the translation of a temperature change into a percentage change in GDP [40]. It usually takes the form of a quadratic function calibrated for +2 °C to +4 °C temperature increase, under certainty, leading to a thin-tailed probability distribution for hotter temperatures. In those cases, there are no particular dynamic interactions, the damages are interpreted as level-effects on GDP and they simply results into a welfare-equivalent consumption loss of similar representative agents.

Before presenting our thoughts on how to implement the latest results into the NICE model, let us review some inherent limitations of conventional damage functions.

3.1.1 Level vs. Growth effects

By ”level effect” we refer to the immediate impact of a temperature shock on GDP, whereas the ”growth effect” pertains to the dynamic relationship between GDP growth rates and climate damages. In the case of a quadratic damage function, the level effect is proportional to temperature changes squared, while the growth effect is disregarded. This is a significant limitation, as the notion that climate change could have persistent effects on the economy (*e.g.*, through damages to physical capital, human capital, or productivity) is gaining traction, although it remains challenging to quantify accurately [41], [42]. To incorporate growth effects into the damage function, it is possible to endogenize Total Factor Productivity (TFP) and capital, provided that a valid estimation of climate change impacts on these variables is available [18], [43].

However, recent estimations of the effects of climate change on GDP have continued to face difficulties in disentangling level effects from growth effects. Studies by Kalkuhl and Wenz (2020), Bilal and Känzig (2024), as well as Kotz, Levermann, and Wenz (2024), have predominantly operated under the assumption of a level effect [11], [12], [28]. Still, the last two studies uses lags to more adequately capture the extent of impact persistence over 10 years for temperature effects. Bilal and Känzig (2024) assume they could modify their model and impose permanent impacts beyond 10 years, leading to growth effects and consequently bigger welfare impacts.

3.1.2 Econometrics and the Challenges of Long-Term Projections

To capture the actual impact of climate change on production, econometric methods have evolved over the past decade. In their meta-analysis, Howard and Sterner (2017) [40] discuss the shift from cross-sectional regressions (which allowed for the identification of local temperature and precipitation effects on national GDP without accessing trends or observing emergent phenomena) to computable general equilibrium analyses (e.g. [44], which allows for sectoral damage assessment), and finally to panel regressions using weather data (e.g. [10], [41], [28]). In their paper, Dell *et al.* (2014) argue that the calibration of the coefficients in the quadratic damage function can be deeply enhanced by panel-based evidence, even though extrapolating to the long run remains challenging [45]. Howard and Sterner (2017) also acknowledge that estimating climate damages at +3 °C or +4 °C become increasingly speculative [40].

Despite the increased precision provided by the evidence-based coefficients of the quadratic damage function, some limitations persist. For instance, the study used to calibrate the coefficients in NICE (Kalkuhl and Wenz, (2020), [28]), which employs an annual panel model, a long-difference model, and a cross-sectional model, lacked data for most African countries, the Middle East, and Southeast Asia. As will be discussed in section 3.1.4, this data gap may understate the estimated impact of climate change, as the poorest and hottest regions are the most severely affected.

Furthermore, their study does not account for non-market damages or damages related to extreme weather events or sea-level rise. It is noteworthy that in earlier versions of NICE, sea-level rise damages were integrated into the quadratic damage function; however, the overall effects were weaker due to global estimates of temperature effects on GDP being lower than those revealed by recent econometric studies.

3.1.3 Extreme Events and Non-Market Damages

”Most IAMs are substantially under-estimating the current economic costs of climate change”. This is what a recent paper reports regarding how anthropogenic GHG have altered the occurrence of specific extreme weather events, and the extent to which damages can be attributed to certain types of these extreme events [46]. The authors show that the biggest share of net damages are due to storms (64% of them), followed by heatwaves (16%), floods and drought (10%) and wildfires (2%). The major part (63%) of the damages are related to the loss of human lives. They also outline the major differences between their methodology and that of IAM-based estimations, which produce a measure of decline in economic flow (proportional to global GDP), while attribution-based estimates measure the loss in economic stock. Additionally, IAMs (such as DICE) sometimes assign an arbitrary percentage of excess damage to their damage functions to account for extreme events, without a scientific basis for such attribution. Bilal and Rossi-Hansberg (2023) develop methodologies to estimate the effects of climate change on the various components of GDP in the USA [47]. Their findings indicate a correlation between storm impacts and capital depreciation shocks within the model, while heat waves are characterized as a combination of amenity and productivity shocks. These findings align with Murtin (2024) [48], who emphasizes that extreme events lead to the destruction of physical capital and reduced productivity. The literature on extreme events is extensive, but the study by Hsiang and Jina (2014) [49] is especially noteworthy. Their regression analysis of tropical cyclones from 1950 to 2008 revealed that while storms are the primary cause of damage, income losses result from a small yet persistent suppression of annual growth rates that extends over the fifteen years following a disaster. These extreme events therefore exert a growth effect on GDP, which can have substantial impact when accumulated over time.

