# Climate change damages on labor and capital, inequality, and the social cost of carbon

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## Abstract

Climate change is poised to generate economic damages through many channels, in particular through shocks to the factors of production. We use an integrated assessment model with sub-regional inequality and introduce direct impacts on capital and productive labor stocks, resulting in endogenously persistent damages. We model and calibrate the joint distribution of labor and capital income, to capture the role played by income composition heterogeneity in within-region inequality. The income-elasticity of damages has a stronger impact than their persistence on future inequality, consumption, and optimal policy. When taking the non-proportionality of damages into account, inequality increases with labor productivity and capital damages, but labor impacts tend to have a stronger effect. In the most affected regions, these factor-specific damages can lead to important consumption losses at the bottom of the distribution, resulting in a large increase in the social cost of carbon.

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# 1 Introduction

The social cost of carbon captures the welfare loss from emitting an additional ton of carbon and is used to guide climate policy. Because of the delay between emissions and climate change, climate policy appears as a primarily inter-generational issue, a trade-off between the wealth of the present and future generations. Heated debates about the appropriate discount rate (with Stern (2007) and Nordhaus (2007) as headliners) reflect the focus on the inter-temporal dimension. Yet, there is also significant spatial and socioeconomic heterogeneity in climate change impacts. For instance, heatwaves are prone to hit warmer and more humid regions, and to reduce the productivity and health of heat-exposed workers (e.g. Kjellstrom et al. (2009)). By and large, vulnerability and exposure are determined by "non-climatic factors and multidimensional inequalities often produced by uneven development processes." (IPCC Working Group II, Field et al. (2014)). Heterogeneity in damages results in impacts of varying durations and interacts with pre-existing social heterogeneity. A proper evaluation of climate policy requires taking these discrepancies into account.

This paper studies the impacts of differential climate damages on incomes, inequality, and optimal climate policy, using an Integrated Assessment Model (IAM). We disentangle damages on the factors of production and analyze their joint distributional and persistent effects. We improve the representation of social heterogeneity through decomposing economic inequality by income source. To do so, we model the joint distribution of capital and labor income and evaluate how it interacts with damages hitting the stocks of capital and labor productivity directly. We investigate the relative importance of these two impact channels for the distributional outcomes of climate policy, contrasting their effect on the duration of damages with their direct distributive effect.

Our paper is not the first to use an IAM to explore the distributional consequences of climate policy. While IAMs have integrated equity weights (Anthoff et al., 2009), the representation of spatial and social heterogeneity is still limited, and in particular impacts on the poor (Rao et al., 2017). Several significant improvements have been made recently. Both process-based and cost-benefit IAMs have introduced sub-regional inequality, either through cross-country inequality (Anthoff and Emmerling, 2019; Taconet et al., 2020; Gazzotti et al., 2021) or through within-region or within-country distributions (Dennig et al., 2015; Budolfson et al., 2021; Soergel et al., 2021; Malafry and Brinca, 2022). Climate change is found likely to increase inequality (Taconet et al., 2020; Gazzotti et al., 2021) and to have significant adverse effects on the poorest (Dennig et al., 2015; Soergel et al., 2021), albeit possibly alleviated by the redistribution of the proceedings from a carbon tax (Budolfson et al., 2021; Soergel et al., 2021). Additionally, cost-benefit IAMs show that introducing inequality considerations can lead to more stringent policy recommendations, captured by an increase in the social cost of carbon (Dennig et al., 2015; Anthoff and Emmerling, 2019).

In this paper, we build on the Nested Inequalities Climate Economy (NICE) model developed by Dennig et al. (2015) based on the RICE[1] model (Nordhaus, 2010). Previous efforts to capture inequality in IAMs rely on aggregate indices or distributions of net income or consumption, except for Malafry and Brinca (2022) who use information on the global wealth Gini index. Our contribution is to introduce a novel source of social heterogeneity by modeling and calibrating jointly labor and capital gross income distributions, as well as consumption distributions.

[1]RICE is the Regional Integrated Climate-Economy model.

Representing these sources of inequality is key to better incorporate the growing evidence on the distributional impacts of climate change, especially on the poor (Hallegatte and Rozenberg, 2017; Hsiang et al., 2019). More destitute households tend to have a higher reliance on labor earnings with greater exposure to unstable weather conditions (Park et al., 2018; Hallegatte et al., 2020; Parsons et al., 2021), and on more vulnerable asset portfolios (Hallegatte et al., 2020). This makes them more prone to suffer from consequential income losses and to fall into poverty traps (Carter et al., 2007). The high concentration of wealth and assets at the top of the distribution also implies that the poorest often have little leeway to smooth consumption in case of a shock and that they are more dependent upon wages. We incorporate this dependence through income composition inequalities—how the composition of income in two sources, such as capital and labor income, varies across the income distribution (Ranaldi, 2021)—and couple it to damages on the factors of production.

