CHIPS
Climate Change Impacts and Policies in Heterogeneous Societies

Deliverable 4.2: Modelling distributional effects in integrated assessment models

CNRS-CES

SEPTEMBER 2022

Modelling distributional effects in integrated assessment models

Stephane Zuber, Nicolas Taconet, Franziska Piontek

Integrated Assessment Models (IAMs), which are model combining descriptions of the economy and the climate system, can be used to guide climate policy by assessing the costs and benefits. But climate policies are developed in a very heterogeneous world: countries, social groups, and generations have different standards of living. Also, costs and benefits of a policy vary greatly though space and time. It is important to be able to model those heterogeneities to better design a transition to a more sustainable world.

In this report, we describe the approaches to model heterogeneity in the two IAMs used in the CHIPS project, namely the REMIND model and the NICE model, which have been (further) developed as part of the project. The application of the models with the inequality feature is described in Deliverable D5.2.

Table of Contents

Integrated assessment models and distributions

Standard IAMs operate on a fairly aggregate level, both in space and regarding sectors of the economy. While process-based IAMs like REMIND have high detail in technologies, just like cost-benefit IAMs as NICE they typically only model representative households per region, thereby ignoring subregional heterogeneity both in the effects of climate policy and in climate change impacts. Damages are usually included as aggregate impacts at the world, regional or at best country level.[1] The models implicitly assume that differences in the burden of costs or climate damages can be dealt with using appropriate redistribution or compensation policy. However, recent literature has highlighted the importance of accounting for within region (or country) heterogeneity for the design of an optimal or fair policy (Dennig et al., 2015; Anthoff and Emmerling, 2019).

There are two main kinds of heterogeneity that have to be taken into account. First, the baseline inequality within a country or region, that is within-country inequality in consumption or income, and its evolution through time. Baseline inequality means inequality absent any climate policy and without accounting for the climate change impacts. Second, there is the heterogeneity in the effects of climate policy. Here there are mainly two questions: the distribution of the costs of climate policy (whether poorer household support a higher relative cost); the distribution of climate damages (whether poorer household suffer more from climate change).

We will discuss below that different tools can be used to deal with those different aspects. Let us first introduce those tools.

Modelling distributions

Lognormal distributions

Modelling income and consumption distribution has often been done using parametric distributions, that is assuming specific distribution functions and estimating their parameters. One of the most common choice is to use a log-normal distribution (see Atkinson and Brandolini 2010). The log-normal density is often viewed as convenient and appropriate for modelling small to medium range incomes. It also fits well actual consumption distributions (Battistin, Blundell and Lewbell, 2009).

A random variable X has a log normal distribution if its logarithm $ln(X)$ has a normal distribution $\mathcal{N}(\mu, \sigma^2)$, with μ the mean and σ^2 the variance of this associate normal distribution. It is also known that the mean of a log-normal distribution $X \sim \mathcal{LN}(\mu, \sigma^2)$ is $\mathbb{E}[X] = e^{\mu + \frac{1}{2}\sigma^2}$, and that its variance is $\mathbb{V}[X] = \left(e^{\sigma^2} - 1\right)e^{2\mu + \sigma^2}$. Reciprocally, we can recover the parameters of the underlying/modelled distribution by matching its moments:

$$\mu = ln(\mathbb{E}[X]) - \frac{1}{2} ln\left(1 + \frac{\mathbb{V}[X]}{\mathbb{E}[X]^2}\right),$$

[1] The DICE model by Nordhaus (Nordhaus, 2014) is a global aggregate model. Several models have representations of different regions: the RICE model (Nordhaus and Yang, 1996), the FUND model (Anthoff and Tol, 2012) or REMIND (Kriegler et al., 2017). More recently, Gazzotti et al. (2021) have produced a model based on RICE but with more than 50 countries or regions, thus increase further the description of between region heterogeneity.

$$\sigma^2 = ln\left(1 + \frac{\mathbb{V}[X]}{\mathbb{E}[X]^2}\right).$$

Log-normal distributions can also be easily related to widely used inequality indices. If the distribution of consumption or income follows a log-normal distribution $\mathcal{LN}(\mu, \sigma^2)$, then the Gini index associated with this distribution is $2\Phi(\sigma/\sqrt{2}) - 1$, where Φ is the cumulative distribution function of a standard normal distribution. Similarly, the associated value of the Atkinson index of parameter ε is $1 - e^{-\varepsilon\sigma^2/2}$. Hence, we can easily match observed or projected values of those inequality indices with a log-normal distribution (provided we also have information on the mean).