Moreover, the damages assessed from extreme events are considered solely through the lens of economic production, neglecting natural capital—a concern highlighted in the Dasgupta review [50]. Integrating natural capital into climate-economy models is crucial for capturing the loss of non-market goods, as demonstrated by Bastien-Olvera and Moore (2021), where natural capital is treated as a form of wealth [51]. In 2012, Weitzman [30] was pleading for a switch to the use of random variables and probability density functions, arguing that the damages from climate change pull us in a case of extreme-uncertainty. To take into account extreme events, he suggested a reactive damage function, adding a term in βT^{γ} (with $\gamma = 6.754$) to the low-polynomial (quadratic) damages expression such that the consumption would be reduced by half in case of a 6 ℃ temperature increase, and by 99% in case of a 12 ℃ increase.

3.1.4 Country-Specific Damage Differentiation

Finally, beyond the need for damage estimates that either are sector-specific or comprehensively aggregate all impacts, it is also essential to account for geographic effects that could potentially amplify these damages. In particular, three characteristics of a country consistently emerge in the literature as significant: its temperature, its income level, and its historical emissions. The question is whether any of these three factors serves as a better explanatory variable than the others.

Burke *et al.* (2015) [41] found that the primary factor differentiating significant from minor temperature impacts on productivity is the level of temperature itself —an observation also supported by Bilal and Känzig (2024) [12]. However, Bilal and Känzig caution against overinterpretation due to the imprecision of their regression estimates across various country categories. In contrast, Dell *et al.* (2012) [10] argue that a country's income level is the predominant factor influencing the impact of climate change on economic growth, rather than its regional location or temperature.

Moore and Diaz (2015) [18] present two hypotheses with significantly different policy implications to explain why GDP growth is more sensitive to warming in poorer countries. The first is a temperature mechanism, suggesting that an increase in average temperature in already warm countries could cause productivity damages when biophysical thresholds are exceeded. The second is a resilience mechanism, which argues that poorer economies are particularly vulnerable because they rely heavily on climate-sensitive sectors such as agriculture. The first explanation advocates for strong mitigation efforts to preserve living conditions, while the second suggests prioritizing economic development over climate concerns, potentially allowing for a temperature increase of up to +6°C by 2150 according to their modified IAM, which accounts for growth effects through TFP changes or capital depreciation.

Based on their findings, Kotz *et al.* (2024) [11] provide an interpretation that integrates the three discussed parameters, stating: ”the largest losses are observed at lower latitudes in regions with lower cumulative historical emissions and lower present-day income”. In the absence of a definitive explanation for which variable best accounts for the variation in economic damage proportions, it is essential to consider these differences among countries.

3.2 Ideas for a new damage function

3.2.1 The latest empirical estimates

Our aim to enhance the damage function of NICE stems from the recent publications by Kotz, Levermann, and Wenz (2024) [11] and Bilal and Känzig (2024) [12], whose findings converge. We particularly focused on the latter, which employs a top-down approach using a time-series local projection method which better predict extreme events. To determine them, they use a model with 10-years persistent level effects, analyzing aggregate time-series variations in global mean temperature to capture a true aggregate effect, incorporating any spillovers and general-equilibrium adjustments. They provide a sound justification for using global temperature, emphasizing the global scale of climate change and the significance of ocean temperature or phenomena such as El Niño, which cannot be fully captured by comparing or summing national data, and argue that global temperature shocks predict a significant and persistent increase in extreme climatic events. With their specifications, Bilal and Känzig (2024) project a 3 °C increase by 2100 with $\rho = 2\%$.

To estimate the effects of temperature on future economic outcomes, they start by estimating potentially persistent deviations from the long-run trend in global mean temperature (*i.e.* temperature shocks). Let h be the periods ($h = 2$), t the time, p the number of lags ($p = 2$), $\widehat{\beta}$ the coefficient estimates of the regression on temperature. The main goal is to isolate shocks that persist for h periods.

$$\widehat{T^{shock}_{t+h}} = T_{t+h} - (\widehat{\alpha} + \sum_{i=0}^{p} \widehat{\beta_{i+1}} T_{t-i}) \tag{3.1}$$

Shocks fluctuate around zero, their maximum value is 0.3 °C. A 1 °C temperature shock does not occur directly in the historical sample: the authors scaled up the linear effect of smaller shocks, abstracting from potential non-linearities. Then, for $h = \{0, ..., 10\}$, y_{t+h} the (log) world real pcGDP, and $\mathbf{x_t}$ a vector of global control (global economic downturns and other financial variables), they compute the dynamic causal effects to global temperature shocks θ_h at horizon h (which is the Impulse Response Function (IRF)):

$$y_{t+h} - y_{t-1} = \alpha + \theta_h T^{shock}_t + \mathbf{x_t}'\beta + \epsilon_{t+h} \tag{3.2}$$

These θ_h values are illustrated in their Figure 3, which shows the response of global pcGDP to a 1 °C temperature shock over a 10-year period. Three years after the shock, the impact is less than a 5% reduction in world pcGDP, but it peaks at -12% six years after the shock and does not fully dissipate even after 10 years.

They find similar results by calculating the following regression over a panel of 173 countries. Given $y_{i,t}$ the (log) real pcGDP of country i in year t, $\mathbf{x_{i,t}}$ a vector of country-specific controls (two lags of country-level GDP growth) and $\epsilon_{i,t}$ an error term,

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \theta_h T_t^{shock} + \mathbf{x_t'}\beta + \mathbf{x_{i,t}'}\gamma + \epsilon_{i,t+h} \tag{3.3}$$

Since the resulting θ_h from (3.2) and (3.3) are analogous, they investigate regional heterogeneity by categorizing countries into regional clusters, average temperature groups, or per capita income groups (calculated on the 1957-1959 period). Eventually, they were able to disantangle the effects of temperature shocks on GDP into Productivity (TFP), investment (I), labor (l) and capital depreciation ($depk$) shocks by inverting in their (standard neoclassical growth) model the estimated IRF of output and capital.