To model channel-specific damages, we build upon a second strand of IAM literature, which introduces climate shocks to different channels at the aggregate level and studies their subsequent persistence and growth effects. Kopp et al. (2012); Dietz and Stern (2015) and Moore and Diaz (2015) investigate the role of impacts on the capital stock or on total factor productivity. Estrada et al. (2015) analyze implicit persistence in IAMs and show that implied impact durations are not consistent with the available evidence. Piontek et al. (2019) study the impact and half-life of damages on a large variety of input channels and discuss possible implications for the labor share. We build on the insights of this strand of literature and adopt labor and capital damages based on Kopp et al. (2012) and Piontek et al. (2019)'s formulations.

We thereby generate an improved representation of heterogeneous income and damages in an IAM. We find that although capital and labor damages lead to more persistent damages and increases in output losses, the aggregate impact does not result in significant alterations in growth paths at the regional level. On the other hand, our results show that the allocation of the burden of channel-specific damages across the income distribution is crucial for the evolution of inequality and the livelihoods of the future poor. Using the empirical literature to find a plausible range of value for the income-elasticities, we find that the social cost of carbon is significantly larger, reflecting important consumption losses in the bottom of the distribution of the most affected regions.

The rest of this paper is structured as follows. Section 2 details the model and the calibration of factor income and consumption inequalities. In section 3 we present aggregate effects from the introduction of capital and labor damages, before turning to distributional outcomes and the impact on the social cost of carbon. We discuss our results and conclude in section 4.

# 2 Methods

In this section, we present the key components of the Integrated Assessment Model we use. We start by introducing the macroeconomic framework, a growth model à la Solow-Swan. We then turn to the breakdown of aggregate income into capital and labor components and detail the distribution of factor-income within regions. Next, we describe our damage specification, including the newly implemented factor-specific damages, as well as their distribution. Lastly, we detail the analytical formulations for the two social cost of carbon (SCC) we derive.

## 2.1 Regional output and consumption

As in RICE (Nordhaus, 2014), gross output at time $t$ in region $r$ is modelled through a Cobb-Douglas production function occurs at the regional level

$$Y^G_{rt} = A_{rt} K^{\alpha}_{rt} L^{1-\alpha}_{rt} \tag{2.1.1}$$

with $A$ exogenous total factor productivity, $K$ the stock of capital, $L$ labor and $\alpha \in [0,1]$ output elasticity of capital. Capital stock and productive labor are shared at the quintile level, and aggregated for production and accumulation at the regional level.

Damages and abatement costs are subtracted from gross output, resulting in net output

$$Y^N_{rt} = (1 - \Lambda_{rt})(1 - D^G_{rt}) Y^G_{rt} \tag{2.1.2}$$

with $D^G_{rt}$ damages as a share of gross output and $\Lambda_{rt}$ abatement costs as a share of net-of-damages output. In the rest of the paper, we will focus on inequality outcomes and the social cost of carbon along a "Business-as-usual" path, which implies that $\Lambda_{rt} = 0$, $\forall r$. Net output is either consumed or invested in capital stock with a fixed savings rate $s$.[2] Capital accumulates at the regional level, with a decadal depreciation rate of $\delta$ (the model has ten year time-steps)

$$K_{r,t+1} = (1 - \delta) K_{r,t} + s Y^N_{r,t}. \tag{2.1.3}$$

Regional aggregate consumption is then given by

$$C_{rt} = (1 - s) Y^N_{rt}. \tag{2.1.4}$$

Population $P_{r,t}$ and labor $L_{r,t}$ are equal in the first period but can differ when shocks to the labor stock occur. Both grow asymptotically according to

$$L_{r,t+1} = L_{rt} \left( \frac{L^{asym}_r}{L_{rt}} \right)^{adj} \tag{2.1.5}$$

with $L^{asym}_r$ the regional asymptotic population as in the RICE model (Nordhaus, 2014) and $adj$ the growth rate as in the DICE model (Nordhaus, 2017).

[2] Piontek et al. (2019) discuss the role of a fixed savings rate and show that endogenous savings slightly reduces deviations from business-as-usual GDP, for output, capital, and labor shocks. However, the relative magnitude of effect across channels is not affected.

## 2.2 Factor income distribution

Next, we relate total net output to the distribution of income across households, splitting the population of each region into quintiles. To avoid the pitfalls of macro-micro discrepancies that arise when coupling aggregate outcomes to household level evidence, we build on the concepts and methods used in the construction of Distributional National Accounts (DINA)[3] (Alvaredo et al., 2016; Piketty et al., 2017).