Log-normal distributions are also useful when computing social welfare, using the common Atkinson welfare measure. Consider a region r where consumption c_{ir} is distributed according to some distribution $F_r\,(c)$ where the index "ir" means that we consider an individual i in region r. The average consumption in the region is $\bar{c_r} = \int c_{ir}\, dF_r$. The Atkinson welfare measure with level of inequality aversion ε is:

$$W = \left(\int {c_{ir}}^{1-\varepsilon}\, dF_r\right)^{1/(1-\varepsilon)} = \bar{c_r}\left(\int \left(\frac{c_{ir}}{\bar{c_r}}\right)^{1-\varepsilon} dF_r\right)^{1/(1-\varepsilon)}.$$

If consumption is distributed as a log-normal distribution $\mathcal{LN}(\mu, \sigma^2)$, then the expression of welfare simplifies to $W = \bar{c_r} \cdot e^{-\varepsilon\sigma^2/2}$. This expression permits to obtain a simple formulation of social welfare, which is useful in cost-benefit analysis models aiming at maximizing inter-temporal welfare.

Income elasticities

To analyse the link between climate damages and the effects of climate change on inequality, Dennig et al. (2015) have proposed to use an income elasticity of damages. This income elasticity measures how much damages increase when income itself increases. A value of the income elasticity larger than one means that climate damages increase more than proportionally to income: high-income households suffer proportionally more. A value of one means that climate damages (as a share of income) are independent from income level: everyone is affected proportionally, so that income inequality is not changed by climate damages (at least if one look at a relative measure of inequality). The case most previous researchers were concerned about is the case where income elasticity is less than one. In that case, poor households suffer more from climate damages.

Formally, let X_i be the value of some variable (for instance damages) for some group i (for instance the 5th percent poorer people). Assuming a constant income elasticity means that:

$$X_i = \lambda \cdot Y_i^{\alpha},$$

where Y_i the income level, λ is some positive constant and α is the elasticity.

This implies that when Y_i increases by 1%, then X_i increases by $\alpha\%$. When α is larger (resp. lower) than one, then the value of variable X_i increases faster (resp. slower) than income. The formulation also easily allows to estimate parameter α through the equation:

$$ln(X_i) = ln(\lambda) + \alpha \cdot ln(Y_i).$$

We simply need to regress the log of the variable on the log of income.

The REMIND model[2]

REMIND (REgional Model of Investment and Development) is a numerical global and multi-regional model incorporating the economy, the climate system and a detailed representation of the energy sector. It has a special focus on the development of the energy sector and the implications for our world climate. The goal of REMIND is to find the optimal mix of investments in the economy and the energy sectors of each model region given a set of population, technology, policy and climate constraints. It also accounts for regional trade characteristics on goods, energy fuels, and emissions allowances. All greenhouse gas emissions due to human activities are represented in the model.

A Ramsey-type growth model with perfect foresight serves as a macro-economic core projecting growth, savings and investments, factor incomes, energy and material demand. The macro-economic production factors are capital, labor, and final energy. A nested production function with constant elasticity of substitution determines the final energy demand. REMIND uses economic output for investments in the macro-economic capital stock as well as for consumption, trade, and energy system expenditures.

The energy system representation differentiates between a variety of fossil, biogenic, nuclear and renewable energy resources. More than 50 technologies are available for the conversion of primary energy into secondary energy carriers as well as for the distribution of secondary energy carriers into final energy. The macro-economic core and the energy system part are hard-linked via the final energy demand and the costs incurred by the energy system.

REMIND operates at the level of 12 big regions (including 5 individual countries), and focuses on the energy costs in different emission scenarios. The inequality module, newly developed and implemented as part of the CHIPS project, accounts for the inequality of consumption within regions, and it models how it is affected in different low-carbon pathways.