Thus, although they do not address issues related to long-term projection uncertainty or the integration of non-market damages, Bilal and Känzig introduce a dynamic aspect to the impact of damages on output that persists for 10 years (more than a level effect but less than a growth effect), by more effectively accounting for the effects of extreme climatic events and extending these results to at least a regional scale.

3.2.2 How can these new estimates be implemented in NICE?

Given our initial functional form (see equations (2.12) and (3.7)) and the dynamics proposed by Bilal and Känzig, there does not appear to be an ”obvious” correction that could be applied to equation (2.12). One idea that was quickly dismissed involved adding a ”excess-damages” function to account for the impacts attributable to extreme events, similar to Weitzman's reactive function. We could have augmented our quadratic function with a term like βT^γ, where β and γ would be calibrated based on the results of Bilal and Känzig, but we would have been missing to capture the interesting 10-year dynamics.

Another possibility would have been to disaggregate our damage function, $\delta_{\text{NICE}}(\Delta T[t,c])$ (which currently applies a level effect on GDP) into its TFP and K components, based on the findings of Bilal and Känzig (2024, Fig. 10) [12]. In this scenario, we could have endogenized TFP (with capital already being endogenous in NICE) and sought to apply a similar modification as proposed by Moore and Diaz (2015) [18] or Alestra *et al.* (2020) [43], introducing a growth effect calibrated from the most recent data. This would have replicated the effect of a 1 °C temperature shock leading to a maximum productivity loss of -2.5% and a peak rise in the capital depreciation rate of -0.3 percentage points. However, the depreciation of capital and TFP are determined as outputs based on Bilal and Känzig model's inputs, meaning they reverse the IRF to derive the shocks on ξ_s and δ_s (which are the structural damage functions associated with TFP and capital depreciation, respectively). However, their estimation has been made under the assumption of optimal growth, *i.e.* that the trajectories of countries maximize social welfare. As it does not hold in NICE, we do not retain this solution.

In practice, we face a considerable challenge: modeling temperature shocks and integrating lags into a global dynamic framework. Our latest approach involves attempting to detect temperature shocks at each time step t in our simulation by analyzing past temperature data through a regression model corresponding to equation (3.1). However, this method assumes that the FAIR module does not overly smooth the projected temperature trajectory, thereby allowing the detection of shocks rather than merely a trend. If such shocks are identified, they could then be translated into output damages spread over 10 years, utilizing the θ_h values provided by Bilal and Känzig (2024, Fig. 3) [12], adjusted according to the magnitude of the global temperature shocks. Notably, in their Figure 3, Bilal and Känzig scaled up the θ_h values of smaller shocks linearly to reflect the impact of a fictitious 1 °C shock. By applying a series of damages over a 10-year period for each detected temperature shock, we can introduce a dynamic response to temperature impacts on GDP while preserving the overall structure of the NICE model. This method would facilitate the calculation of global damages, which could subsequently be disaggregated at the national level by utilizing the θ_h coefficients from Figures 11 and 12 of their study, which are based on regressions of a panel of countries grouped by average temperature, per capita income, or region. Given the multiple regressions performed, each country is associated with $\theta_h^{i,j}$ values, depending on which of its three characteristics (i, $i = \{1, 2, 3\}$, corresponding to region, temperature, or income) and within each characteristic which sub-group (j) it belongs to. Assuming that potential estimation biases cancel each other out, we could calculate the country-specific damages, $\theta_h[c]$, by averaging the $\theta_h^{i,j}$ values associated with each country, weighted by the inverse of the number of countries in each sub-group j of a characteristic i ($\frac{1}{n_{i,j}}$). For each global temperature shock, we could then assign specific damages to each country, distributed over a 10-year period, which would accumulate with previous shocks. The damages would be determined as follows:

$$\theta_h[c] = \frac{\sum_{i=1}^{3} \frac{\theta_h^{i,j}}{n_{i,j}}}{\sum \frac{1}{n_{i,j}}} \tag{3.4}$$

To illustrate our approach, let's imagine a world consisting of three regions (Eurasia, Africa, and the Americas), three temperature levels (below 10 °C, between 10 °C and 20 °C, and above 20 °C), and three levels of per capita income (low, medium, and high). Consider that there are only two countries in Eurasia ($n_{1,1} = 2$), two in Africa ($n_{1,2} = 2$), and three in the Americas ($n_{1,3} = 3$), making a total of $n = 7$ countries. Let's assume there is one cold country, three hot countries, and the remaining three have annual average temperatures between 10 °C and 20 °C ($n_{2,1} = 1$, $n_{2,2} = 3$, $n_{2,3} = 3$). Additionally, suppose there are three poor countries, two with intermediate income levels, and two wealthy countries ($n_{3,1} = 3$, $n_{3,2} = 2$, $n_{3,3} = 2$). Now, considering that Denmark is included in our selected panel of countries, we can estimate the damages it would experience over 10 years following a 1 °C temperature shock using the method described above. Denmark is a cold country ($i = 2$, $j = 1$) located in Eurasia ($i = 1$, $j = 1$), with high incomes level ($i = 3$, $j = 3$). Thus, we define:

$$\theta_h[\text{Denmark}] = \frac{\frac{\theta_h^{1,1}}{n_{1,1}} + \frac{\theta_h^{2,1}}{n_{2,1}} + \frac{\theta_h^{3,3}}{n_{3,3}}}{\frac{1}{n_{1,1}} + \frac{1}{n_{2,1}} + \frac{1}{n_{3,3}}} = \frac{\frac{\theta_h^{1,1}}{2} + \frac{\theta_h^{2,1}}{1} + \frac{\theta_h^{3,3}}{2}}{\frac{1}{2} + \frac{1}{1} + \frac{1}{2}} = \frac{1}{2}(\frac{\theta_h^{1,1}}{2} + \theta_h^{2,1} + \frac{\theta_h^{3,3}}{2}) \tag{3.5}$$

While this approach could potentially incorporate the dynamic effects of temperature shocks on national GDP, the authors caution that the $\theta_h^{i,j}$ values were not estimated with precision, without providing clear reasons for these inaccuracies. We ultimately decided to calibrate the coefficients of our quadratic damage function (see (2.12)) using the global θ_h values provided by Bilal and Känzig's regression (3.2) (2024, Fig. 3) [12], opting for efficiency over complexity.

3.3 NICE's new damage function(s)

The calibration thus leads to:

$$\begin{aligned} LOCAL\_DAMFRAC\_BK[t,c] &= \beta 1\_BK[c] \cdot global\_temperature[t] \\ &\quad + \beta 2\_BK[c] \cdot global\_temperature^2[t] \end{aligned} \tag{3.6}$$

with:

- $\beta 1\_BK[c] = \alpha_{BK} + 2\beta_{BK} T_0[c]$
- $\beta 2\_BK[c] = \beta_{BK}$
- $\alpha_{BK} = -0.0579$
- $\beta_{BK} = 0.0043478$

And the final damages on the net economy are computed as:

$$\delta_{BK,\mathrm{NICE}}(\Delta T[t,c]) = \frac{1}{1 + LOCAL\_DAMFRAC\_BK} \tag{3.7}$$

Note that we are considering the global temperature anomaly, denoted as $global\_temperature$, which remains from Bilal and Känzig's analysis, thereby bypassing the scaling module discussed in section 2.1.5. With this function now established, we turn our attention to potential variations and their effects on the results of NICE.

1^{st} suggestion: We examine the effect of incorporating country-specific rescaled temperatures into the new damage function.

$$\begin{aligned} LOCAL\_DAMFRAC\_BK[t,c] &= \beta 1\_BK[c] \cdot local\_temp\_anomaly[t,c][t] \\ &\quad + \beta 2\_BK[c] \cdot local\_temp\_anomaly[t,c]^2[t] \end{aligned} \tag{3.8}$$

2^{nd} suggestion: We introduce a dynamic effect into the damage function.

$$\begin{aligned} LOCAL\_DAMFRAC\_BK[t,c] = \beta1\_BK[t-5,c] \cdot global\_temperature[t] \\ + \beta2\_BK[c] \cdot global\_temperature^2[t] \end{aligned} \tag{3.9}$$

with:

- $\beta1\_BK[t-5,c] = \alpha_{BK} + 2\beta_{BK} \cdot actual\_temp[t-5,c]$
- $actual\_temp[t,c] = T_0[c] + local\_temp\_anomaly[t,c]$

Instead of calculating $\beta1\_BK$ based on each country's pre-industrial temperatures ($T_0[c]$), we consider the temperature of the country at time $(t-5)$. According to Bilal and Känzig's findings, temperature shocks tend to reach their maximum effect around this period. This approach allows us to better capture the impact of warming by virtually adding a second quadratic term in temperature anomaly (the last one in equation (3.10)).

$$\begin{aligned} \beta1\_BK[t-5,c] \cdot global\_temperature[t] = \alpha_{BK} \cdot global\_temperature[t] + \\ 2\beta_{BK} \cdot T_0[c] \cdot global\_temperature + \\ 2\beta_{BK} \cdot local\_temp\_anomaly[t,c] \cdot global\_temperature[t] \end{aligned} \tag{3.10}$$

3^{rd} suggestion: The shape of the damage function $\delta_{BK,\mathrm{NICE}}(\Delta T[t,c])$ could also be modified. It is used to convert the quadratic temperature effect into percentage which is applied to gross production. In the latest version of the DICE model [14], Nordhaus shifts away from the $\frac{1}{1+\Omega(\Delta T)}$ form, adopting instead $\delta_{\mathrm{newDICE}}(\Delta T[t,c]) = 1 - \Omega(\Delta T)$, where $\Omega(\Delta T)$ is a second-degree polynomial (similar to $LOCAL\_DAMFRAC\_BK$).

In their appendix, Young-Brun *et al.* (2024) [22] consider the current form of $LOCAL\_DAMFRAC$ as a Taylor expansion around 0 of $(1 - \exp^{-LOCAL\_DAMFRAC})$, which they propose as a share of damages (as a fraction of gross GDP in a country). Therefore, it would be straightforward to adopt the exact shape they recommend, namely $\delta_{BK,\mathrm{YB}}(\Delta T[t,c]) = 1 - (1 - \exp^{-LOCAL\_DAMFRAC}) = \exp^{-LOCAL\_DAMFRAC}$. Alternatively, other methods of normalizing a second-degree polynomial could be considered, such as using $\tanh(0.5 \cdot \Omega(\Delta T))$.