We equate net output to pretax regional income. In turn, net income is split between a capital income component $Y^K$ and labor income component $Y^L$. With a Cobb-Douglas production function, output elasticity $\alpha$ also captures factor shares:

$$
\begin{aligned}
Y^K &= \alpha Y^N && (2.2.1)\\
Y^L &= (1-\alpha) Y^N && (2.2.2)
\end{aligned}
$$

Factor income in each region is shared across quintiles. The distribution of factor income reflects an implicit distribution of wealth, returns and wages. Denoting $y_q^K$ (resp. $y_q^L$) capital (labor) income of quintile $q$ and $\mathrm{sh}_q^{Y^K}$ (resp. $\mathrm{sh}_q^{Y^L}$) quintile $q$'s share in capital income (resp. labor income), pretax income of quintile $q$ writes

$$
\begin{aligned}
y_q &= y_q^K + y_q^L = \mathrm{sh}_q^{Y^K} Y^K + \mathrm{sh}_q^{Y^L} Y^L && (2.2.3)\\
&= \left(\alpha \mathrm{sh}_q^{Y^K} + (1-\alpha)\mathrm{sh}_q^{Y^L}\right) Y^N && (2.2.4)
\end{aligned}
$$

It follows that quintile $q$'s share in pretax regional income is

$$
\mathrm{sh}_q^Y = \frac{y_q}{Y^N} = \alpha \mathrm{sh}_q^{Y^K} + (1-\alpha)\mathrm{sh}_q^{Y^L} \qquad (2.2.5)
$$

Next, we relate the functional distribution of regional income (how is regional income split between capital and labor) to the composition of quintile income (what proportion of quintile income stems from capital or labor) (Ranaldi, 2021). The share of labor income in the pretax income of quintile $q$ is

$$
\begin{aligned}
\mathrm{sh}_q^{y^L \,\mathrm{in}\, y} &= \frac{y_q^L}{y_q} = \frac{(1-\alpha)\mathrm{sh}_q^{Y^L} Y^N}{\alpha \mathrm{sh}_q^{Y^K} Y^N + (1-\alpha)\mathrm{sh}_q^{Y^L} Y^N} && (2.2.6)\\
&= (1-\alpha)\frac{\mathrm{sh}_q^{Y^L}}{\mathrm{sh}_q^Y} && (2.2.7)
\end{aligned}
$$

and the share of capital income is

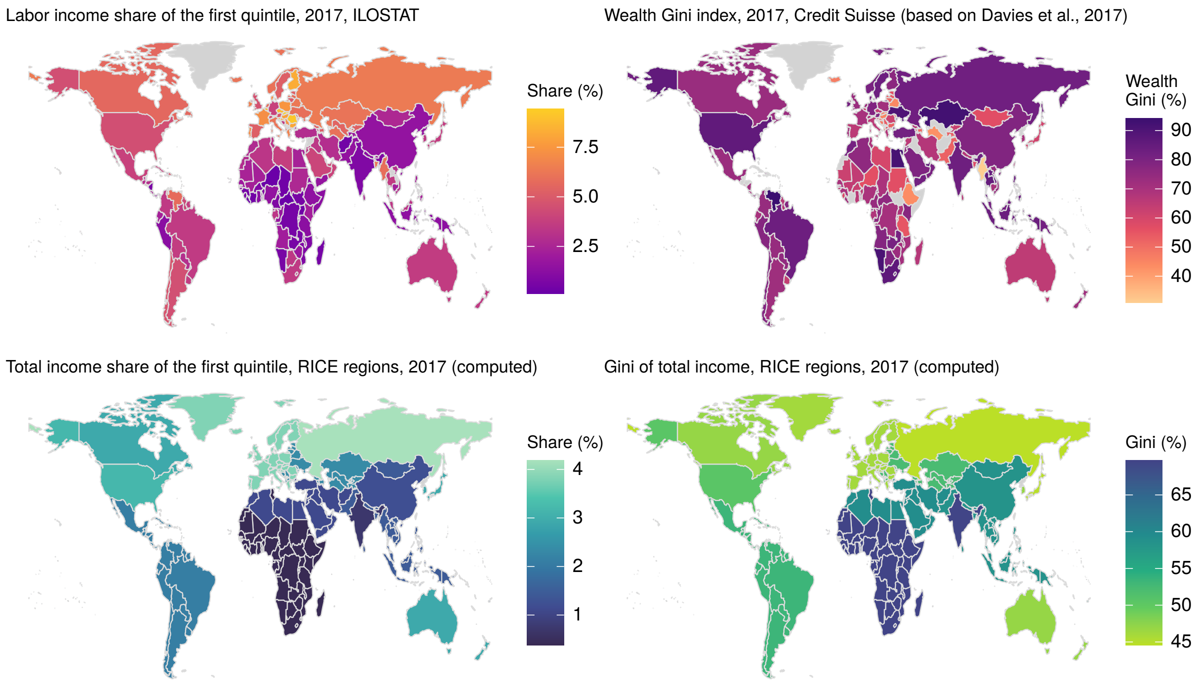
$$
\begin{aligned}
\mathrm{sh}_q^{y^K \,\mathrm{in}\, y} &= \alpha \frac{\mathrm{sh}_q^{Y^K}}{\mathrm{sh}_q^Y} && (2.2.8)\\
&= 1 - \mathrm{sh}_q^{y^L \,\mathrm{in}\, y} && (2.2.9)
\end{aligned}
$$