Baseline inequality modelling

Baseline inequality modelling in REMIND is done using the log-normal assumption. The distribution of consumption within each region is supposed to be log-normal with parameters such that the average consumption matches the 'Baseline' scenario of REMIND 2.1, which is based on the SSP2 scenario.

To calibrate the value of parameter σ, it is assumed that future inequality will be the one implied by Rao et al.'s Gini projections for SSP2 (Rao et al., 2019). Specifically, any given level of the Gini index can be matched with a value of σ as explained above.[3] This can be done for each region of REMIND, so that the model also includes region-specific baseline inequality.

Distributional effects of climate policy and impacts: the inequality module

The inequality module described how we go from the pre-policy distribution to the new distribution accounting for the additional energy expenditure and additional revenue (through carbon tax recycling) of a climate policy as well as for the effects of climate damages.

[2] The REMIND model is open source and available at https://github.com/remindmodel/remind.

[3] Denoting G the value of the Gini index, and under the log-normal assumption, we know that $G = 2\Phi(\sigma/\sqrt{2}) - 1$. Reciprocally, $\sigma = \sqrt{2} \cdot \Phi^{-1}\left(\frac{1+G}{2}\right)$.

Let denote individual in a specific region at a specific time by i, and let c_i^{pre} be the pre-policy consumption of individual i and c_i^{post} be the post-policy consumption of individual i. It is assumed that:

$$c_i^{post} = \gamma\left(c_i^{pre} - e\left(c_i^{pre}\right) + r\left(c_i^{pre}\right) - \omega\left(c_i^{pre}\right)\right),$$

Where γ is a scaling constant (to match macro aggregates), $e\left(c_i^{pre}\right)$ is the additional energy expenditure, $r\left(c_i^{pre}\right)$ is the additional revenue and $\omega\left(c_i^{pre}\right)$ is the change in consumption due to climate change damages. We denote $e_0 = \frac{\bar{e}}{\bar{c}}$ the share of aggregate energy expenditure, and similarly r_0 the share of aggregate tax revenues and ω_0 the share of impacts. An additional assumption of constant income elasticity is made for the additional energy expenditure, revenue and impacts, plus a normalization so that:

$$e\left(c_i^{pre}\right) = \frac{e_0\left(c_i^{pre}\right)^{\alpha}}{\int\left(c^{pre}\right)^{\alpha} dF(c)},$$

$$r\left(c_i^{pre}\right) = \frac{r_0\left(c_i^{pre}\right)^{\beta}}{\int\left(c^{pre}\right)^{\beta} dF(c)},$$

$$\omega\left(c_i^{pre}\right) = \frac{\omega_0\left(c_i^{pre}\right)^{\xi}}{\int\left(c^{pre}\right)^{\xi} dF(c)},$$

with α the income elasticity for energy expenditure, β the income elasticity for revenue and ξ the income elasticity of climate impacts.

In the end:

$$c_i^{post} = \gamma\left(c_i^{pre} - \frac{e_0\left(c_i^{pre}\right)^{\alpha}}{\int\left(c^{pre}\right)^{\alpha} dF(c)} + \frac{r_0\left(c_i^{pre}\right)^{\beta}}{\int\left(c^{pre}\right)^{\beta} dF(c)} - - \frac{\omega_0\left(c_i^{pre}\right)^{\xi}}{\int\left(c^{pre}\right)^{\xi} dF(c)}\right).$$

Let $\boldsymbol{\sigma_{post}^2}$ denote the variance of the post policy consumption. Using the log-normal assumption, it can be shown that