Thus, for given quadratic damages, we propose to investigate the effect of these forms of damage functions:

$$\delta_{BK,\text{newDICE}}(\Delta T[t,c]) = 1 - LOCAL\_DAMFRAC\_BK[t,c] \tag{3.11}$$

$$\delta_{BK,\text{YB}}(\Delta T[t,c]) = \exp^{-LOCAL\_DAMFRAC\_BK[t,c]} \tag{3.12}$$

$$\delta_{BK,\text{tanh}}(\Delta T[t,c]) = \tanh(0.5 \cdot LOCAL\_DAMFRAC\_BK[t,c]) \tag{3.13}$$

$$\delta_{BK,\text{NICE}}(\Delta T[t,c]) = \frac{1}{1 + LOCAL\_DAMFRAC\_BK[t,c]} \tag{3.14}$$

We will therefore examine the impact of three formal modifications on the outcomes of NICE, with a particular emphasis on the warming trajectories, output damages, and changes in inequalities and welfare. These modifications involve: 1) the effect of selecting different temperature scales on the damages, 2) the incorporation of dynamic elements into the damage function, and 3) the alteration of the shape of the damage function. They can be applied individually or combinatively.

4 Conclusion

Despite accurately acknowledging the impossibilty of achieving the 1.5 °C target (see [14]), IAMs have significant limitations. Our focus has been on the calibration of the damage function, an area that Murtin (2024) notes is heavily debated [48]. The impacts of climate change extend beyond the gross output, affecting productive capital in its various forms—human, natural, and physical. It is therefore essential to develop damage functions that incorporate growth effects by integrating feedback mechanisms directly into productive capital and considering the persistence of climate impacts.

Furthermore, a paradigm shift in the formulation of damage functions is necessary to adequately capture the non-linearities in climate sensitivity to temperature [52]–[54], potential tipping points (such as permafrost thaw, glacier and polar ice cap melting, and ecosystem collapse [55], [56]), and the escalating risks of extreme climate events that remain insufficiently addressed, even in recent econometric analyses [11]. This evolution requires moving from a deterministic framework to a probabilistic one, better reflecting the structural uncertainties that dominate economic projections within IAMs.

It is also crucial to recognize that numerous other parameters can significantly impact the optimal warming trajectory. The Nordhaus vs. Stern debate remains relevant today, with results still highly sensitive to the choice of the discount rate, despite the profound policy implications at stake. The adoption of a declining discount rate could offer a way forward in addressing this normative conflict [57].

Despite ongoing efforts to improve IAMs, certain criticisms remain compelling. Under uncertainty, it is challenging to determine the appropriate functional forms or parameter values for catastrophic outcomes [30], [58]. Pindyck argues that ”the damage functions used in most IAMs are completely made up, with no theoretical or empirical foundation.” Even with significant advances in causal inference and data-driven estimations, his critique may still be valid [59]. We can only assess damages based on past events, and our understanding of potential impacts on the economy beyond +4°C is severely limited. It might indeed be preferable that we never have to discover these impacts empirically.

In this context, how can the use of these models for decision-making be justified when the results are so heavily dependent on the initial assumptions? Should we rely on the possibility that these models are robust enough to provide some directional guidance, or is it wiser to abandon the illusion of certainty?

When it comes to non-market damages and the degradation of public goods, including nature, can they simply be integrated into a cost-benefit framework based on GDP? Rethinking how we account for mitigation costs [60], disaggregating our indicators [61] and models to account for sectoral impacts, agent interactions, and rigorous tracking of flows and stocks (including natural capital) could provide a potential solution. By balancing precision and simplicity, such an approach could maintain the necessary rigor in light of the climate challenges facing humankind.

Abandoning traditional cost-benefit approaches becomes even more compelling given that markets appear unable to assign an appropriate value to the future [62]. Moreover, investment in renewable energies still remains insufficient due to their low profitability in a competitive energy market [63].

In 1987, George E. P. Box wrote: "Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful" [64]. Perhaps we should acknowledge that IAMs are too wrong to be useful and to embrace the call of Stern, Stiglitz, and Taylor in striving to sustain life on Earth [65].

A

NICE indices, variables and parameters

A

Contents

A.1 Model - Indices

Symbol Name	Model Name	Short description
c	`country`	Countries included in the model
q	`quantile`	Index of income quantiles
$rrice$	`regionrice`	Regions defined by the RICE model
$rwpp$	`regionwpp`	Regions defined from the World Population Prospects database (UN)
t	`time`	Time index

A.2 Model - Parameters

N.B. : \$ = 2017 US dollars. pers. = person. yr = year.