We calibrate capital income distribution using wealth distribution data from the Credit Suisse Global Wealth databooks (Davies et al., 2017). The Gini index is converted into wealth quintiles with log-normal distributions. We assume that capital income and wealth

[3] In particular, the DINA methodolody aims at reconciling inequality measurement and national accounting (Alvaredo et al., 2016).

are identically distributed. Given the evidence for higher returns at the top of the wealth distribution (Benhabib and Bisin, 2018; Garbinti et al., 2021), we expect our calibration is a lower bound of capital income inequality. We combine the resulting capital income distribution with data on labor income distribution at the decile level from the International Labour Organization (Gomis, 2019). Under the assumptions of equal ranking between labor and capital income distribution and given the fixed aggregate labor share $(1-\alpha)$, we retrieve total income distributions for the twelve regions in RICE. We take this approach rather than relying on available factor income micro-data because it is likely that a significant proportion of national income is missing from micro sources (see e.g. Flores (2021)). Figure 1 displays the input data for labor and capital income distribution on the two top panels, and the resulting total income on the two bottom panels.

Figure 1: Maps of input data and resulting inequality estimates




Income is more unequally distributed than consumption (e.g. World Bank (2016)). This results from consumption smoothing, redistribution and consumption of public goods, etc. To capture this expected discrepancy, we construct for each region a scaling matrix relating income shares and consumption shares from the World Bank (Pinkovskiy and Sala-i Martin, 2009). With $\beta_{rq}$ the scaling factor, the share of quintile $q$ in consumption is

$$\mathrm{sh}^C_{rq} = \frac{\beta_{rq}\mathrm{sh}^Y_{rq}}{\sum_q(\beta_{rq}\mathrm{sh}^Y_{rq})} \tag{2.2.10}$$

The resulting distributions of labor income, capital income, total income and consumption for different regions is depicted in the Appendix, Figure 11. Consistent with evidence on factor income distribution, our calibration features a more unequal distribution of capital income than labor income. The resulting total income is more unequally distributed than labor income but less than capital income.

## 2.3 Aggregate damages

Damages from climate change on gross output result from a temperature increase above the pre-industrial level. We keep the climate model from the RICE model (Nordhaus, 2014). Emissions from regional production sum to a global emission pulse leading to an increase in the carbon content in the atmosphere. The climate model is a three-box model consisting of atmosphere, upper and lower ocean with carbon flow between atmosphere and upper ocean, and upper and lower ocean. The atmospheric carbon content determines the temperature increase above the pre-industrial level through an increase in radiative forcing. Damages from the resulting temperature increase are assumed to follow a quadratic function with temperature

$$D_{rt} = \lambda_{1r} T_t + \lambda_{2r} T_t^2 \tag{2.3.1}$$

with $\lambda_{1r}$ and $\lambda_{2r}$ the region-specific damage parameters and $T_t$ the temperature above preindustrial levels. We use the calibration of $\lambda_{1r}$ and $\lambda_{2r}$ as in Dennig et al. (2015).

## 2.4 Capital and labor damages

In Nordhaus (2014) and Dennig et al. (2015), damages fall directly on aggregate output. Although this formulation is meant to capture the overall impact from the myriad of ways in which climate change manifests, it misses some of the endogenous economic responses. In the RICE model, production is modeled with a Cobb-Douglas function taking labor and capital inputs. We introduce impacts hitting directly these factors of production. We then use a National Distributional Accounts type framework to relate the aggregate damages to their impacts on earnings.

First, the productivity of labor and the number of hours worked are adversely affected by climate change. Increases in temperatures and heat stress can lead to a reduction in productivity in exposed sectors and an overall increase in absenteeism, resulting in decreased output (Heal and Park, 2020; Dasgupta et al., 2021; Parsons et al., 2021; Somanathan et al., 2021; Acevedo et al., 2020). Impacts on labor productivity can be long lasting, for instance through reductions in educational outcomes (Park et al., 2021) and health (Hallegatte et al., 2020).