$$\begin{aligned}\boldsymbol{\sigma_{post}^2} = \boldsymbol{ln}\Bigg(& \boldsymbol{e^{\sigma^2} - 2e^{\sigma^2\alpha}\frac{\bar{e}}{\bar{c}} + 2e^{\sigma^2\beta}\frac{\bar{r}}{\bar{c}} - 2e^{\sigma^2\xi}\frac{\bar{\omega}}{\bar{c}} + e^{\sigma^2\alpha^2}\left(\frac{\bar{e}}{\bar{c}}\right)^2 + e^{\sigma^2\beta^2}\left(\frac{\bar{r}}{\bar{c}}\right)^2 + e^{\sigma^2\xi^2}\left(\frac{\bar{\omega}}{\bar{c}}\right)^2} \\ & \boldsymbol{- 2e^{\sigma^2\alpha\beta}\left(\frac{\bar{e}}{\bar{c}}\right)\left(\frac{\bar{r}}{\bar{c}}\right) + 2e^{\sigma^2\alpha\xi}\left(\frac{\bar{e}}{\bar{c}}\right)\left(\frac{\bar{\omega}}{\bar{c}}\right) - 2e^{\sigma^2\beta\xi}\left(\frac{\bar{r}}{\bar{c}}\right)\left(\frac{\bar{\omega}}{\bar{c}}\right)}\Bigg) \\ & \boldsymbol{- 2ln\left(1 + \left(\frac{\bar{r} - \bar{e} - \bar{\omega}}{\bar{c}}\right)\right)},\end{aligned}$$

where $\boldsymbol{\bar{e}}$ is the average additional energy expenditure, $\boldsymbol{\bar{r}}$ is the average additional revenue and $\boldsymbol{\bar{\omega}}$ is the average damage.

When $\boldsymbol{\sigma}$ is small, the following approximation holds:

$$\boldsymbol{\sigma_{post}^2 \approx \sigma^2\left(\frac{\bar{c} + \beta\bar{r} - \alpha\bar{e} - \xi\bar{\omega}}{\bar{c} + \bar{r} - \bar{e} - \bar{\omega}}\right)^2}.$$

The inequality module assumes that this approximation holds and that the new distribution of consumption – i.e. the post policy/post damage consumption – is still distributed according to a log-normal law, with the new average and the new $\boldsymbol{\sigma_{post}^2}$. Tests have been performed to show that the log-normal assumption is performing well, although there are cases where $\boldsymbol{\sigma}$ increases above 1.5. However, given the inherent uncertainties in measuring inequalities even in present-day data we consider this still a reasonable approximation.

Hence the projection of future (post-policy) inequality only depends on the elasticities $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\xi}$, and on average quantities $\bar{\boldsymbol{c}}, \bar{\boldsymbol{e}}, \bar{\boldsymbol{r}}$ and $\bar{\boldsymbol{\omega}}$. In the absence of impacts, inequality will increase in the policy scenario compared to the baseline case when $\boldsymbol{\alpha} \leq \mathbf{1} - \frac{\bar{r}}{\bar{e}}(\mathbf{1} - \boldsymbol{\beta})$. In the case of distributionally neutral redistribution of revenues ($\boldsymbol{\beta} = \mathbf{1}$) inequality increases when $\boldsymbol{\alpha} \leq \mathbf{1} + \frac{\bar{\omega}}{\bar{e}}(\mathbf{1} - \boldsymbol{\xi})$.

Implementation in the REMIND model

The log-normal approximation is included in the welfare module of the REMIND model and the distribution is updated based on changes in energy expenditures compared to the baseline case, tax revenues from carbon taxes applied in the model on emissions from the energy sector, process/fugitive emissions from non-energy sectors and emissions from carbon dioxide removal. Land-use based emissions as well as exogenous emissions from aviation/shipping are excluded for now. In particularly in ambitious climate policy scenarios, negative emissions occur in the second half of the century to achieve a given climate target, meaning revenues from carbon tax would be negative. For now, it is assumed that in this case no distributional effects occur as it is unclear what these would be for tax to be levied to finance negative emission technologies.

Climate change damages in REMIND are modelled using temperature-dependent aggregate damage functions reducing output (see also Deliverable D2.2 for more details). As the output effect does not directly translate into a consumption effect (since investment decisions are free in REMIND), we use a series of baseline and policy runs with damages to estimate a region-specific relation between output damages and consumption loss. Generally, consumption loss is higher than direct output loss.

Damages are endogenized via the social cost of carbon which is calculated through an analytical approach, with a solution found in an iterative way (Schultes et al. 2021). To enable the feedback of inequality of damages on the transformation pathway, the social cost of carbon calculation is amended with an extra term, based on the derivations by Anthoff & Emmerling (2019). That increases the social cost of carbon.