Name	**Short description**	**Unit**	**Value**
$\beta 1$	Linear damage coefficient on temperature. This parameter represents the direct impact of the temperature anomaly on the economy	$T^{-\beta 2}$	0.0236
$\beta 1\_KW[t,c]$	Linear damage coefficient on local temperature anomaly for Kalkuhl and Wenz based damage function	T^{-1}	—
$\beta 2$	Power damage coefficient on temperature. This parameter captures the non-linear effects of temperature anomalies on the economy	—	2
$\beta 2\_KW[t,c]$	Quadratic damage coefficient on local temperature anomaly for Kalkuhl and Wenz based damage function	T^{-2}	—
$\beta\_temp[c]$	Temperature scaling coefficients, which translate global temperature anomalies into country-level temperature anomalies	—	—
η	Inequality aversion.	—	1.5 (by default)
$\sigma[t,c]$	Emissions output ratio. This parameter is used for modelling emissions intensity as a function of economic activity	$GtCO_2/(10^6\ \$)$	—
$\theta 2$	Exponent of abatement cost function (DICE-2023 value)	—	2.6
$\mu\_input[t,c]$	Input mitigation rate, used with option 3 "country_abatement_rate"	%	—

Name	Short description	Unit	Value
control_regime	Switch for emissions control regime ; 1 = "global_carbon_tax", 2 = "country_carbon_tax", 3 = "country_abatement_rate"	—	3 (by default)
daily_poverty_line	Daily poverty line	$/pers/day	2.15
damage_elasticity	Income elasticity of climate damages (1 = proportional to income)	—	0.85
depk[t,c]	Depreciation rate on capital	%	—
elasticity	Income elasticity with respect to climate damage, mitigation costs, etc. It can either be `damage_elasticity` or `CO2_income_elasticity`	—	—
elasticity_intercept[t]	Intercept term for estimating income elasticity	—	3.22[a]
elasticity_slope[t]	Slope term for estimating income elasticity	—	-0.2[a]
global_carbon_tax[t]	Global carbon tax	$\$/tCO_2$	—
global_recycle_share[c]	Share of country revenues that are recycled globally in the form of international transfers (1 = 100%)	%	1 (by default)
global_temperature[t] = temp_anomaly[t]	Global average surface temperature excess (above pre-industrial [year 1750] level)	°C	—
income_shares[c,q]	An array of income shares by quantile (where rows represent countries and columns represent quantiles)	—	—
increase_value	The annual tax increase value. By default, it is equal to `tax_start_value`, which means that the tax increases by its initial value each year	$\$/tCO_2$	—
k0[c]	Initial level of capital. Determines the starting point for capital accumulation	10^6 \$/yr	—

Name	Short description	Unit	Value
l[t,c]	Labor/population. This parameter represents either the population or the available workforce for production of a given country	10^3 pers.	—
list_llmic_flag[c]	Equal to 1 if the country is on the list of low and middle income countries, 0 otherwise	—	—
list_risk_index[c]	Risk index	—	—
local_temp_anomaly[t,c]	Country-level average surface temperature anomaly (above pre-industrial [year 1750] level)	°C	—
lost_revenue_share	Portion of carbon tax revenue that is lost and cannot be recycled (1 = 100% of revenue lost, 0 = no revenue lost)	%	0 (by default)
mapcrrice[c]	Mapping from country index to RICE region index	—	183 countries to 12 regions
mapcrwpp[c]	Mapping from country index to UN WPP region index	—	183 countries to 20 regions
max_study_gdp	Maximum value of GDP per capita observed in elasticity studies	$/pers.	48892
min_study_gdp	Minimum value of GDP per capita observed in elasticity studies	$/pers.	647
nb_country	Number of countries	—	183
nb_quantile	Number of quantiles	—	10 (by default)
pbacktime[t]	*Backstop price* from DICE 2023	$/t$CO_2$	—
quantile_income_shares[t,c,q]	Income shares of quantile	—	—

Name	**Short description**	**Unit**	**Value**
recycle_share[c,q]	Share of carbon tax revenues recycled to each quantile	—	$\frac{1}{nb\_quantile}$ (by default)
reference_carbon_tax[t]	Reference carbon tax	$/t$CO_2$	—
reference_country_index	Reference country index	—	USA
s[t,c]	Savings rate	%	—
share	Capital's share of production. This parameter is global and affects the distribution of income between capital and labor	%	0.3
switch_dam _abs_llmic_recycle	Boolean, carbon tax revenues are recycled globally in proportion to absolute damage in LLMICs	—	0 or 1
switch_dam _rel_llmic_recycle	Boolean, carbon tax revenues are recycled globally in proportion to population-weighted relative damages in low- and middle-income countries (LLMICs)	—	0 or 1
switch_global _pc_recycle	Boolean, carbon tax revenues are recycled globally on an equal per capita basis	—	0 or 1
switch_recycle	Boolean for recycling carbon tax revenue	—	0 or 1
switch_risk _llmic_recycle	Boolean, carbon tax revenues are recycled according to a population-weighted risk index in LLMICs	—	0 or 1
switch_scope_recycle	Boolean, carbon tax revenues are recycled at national (0) or global (1) level	—	0 or 1
tax_start_value	The initial value of the carbon tax	$/t$CO_2$	Depends on the chosen carbon tax pathway
temp_anomaly[t] = global_temperature[t]	Global average surface temperature excess (above pre-industrial [year 1750] level)	°C	—

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Name	**Short description**	**Unit**	**Value**
tfp[t,c]	Total factor productivity	—	—
year_model_end	The end of the model. If it is less than `year_tax_end`, the last tax value is repeated up to this year	yr	2300 (by default)
year_step	The step in years between two tax values	yr	1 (by default)
year_tax_end	The last year for which to calculate the tax	yr	2200 (by default)
year_tax_start	The first year of the tax increase	yr	2020 (by default)

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A.3 Model - Variables

Name	**Short description**	**Unit**
$\mu[t,c]$	GHG emissions mitigation rate	%
μ_cons$[t,c]$	μ parameter of the lognormal distribution of consumption	—
σ_cons$[t,c]$	σ parameter of the lognormal distribution of consumption	—
$\theta 1[t,c]$	Multiplicative parameter of abatement cost function. Equal to ABATEFRAC at 100% mitigation	—
ABATECOST[t,c]	Cost of emission reductions	10^6 \$/yr
ABATEFRAC[t,c]	Cost of emission reductions as a share of gross economic output	%

[a] Results from the meta-regression computed by Budolfson *et al.* (2021) [21] based on study results to calculate elasticity vs. ln gdp per capita relationship.