Second, climate change also impacts the capital stock. The increased frequency and magnitude of extreme events, for instance cyclones, floods, landslides or fires, leads to more damages on physical capital such as plants or infrastructure. Productive assets owned by households such as plantations, livestock or land can also be damaged by extreme events (e.g. Carter et al. (2007)) or by slow onset changes such as sea level rise (Islam and Winkel, 2017).

We capture the aggregate effect of damages on labor and capital by splitting up output damages. Following Kopp et al. (2012) and Piontek et al. (2019), we model capital, labor, and output damages to ensure the overall impact on output at time $t$ matches output damages in the absence of factor specific damages. We add damages to productive labor, leaving population unchanged, to the formulation used in Kopp et al. (2012). In this way, output net of damages

$$(1 - D_{rt}^G) A_{rt} L_{rt}^{1-\alpha} K_{rt}^{\alpha} \tag{2.4.1}$$

can be rewritten as

$$(1 - D_{rt}^G)^{f_Y} A_{rt} \left( (1 - D_{rt}^G)^{\frac{f_L}{1-\alpha}} L_t \right)^{1-\alpha} \left( (1 - D_{rt}^G)^{\frac{f_K}{\alpha}} K_{rt} \right)^{\alpha} \tag{2.4.2}$$

with $f_Y$, $f_K$, and $f_L$ the share of damages falling respectively on output, capital and labor, and $f_Y + f_L + f_K = 1$. The direct impact on output is captured by $(1 - D^G_{rt})^{f_Y} Y^G_{rt}$, and post-damage stocks of capital and productive labor write

$$\begin{aligned} K^N_{rt} &= (1 - D^G_{rt})^{\frac{f_K}{\alpha}} K_{rt} && (2.4.3) \\ L^N_{rt} &= (1 - D^G_{rt})^{\frac{f_L}{1-\alpha}} L_{rt}. && (2.4.4) \end{aligned}$$

Damages on capital and labor stocks result in persistent impacts through two channels. First, stock damages produce a direct impact, as output remains diminished while the productive stocks have not recovered their counterfactual level. The asymptotic growth of labor (see eq. (2.1.5)) implies a faster increase after a shock, but the catch-up is not instantaneous. Thus, recurring shocks could permanently reduce labor productivity. We control for the level of persistence of these shocks through the law of motion of the labor stock, which becomes:

$$L_{r,t+1} = (\lambda L^N_{rt} + (1 - \lambda) L_{rt}) \left( \frac{L^{asym}_r}{\lambda L^N_{rt} + (1 - \lambda) L_{rt}} \right)^{adj}, \tag{2.4.5}$$

with $\lambda$ between 0 (full and instantaneous dissipation of the labor stock shock) and 1 (dissipation of the shock only through the asymptotic growth mechanism).

The persistence of capital damages depends on the rate of depreciation, which determines how fast new investment replaces the capital stock. With a depreciation rate of 100% over a decade, capital damages have no direct persistent impact, as the next period capital stock is entirely replaced by investment. In a neo-classical growth framework, labor damages tend to be more persistent than capital damages (Piontek et al., 2019).

Second, lower output begets lower investment in capital stock which causes an indirect persistent impact. Indirect persistence increases with the depreciation rate–contrary to direct persistence–and with the output elasticity (Estrada et al., 2015). This indirect impact occurs even in the absence of any channel-specific damage. It plays a role in compounding the direct output impacts, albeit limited.

We recover persistent damages as a share of gross output, $D^{G,P}_{rt}$, by comparing gross output and a counterfactual with no channel-specific impacts, or "unpersistent" output. This counterfactual, $Y^{G,cf}_{rt}$, corresponds to gross output in the case where all damages fall directly on output, all other parameters in the model being equal, i.e. $Y^G_{rt|f_Y=1}$. In turn, persistent damage is

$$D^{G,P}_{rt} = \frac{Y^{G,cf}_{rt} - Y^G_{rt}}{Y^{G,cf}_{rt}} \tag{2.4.6}$$

This metric of persistent damages captures direct persistence and indirect persistence from capital and labor damages, but not persistence from damages that fall directly on output. As a result, this metric captures the additional persistence resulting from channel-specific damages.

## 2.5 Distribution of damages and abatement cost

Damages are allocated between labor productivity, capital stock, and direct output impacts according to damages shares $f_i$, $i \in \{L, K, Y\}$. These damages are then distributed according to labor income, capital income and total income respectively, with an income-elasticity parameter $\xi$ reflecting how proportional damages are with respect to the specific income distribution. $\xi_i$ equivalently captures the income-elasticity of damages in absolute terms, and the elasticity between the quintile's share in income of type $i$, $sh_q^{Y_i}$ and the quintile's share in damages of type $i$, $sh_q^{D_i}$, i.e.

$$\xi_i = \frac{\partial \ln d_q^i}{\partial \ln y_q^i} = \frac{\partial \ln sh_q^{D_i}}{\partial \ln sh_q^{Y_i}}, \tag{2.5.1}$$

with $i \in \{L, K, Y\}$ and $d_q^i$ the damages of type $i$ hitting quintile $q$. An income-elasticity $\xi$ of 1 implies that damages fall proportionally to income shares. $\xi = 0$ means that the each quintile bears a fifth of the damages, i.e. that damages are independent of the income share.