The elasticity of energy expenditure $\boldsymbol{\alpha}$ Is estimated through an empirical approach using country-level data for four income groups from the Global Consumption Database. This is further described in Soergel et al. (2021). The elasticity of revenues β is a modeling choice, depending if the redistribution should be distributionally neutral ($\beta = 1$) or progressive ($\beta < 1$). No robust quantification of the elasticity of damages ξ is available in the literature yet, though many studies find larger impacts on the poor than on the rich (e.g. Hallegatte & Rozenberg 2017). As a standard case we assume $\xi = 0.5$, but also run sensitivity analyses with $\xi = 0$ and $\xi = 1$.

The NICE model

The Nested Inequalities Climate Economy (NICE) model is a modification of the RICE model William Nordhaus (Nordhaus and Yang, 1996). RICE is a regionally disaggregated optimization model that includes an economic component and a climate component that are linked. RICE divides the world into 12 regions, some of which are single countries while others are groups of countries. Each region has a distinct endowment of economic inputs including capital, labor, and technology, which together produce that region's gross output via a Cobb-Douglas production function. Carbon emissions are a function of gross output and an exogenously determined, region-specific, carbon intensity pathway. These carbon emissions can be abated (mitigating climate change) at a cost to gross output via regional control policies that are selected so that in every period the marginal cost of abatement – or carbon price – is the same for all regions. The climate module determines how unabated carbon emissions affect global temperature and, ultimately, the future economy through climate-related damages. Region-specific damage functions capture this relationship between increased temperature and economic damage, with poorer regions generally more vulnerable as a proportion of income.

The NICE model extends RICE by disaggregating regional consumption into five (or ten) socio-economic groups with consumption levels reflecting the current distribution of consumption within the regions. So as not to affect any of the aggregate economic variables (investment, capital, output, etc.), this is done by splitting average regional consumption into five units (or quintiles) after aggregate savings have been determined.

Baseline inequality modelling

Let denote regions by index i, quantiles by j, and periods by t. Quantities without a j index are regional aggregates. Average gross consumption (pre-damage and pre-mitigation cost) in a given region at a specific time is

$$\bar{c}_{it}^{pre} = \frac{1 - s_{it}}{L_{it}} Q_{it}.$$

To model baseline distribution, we need to obtain average consumption at the quintile or the decile level. For the sake of this discussion, let us assume that the description is at the quintile level. The baseline distribution is produced using quintile weights q_{ijt} that denote the ratio between quintile consumption and average consumption. That is $\bar{c}_{ijt}^{pre} = q_{ijt} \cdot \bar{c}_{it}^{pre}$ If for quintile j in region i and period t, $q_{ijt} > 1$, its consumption is greater than average regional consumption in that period, and if $q_{ijt} < 1$ its consumption is less than the average. Since the five quintiles comprise equal proportions of the population, $\sum_j q_{ijt} = 5$ in all regions and periods.

The initial quintile weights are the current distribution of consumption. For the future, NICE uses an approach similar to that of REMIND 2.1. Namely, region distributions are based on Rao et al.'s Gini projections for SSP2 (Rao et al., 2019). Specifically, levels of the Gini index are matched with a value of σ using the assumption that the distribution is log-normal. Then, keeping the assumption of a log-normal distribution, the quintiles or deciles of the distribution can be retrieved.

Distributional effects of policy

The baseline inequality will be affected by policy through three channels. First, the (mitigation) costs of the policy have to be distributed. Second, climate damages can affect different income groups in different ways. Last, the carbon tax that is used as a policy tool have different impacts on different groups and can be redistributed.

Given the mitigation costs and climate damages, net output Y_{it} of country i at period t is given by

$$Y_{it} = \frac{1-\lambda_{it}}{1+D_{it}} Q_{it}$$

where Q_{it} denotes gross output, λ_{it} mitigation cost (opportunity costs of reducing CO_2 emissions as a share of GDP) and D_{it} climate damages. Note that those numbers a region specific. In each period the regional mitigation costs are chosen so that they are consistent with a globally uniform carbon price, which is implemented as a local tax, tax_t in each region.