Name	Short description	Unit
abatement_cost _dist[t,c,q]	Share of the distribution of abatement costs per quantile	—
C[t,c]	Country consumption	10^6 \$/yr
carbon_tax_dist[t,c,q]	Shares of the distribution of CO2 tax burden per quantile	—
cons_EDE_country[t,c]	Consumption equivalent to equitably distributed well-being in a given country	10^3 \$/pers/yr
cons_EDE_global[t]	Global consumption equivalent to equitably distributed well-being	10^3 \$/pers/yr
cons_EDE_rwpp[t,rwpp]	Consumption equivalent to equitably distributed well-being for WPP regions	10^3 \$/pers/yr
country_carbon_tax[t,c]	CO2 tax rate	\$/tCO_2
country_pc_dividend[t,c]	Total fiscal dividends per person, including all international monetary transfers	10^3 \$/pers/yr
country_pc_dividend _domestic_transfers[t,c]	Fiscal dividends per person from domestic redistribution, i.e., within a country	10^3 \$/pers/yr
country_pc_dividend _global_transfers[t,c]	Tax dividends per person from international transfers	10^3 \$/pers/yr
country_pc_dividend _llmic[t,c]	Tax income per person in LLMIC	10^3 \$/pers/yr
CPC[t,c]	Country level consumption per capita	10^3 \$/pers/yr
CPC_post[t,c]	Country level consumption per capita after recycling	10^3 \$/pers/yr
CPC_post_global[t]	World consumption per capita after recycling	10^3 \$/pers/yr
CPC_post_rwpp[t,rwpp]	Regional per capita consumption after recycling	10^3 \$/pers/yr
CPC_rwp[t,rwpp]	Regional level consumption per capita	10^3 \$/pers/yr
DAMFRAC[t,c]	Country-level damages as a share of net GDP based on global temperatures	%

Name	**Short description**	**Unit**
damage_dist[t,c,q]	Share of the distribution of climate damage per quantile	—
E_gtco2[t,c]	Country-level total GHG emissions	10^9 tCO2/yr
E_Global_gtco2[t]	Global emissions (sum of all country emissions)	10^9 tCO2/yr
E_Global_gtco2 _rrice[t,rrice]	Regional GHG emissions for the regions defined in the RICE model	10^9 tCO2/yr
E_Global_gtc[t]	Global emissions in units of gigatonnes of carbon, giving compatible units with FAIR	10^9 tC/yr
GLOBAL_ABATEFRAC _full_abatement[t]	Global `ABATEFRAC[t]` in case of full mitigation	%
global_gini_cons[t]	Gini index of world consumption	—
global_poverty _population_cons[t]	Number of people living in poverty in the world, based on consumption	10^3 pers
global_revenue[t]	Carbon tax revenue, derived from the total recycled revenue of all countries	$/yr
global_pc_revenue[t]	Carbon tax revenue per person, derived from the total recycled revenue of all countries	10^3 $/pers/yr
gini_cons[t,c]	Gini index of country consumption	—
gini_cons_rwpp[t,rwpp]	Gini index of regional consumption	—
I[t,c]	Investment	10^6 $/yr
K[t,c]	Capital	10^6 $/yr
l_rwpp[t,rwpp]	Regional population	10^3 pers.
llmic_population[t]	Total population in low- and middle-income countries	10^3 pers.
LOCAL_ DAMFRAC_KW[t,c]	Country-level damages as a share of net GDP based on local temperatures and on Kalkuhl & Wenz	%

Name	Short description	Unit
local_temperature[t,c]	Excess temperature at country level (above pre-industrial [year 1750] level)	°C
pc_gdp[t,c] = Y_pc[t,c]	Net GDP per capita after damages and mitigation costs	$/pers/yr
poverty_population _cons[t,c]	Number of people living in poverty in each country, according to consumption	10^3 pers
poverty_population _cons_rwpp[t,rwpp]	Number of people in poverty at regional level, based on consumption	10^3 pers
poverty_rate_cons[t,c]	Poverty rate in a country, according to consumption. The poverty line is defined as $ 2.15 per capita per day	%
qc_base[t,c,q]	Consumption per quantile per capita before damage, before abatement cost, before tax	10^3 $pers/yr
qc_post _damage_abatement[t,c,q]	Consumption per quantile per capita after damage, after abatement	10^3 $/pers/yr
qc_post_recycle[t,c,q]	Consumption per quantile per capita after recycling the carbon tax to each quantile	10^3 $/pers/yr
qc_post_tax[t,c,q]	Consumption per quantile per capita after subtraction of the carbon tax	10^3 $/pers/yr
qc_share[t,c,q]	Proportion of consumption per quantile per capita	%
qpop[t,c,q]	Population per quantile	10^3 pers
revenue_recycled _global_level[t]	Recycle a share `global_recycle_share` of `tax_revenue` at global level	10^3 $/yr
tax_pc_revenue[t,c]	Carbon tax revenue per capita from country emissions	10^3 $/pers/yr
tax_revenue[t,c]	Carbon tax revenue for a given country	$/yr
tax_values[t]	Array containing the carbon tax values over time, until the last year of tax defined	—