In turn, a quintile's share in total damages, adding up damages from labor, capital and directly on output, is

$$sh_q^D = \sum_{i \in \{Y,K,L\}} f_i sh_q^{D_i} \tag{2.5.2}$$

$$= \sum_{i \in \{Y,K,L\}} f_i \frac{(sh_q^{Y_i})^{\xi_i}}{\sum_{j=1}^{5} (sh_j^{Y_i})^{\xi_i}}. \tag{2.5.3}$$

The progressivity (or regressivity) of damages overall will stem from the pre-damage income distributions, the composition of damages across channels ($f_L$, $f_K$, $f_Y$) and the progressivity of each damage type. The distribution of damages overall can be synthesized by applying the Suits index (Suits, 1977) to the damage shares:

$$S_D \approx 1 - \frac{1}{0.5} \left[ \sum_{i=1}^{5} \frac{1}{2} \left( \sum_{q=0}^{i} sh_q^D + \sum_{q=0}^{i-1} sh_q^D \right) sh_i^Y \right]. \tag{2.5.4}$$

The literature on the distribution of climate impacts cannot provide a central estimate of the income-elasticities of labor and capital damages, but it can help outline a plausible range of values. Disadvantaged groups are found to suffer *disproportionately* from climate change because of i) higher exposure to climate hazards, ii) higher vulnerability, and iii) lower ability to cope with adverse impacts (Islam and Winkel, 2017; Hallegatte and Rozenberg, 2017). The *disproportionality* of climate impacts is an umbrella concept that references a vulnerable group ("the poor" or "the disadvantaged" across one or several welfare dimensions) and ties into fairness considerations over Loss and Damages (Dorkenoo et al., 2022). Evidence for damage disproportionality indicates that the income-elasticity is likely below 1, but a more detailed description of the distribution of damages is needed to pinpoint its value more precisely. In particular, whether the poorest bear a larger damage share in *absolute value* is key to restricting the range of plausible values for the income-elasticities of damages.

The poorest, in particular in hot countries, are more likely to work in sectors with higher exposure to heat stress (Park et al., 2018) and in which the hours worked and productivity losses are largest (Graff Zivin and Neidell, 2014). They are also less likely to have access to a variety of income sources, making them more vulnerable to natural disasters (Hallegatte et al., 2020). However, significant losses from the perspective of the poorest households does not necessarily translate into the largest share at the national and regional scale, because the income of the poor make up only a small fraction of aggregate income (Hallegatte et al., 2020). For example, a case study of effects of current heat stress in Australia showed that the most expensive productivity loss in absolute value corresponded to the higher payed occupations, altjough these were not the most exposed (Zander et al., 2015). It is therefore likely that the income elasticity of labor damages is significantly larger than zero.

Turning to effects on capital (or asset) income, natural disasters are more prone to strike the assets of the poor, because of higher exposure and vulnerability. Indeed, asset composition differs across the wealth distribution: the portfolio of the poorer tends to be less diversified and more vulnerable (e.g. housing and livestock rather than financial assets) (Hallegatte et al., 2020). For instance, the asset-elasticity of asset loss can be recovered from Carter et al. (2007)'s analysis of hurricane Mitch, which hit Honduras in 2001. Using the data on average losses by asset quartile (Table 1 in Carter et al. (2007)) yields an elasticity of 0.68, meaning that these damages disproportionally hit the poor but the richest still bore the largest share of the burden in absolute. In the rest of the paper, we use income-elasticities between 0.5 and 1.

Finally, we recover the share of quintile $q$ in net regional income, by combining income and damages distributions. We focus on a "Business-as-Usual" case, in which there is no abatement. The share of quintile $q$ in net regional income then writes

$$\mathrm{sh}^{Y^N}_{rqt} = \frac{y^N_{rqt}}{Y^N_{rt}} \tag{2.5.5}$$

$$= \frac{\left(\mathrm{sh}^Y_{rqt} - \mathrm{sh}^D_{rqt} D^G_{rt}\right) Y^G_{rt}}{(1 - D^G_{rt}) Y^G_{rt}} \tag{2.5.6}$$

Put differently, the net income share captures the gap between equally distributed income and damages, and their actual joint distribution.