Defining the aggregate savings rate s_{it} and population L_{it}, the average (net) regional consumption is

$$\bar{c}_{it} = \frac{1-s_{it}}{L_{it}} Y_{it}$$

while the average gross consumption (pre-damage and pre-mitigation cost) is

$$\bar{c}_{it}^{pre} = \frac{1-s_{it}}{L_{it}} Q_{it} = \frac{1+D_{it}}{1-\lambda_{it}} \bar{c}_{it} \approx (1+\lambda_{it}+D_{it})\bar{c}_{it}.$$

Hence, we obtain the following equation at the aggregate level:

$$\bar{c}_{it} \approx \bar{c}_{it}^{pre} - \lambda_{it}\bar{c}_{it} - D_{it}\bar{c}_{it}$$

Then a first question is how to distribute the per capita mitigation costs $\lambda_{it}\bar{c}_{it}$ and the per capita damages $D_{it}\bar{c}_{it}$. It is assumed that each income group bears a share d_{ijt} and m_{ijt} of the damages and mitigation cost. Those distributional weights of damage and of mitigation costs (d_{ijt} and m_{ijt}) are determined by a constant elasticity relationship to the consumption distribution:

$$d_{ijt} = \frac{q_{ijt}^{\xi}}{5\sum_k q_{ikt}^{\xi}}$$

and

$$m_{ijt} = \frac{q_{ijt}^{\omega_{it}}}{5\sum q_{ikt}^{\omega_{it}}}.$$

On top of those effects, policy can take the form of a carbon tax that may be redistributed. Within a region, the burden of the carbon tax is distributed across quintiles according to the weights τ_{ijt}, with $\tau_{ijt} = 5\frac{q_{ijt}^{\omega_{it}}}{\sum_k q_{ikt}^{\omega_{it}}}$. Then the proceed is redistributed according to the weights δ_{ijt}. The per capita amount of the carbon tax is $\frac{E_{it}}{L_{it}} \cdot tax_t$, so that for a given income group the net effect of the tax is:

$$\frac{E_{it}}{L_{it}} \cdot tax_t \cdot (\tau_{ijt} - \delta_{ijt}).$$

Two important sets of assumptions are made. The first substantive assumption of is that the mitigation cost and the tax payment are distributed according to the same elasticity ω_{it}. The second substantive assumption concerns the description of the available tax policies. A first policy (Distributionally neutral) implies that the carbon tax has no redistributive impact, i.e. $\tau_{ijt} - \delta_{ijt} = 0$. A second policy is per capita redistribution that is $\delta_{ijt} = 1$.

In the end, the quantile net consumption levels are given by:

$$c_{ijt} = \underbrace{\bar{c}_{it}^{pre} \cdot q_{ijt}}_{\text{gross consumption}} - \underbrace{\bar{c}_{it} D_{it} d_{ijt}}_{\text{damage cost}} - \underbrace{\bar{c}_{it}^{pre} \lambda_{it} \tau_{ijt}}_{\text{mitigation cost}} - \underbrace{\frac{E_{it}}{L_{it}} \cdot tax_t \tau_{ijt}}_{\text{tax payments}} + \underbrace{\frac{E_{it}}{L_{it}} \cdot tax_t \delta_{ijt}}_{\text{refund}}.$$

This equation produces the new (post policy) distribution.

New developments in the CHIPS project

NICE has been adjusted to match the current state-of-the art socioeconomic scenarios, the Shared Socioeconomic Pathways (SSPs, Riahi et al. 2017), in particular SSP2, the middle of the road scenario. This allows a more direct comparison of NICE results with that of other integrated assessment models. Also, we have developed a version of NICE where regions are actually countries, that is we use 183 countries instead of the 12 RICE aggregated regions. Correspondingly, damages have been differentiated at the country-level depending on the local climate anomaly.

The preferred specification for the income elasticity of climate damages ξ is set to 0.85, based on a work done by M. Gilli in collaboration with the CHIPS project (Gilli, 2020). The preferred specification for the income elasticity of mitigation cost is based on Budolfson et al. (2021).