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Name	**Short description**	**Unit**
total_c_post_recycle[t,c]	Total consumption per country after recycling	10^3 $/pers/yr
total_tax_pc_revenue[t]	Total carbon tax revenue per person, sum of tax revenues in all countries per person	10^3 $/pers/yr
total_tax_revenue[t]	Total carbon tax revenue, sum of tax revenues in all countries	$/yr
TRANSFRAC_dam _abs_llmic[t,c]	Proportion of absolute damages (in net GDP loss) suffered in the country in relation to global damage (damage costs ratio)	%
TRANSFRAC_dam _rel_llmic[t,c]	Proportion of damage suffered in the country in relation to global damage (share of population-weighted global net output ratio)	%
TRANSFRAC_risk _llmic[t,c]	Proportion of risk based on the population-weighted 2023 risk index in LLMIC	%
updated_quantile _distribution[t,c,q]	An array which contains the updated quantile share distribution for each country, considering the given income elasticity	—
welfare_country[t,c]	Welfare for countries	—
welfare_global[t]	Global welfare	—
welfare_rwpp[t,rwpp]	Welfare in a given WPP region	—
YGROSS[t,c]	Gross output	10^6 $/yr
YGROSS_global[t]	Global gross output, represents the sum of all countries' gross production	10^{12} $/yr
Y[t,c]	Output net of damages and abatement costs	10^6 $/yr
Y_pc[t,c] = pc_gdp[t,c]	Net GDP per capita after damages and mitigation costs	$/pers/yr
Y_pc_rwpp[t,rwpp]	Regional per capita output net of abatement and damages	$/pers/yr

B

Shared Socio-economic Pathways

SSPs are a series of scenarios that outline alternative futures of societal development in the context of climate change and its associated impacts. These scenarios encompass varying demographic, economic, and social trends. SSPs complement the Representative Concentration Pathways (RCPs), which concentrate on greenhouse gas emissions trajectories [66].

SSPs can be characterized by their projected directions for future development [67] or by the primary policy challenges associated with implementing climate change adaptation and mitigation frameworks [68]. Table B.2 provides an overview of the five SSPs and their main characteristics.

B

	Projected direction	**Policy challenges**	**Policy orientation (growth)**	**Population dynamic**	**Expected global warming by 2100**	**Inequalities dynamic**
SSP1, SSP1-2.6	Sustainability	Low challenges	Green growth (2%)	Lower population growth	1.8 [1.3 to 2.4] °C	Fall in inequalities
SSP2, SSP2-4.5	Middle of the Road	Intermediate challenges	No drastic changes (1.7%)	Moderate demographic growth	2.7 [2.1 to 3.5] °C	Moderate decrease in inequalities
SSP3, SSP3-7.0	Regional Rivalry	High challenges	Nationalistic priorities (0.7%)	High population growth	3.6 [2.8 to 4.6] °C	Rise in inequalities within- and between-countries
SSP4, SSP4-6.0	Inequality	Adaptation challenges	Deepening global inequalities (1.3%)	Divergent demographic trends	$\simeq$ 3 °C (No data available)	Rise in inequalities
SSP5, SSP5-8.5	Fossil-fueled Development	Mitigation challenges	High economic growth (2.6%)	Moderate demographic growth	4.4 [3.3 to 5.7] °C	Fall in inequalities

Table B.2: SSPs main characteristics ([1], [48])

C

List of LLMICs

C.1 Low income countries

Afghanistan, Burundi, Burkina Faso, Central African Republic, Democratic Republic of the Congo, Eritrea, Ethiopia, Guinea, The Gambia, Guinea-Bissau, Liberia, Madagascar, Mali, Mozambique, Malawi, Niger, The Democratic People's Republic of Korea, Rwanda, Sudan, Sierra Leone, Somalia, South Sudan, Syrian Arab Republic, Chad, Togo, Uganda, Yemen, Republic of Zambia.

C.2 Low-middle income countries

Angola, Benin, Bangladesh, Bolivia, Bhutan, Côte d'Ivoire, Cameroon, Republic of the Congo, Comoros, Cabo Verde, Djibouti, Algeria, Arab Re- public of Egypt, Federal States of Micronesia, Ghana, Honduras, Haiti, Indonesia, India, Islamic Republic of Iran, Kenya, Kyrgyz Republic, Cambodia, Kiribati, Lao People's Democratic Republic, Lebanon, Sri Lanka, Lesotho, Morocco, Myanmar, Mongolia, Mauritania, Nigeria, Nicaragua, Nepal, Pakistan, Philippines, Papua New Guinea, West Bank and Gaza, Senegal, Solomon Islands, El Salvador, São Tomé and Príncipe, Eswatini, Tajikistan, Timor-Leste, Tunisia, Tanzania, Ukraine, Uzbekistan, Vietnam, Vanuatu, Samoa, Zimbabwe.

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