In turn, re-scaling the net income share $\mathrm{sh}^{Y^N}_{rqt}$ with the income-to-consumption scaling factor $\beta$ yields the share of quintile $q$ in regional consumption

$$\mathrm{sh}^C_{rqt} = \frac{\beta_{rq}\mathrm{sh}^{Y^N}_{rqt}}{\sum_q (\beta_{rq}\mathrm{sh}^{Y^N}_{rqt})}. \tag{2.5.7}$$

Climate damages thus impact final consumption in two ways: by reducing the amount of aggregate consumption, and by affecting the share of each quintile in this regional consumption.

## 2.6 The social cost of carbon

The social cost of carbon captures the present loss of consumption which is as costly as the loss of consumption in the future due to the emission of an additional ton of carbon. To put a value on consumption losses, we use an utilitarian social welfare function (SWF) in which welfare is derived from consumption. The SWF features two key normative parameters: $\eta$ captures aversion to inequality (inter- and intra-generational) and $\rho$ is the pure rate of time preference.

We first focus on welfare analyzed with a global representative consumer. With $c_t = \frac{C_t}{P_t}$ world consumption per capita at time $t$, the discounted utilitarian global SWF is

$$W^G(c_t) = \sum_t P_t \frac{c_t^{1-\eta}}{(1+\rho)^{10t}(1-\eta)} \tag{2.6.1}$$

The social cost of carbon at time $T$ is then the ratio between the marginal impact of one additional ton of carbon on global welfare and the welfare cost of losing one unit of global consumption in $T$ (Nordhaus, 2014).

$$SCC_G(T) = \frac{\sum_{t \geq T} \Delta C_t \frac{\partial W^G}{\partial C_t}}{\frac{\partial W^G}{\partial C_T}} \tag{2.6.2}$$

The global social cost of carbon uses aggregate consumption at the world level, and thus cannot reflect inter- and sub-regional impacts of climate change.

Hence, we turn to a welfare function with quintile consumption. As in Dennig et al. (2015), inequality aversion is assumed to be equal across and within generations, as well as between and within regions.[4] With $c_{rqt} = \frac{C_{rqt}}{P_{rt}/5}$ consumption per capita for quintile $q$ in region $r$, the social welfare function is

$$W^Q(c_{rqt}) = \sum_{rqt} \frac{P_{rqt}}{(1+\rho)^{10t}} \frac{c_{rqt}^{1-\eta}}{(1-\eta)} \tag{2.6.3}$$

When going from the global scale, with an averaged measure of consumption, to a scale with heterogeneity in consumption, the question of the normalization of today's consumption arises. For instance, with consumption at the regional level, a normalization region (or another metric based on regional consumption) needs to be chosen. Because marginal utility of consumption is decreasing, the welfare cost of a unit of consumption is lower in richer regions than in poorer regions. As a result, the SCC mechanically increases when normalizing with the consumption of a richer region (Adler et al., 2017).

In addition, because the normalization term reflects the cost of not emitting an additional ton of carbon today, it can also be understood as the cost of mitigating at time $T$. Following the structure of the NICE model and the normative assumption of a globally impartial decisionmaker, we assume that the cost of mitigation is borne by regions in proportion to their consumption share in global consumption, and by quintiles in proportion to their consumption share in the region, weighted by the income-elasticity of mitigation costs $\xi_\Lambda$. Expanding the concept of a "World-Fair normalization" presented in Adler et al. (2017), the global social cost of carbon with quintile-level consumption then writes:

$$SCC_Q(T) = \frac{\sum_{t \geq T} \sum_r \sum_q \Delta C_{trq} \frac{\partial W^Q}{\partial C_{trq}}}{\sum_r \sum_q \pi_{rq} \frac{\partial W^Q}{\partial C_{Trq}}} \tag{2.6.4}$$

with $\pi_{rq} = \frac{C_{Tr}}{C_T} \left( \frac{C_{Trq}}{C_{Tr}} \right)^{\xi_\Lambda}$ the weight of quintile $q$ in region $r$ in the normalization.

[4] An alternative is the approach by Anthoff and Emmerling (2019), who disentangle the intertemporal inequality aversion from the regional inequality aversion.

# 3 Results

We turn to the main outcomes of our model along a business-as-usual scenario. When not stated otherwise, we use a decadal depreciation $\delta$ of 0.7, which is equivalent to compounding approximately 10% yearly depreciation .

We first quantify the effect of capital and labor damages on overall regional damages and persistence. Second, we report the distributional outcomes of channel-specific impacts and damage elasticities. Finally, we assess how the social cost of carbon responds to the persistence and distributive effects of the labor and capital damages.