Furthermore, multiple different redistribution mechanisms for carbon tax revenues have been implemented, including regional and global redistribution, as well as a new form where the amount redistributed is proportional to the regional climate change damages. This is inspired by the current loss-and-damage debate and further discussed in Deliverable 5.2.

References

Anthof D, Emmerling J (2019) Inequality and social cost of carbon. J Assoc Environ Resour Econ **6**, 243–273

Anthoff D, Tol RS (2012) The Climate Framework for Uncertainty, Negotiation and Distribution (FUND)", Technical Description. Version 3.6. URL http://www.fund-model.org

Atkinson A B, Brandolini A (2010) On analyzing the world distribution of income. World Bank Econ Rev **24**, 1–37

Battistin E, Blundell R, Lewbel A (2009) Why Is Consumption More Log Normal than Income? Gibrat's Law Revisited. J Pol Economy **117** (6), 1140–1154

Budolfson M, Dennig F, Errickson F, Feindt S, Ferranna M, Fleurbaey M, Klenert D, Kornek U, Kuruc K, Méjean A, Peng W, Scovronick N, Spears D, Wagner F, Zuber S (2021) Climate action with revenue recycling has benefits for poverty, inequality and well-being. Nature Climate Change **11**(12,: 1111–1116.

Dennig F, Budolfson MB, Fleurbaey M, Siebert A, Socolow RH (2015) Inequality, climate impacts on the future poor, and carbon prices. PNAS **112**(52), 15827–32

Gazzotti P, Emmerling J, Marangoni G, Castelletti A, van der Wijst K-I, Hof A, Tavoni M (2021) Persistent inequality in economically optimal climate policies. Nat Commun **12**, 3421.

Gilli M (2022) Estimating damages from climate change and the income elasticity of damage. Master thesis, Paris School of Economics

Hallegatte, S, Rozenberg, J (2017) Climate change through a poverty lens. Nature Climate Change **7**, 250-256.

Kriegler E, Bauer N, Popp A, Humpenöder F, Leimbach M, Strefler J, Baumstark L, Bodirsky BL, Hilaire J, Klein D, Mouratiadou I, Weindl I, Bertram C, Dietrich J-P, Luderer G, Pehl M, Pietzcker R, Piontek F, Lotze-Campen H, Biewald A, Bonsch M, Giannousakis A, Kreidenweis U, Müller C, Rolinski S, Schultes A, Schwanitz J, Stevanovic M, Calvin K, Emmerling J, Fujimori S, Edenhofer O (2017) Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change **42**, 297–315

Nordhaus, WD (2014) Estimates of the social cost of carbon: Concepts and results from the DICE-2013R model and alternative approaches. J of the Association of Env and Resource Econ **1**, 273– 312

Nordhaus, WD, Yang Z (1996) A regional dynamic general-equilibrium model of alternative climate-change strategies. American Econ Rev **86**, 741–65

Riahi, K, van Vuuren, DP, Kriegler, E, Edmonds, J, O'Neill, BC, Fujimori, S, Bauer, N, Calvin, K, Dellink, R, Fricko, O, Lutz, W, Popp, A, Cuaresma, JC, KC, S, and Leimbach, M (2017) Shared Socioeconomic Pathways: An Overview. Global Environ. Change **42**, 153–168, https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rao ND, Sauer P, Gidden M, Riahi K (2019) Income inequality projections for the shared socioeconomic pathways (SSPs). Futures **105**, 27–39.

Schultes, A, Piontek, F, Soergel, B, Rogelj, J, Baumstark, L, Kriegler, E, Edenhofer, O, Luderer, G (2021) Economic damages from on-going climate change imply deeper near-term emission cuts. Environ. Res. Lett. **16**, 104053.

Soergel, B, Kriegler, E, Bodirsky, BL, Bauer, N, Leimbach, M, Popp, A (2021) Combining ambitious climate policies with efforts to eradicate poverty. Nature Communications **12**, 2342.

Taconet N. (2021) A note on REMIND inequality module

Acknowledgement

The project CHIPS is part of AXIS, an ERA-NET initiated by JPI Climate, and funded by FORMAS (SE), DLR/BMBF (DE, Grant No. 01LS1904A), AEI (ES) and ANR (FR) with co-funding by the European Union (Grant No. 776608).