## 3.1 Persistence and growth effects of labor and capital damages

We start by analyzing the effect of capital and labor damages on total damages, persistence of damages and output growth. To this end, we allocate up to 50% of recurring and instantaneous damages on the capital and labor stocks. For 50% damages on *both* input factors, $f_K = f_L = 0.5$, all damages are allocated between the two channels, and there is no direct output damage. No damages on either capital or labor, $f_L = f_K = 0$, reflects the case with only direct output losses and no additional persistence. We use this case as a counterfactual, by reporting total and persistent damages as a share of gross output when $f_Y = 1$, or equivalently when $f_L = f_K = 0$ (the exact definition of persistent damages can be found in subsection 2.4).

As shown in Table 1, both capital and labor damages yield a reduction in output with respect to the benchmark case. However, labor damages have a stronger effect than capital damages, in line with the results from Piontek et al. (2019)[5]. Indeed, allocating half of the damages to labor results in more than a doubling of total damages by 2105, whereas allocating half to capital results in a much smaller rise.

| $f_K \setminus f_L$ | 0 | 0.5 |
|---|---|---|
| 0 | 1.4-4.6% | 3.4-11.4% |
| 0.5 | 1.6-5.0% | 3.6-11.8% |

Table 1: Damages, as a share of gross output with damages only on output, for different channel-specific impacts, 2105, $\delta = 0.8$

We also find that the increase in overall output loss from labor and capital damages occurs proportionally to baseline damages in each region. Figure 2a shows total damages (as in Table 1) during the century and for the twelve regions. By 2100, channel-specific damages scale up the baseline damages, but do not affect the ordering of regions according to share of output lost.

Furthermore, the stronger effect of labor respective to capital damages is explained by the stronger persistence of labor damages. Figure 2b shows the share of losses which are due persistence, among total damages. With half of all damages falling on the capital stock, $f_K = 0.5$, persistent damages amount to around 10% by 2100, while they reach

[5] Piontek et al. (2019) test alternative channels by allocating 100% damages to each in turn. They find capital damages yield around 5% GDP loss, whereas non-dissipating labor productivity damages amount to around 20% loss.

60% of damages when $f_L = 0.5$. Shocks to labor thus accumulate more over time than shocks to capital.

Persistence of capital shocks hinges significantly on the rate of depreciation. A decrease of a third in decadal depreciation produces a three-fold increase in the share of persistent damages (Figure 12b, in the Appendix). Full depreciation within a decade would disperse the persistent effect of damages on the capital stock. We thus chose a calibration for the decadal depreciation rate that is lower than unity, and assume $\delta = 0.8$.

Finally, turning to per capita growth, the effect of persistent damages is relatively modest with respect to the long-run growth dynamic (Figure 3). In 2100, the damage function as in Dennig et al. (2015) results in damages of less than 5% of gross output for a warming of 3.5°C above pre-industrial levels. Although channel-specific impacts can produce a two-fold increase in total damages (Table 1), the absolute level of damages implies only a small growth deceleration (Figure 3b). Comparing our results to those of Moore and Diaz (2015), who calibrate capital damages to reproduce growth impacts estimates, the effects on growth are below those they find for poor regions, but closer to those for rich regions.

## 3.2 Distributional impacts of labor and capital damages

We now explore how channel-specific impacts change inequality and income levels of the most vulnerable populations. We make the assumption that pre-damage income shares within regions remain constant through time. We analyze the sub-regional distributional impacts from damages on labor and capital, as well as the role of labor income elasticity of labor damages, $\xi_L$ and capital income elasticity of capital stock damages, $\xi_K$. We first focus on the damage distribution with the Suits index [ADD], and then turn to impacts on global and regional inequality as well as the effect on the poorest within regions.

### 3.2.1 Global and regional inequality

We start by computing the global Gini index by pooling together all quintile consumption at the world level (Figure 4). In the absence of any channel-specific impact, the assumption of constant intra-regional inequality leads to a decrease in the global consumption Gini index, from 66 to 54%. Having half of total damages fall on capital stock and half on labor productivity produces a small increase in the global Gini index, of less than a percentage point (Figure 4 top right panel). As the elasticities of labor and capital damages with respect to respective income decrease towards negative values, reduction of the global Gini index is stalled. In the extreme case in which factor-specific damages borne by the quintiles are inversely proportional to factor-specific income (bottom left panel), the Gini decrease is halved.

To understand how global inequality is affected by labor and capital damages, we decompose inequality into a between region and a within region component. The Gini index is additively decomposable only if groups –here regions– have no overlap when ordering quantiles of all groups pooled together[6]. Given this condition is not satisfied in our case, we turn to Theil's L index (or Generalized Entropy with parameter 0), an additively decomposable measure of inequality (Shorrocks, 1980). Theil's L is more sensitive to changes

[6]For instance, the Gini is not additively decomposable if the richer quantile in the poorer group is richer than the poorer quantile in the richer group.

Figure 2: Impact of channel-specific damages on overall damages and on share of persistent damages, $\delta = 0.8.$, for capital and/or labor damages either 0 or 50% of damages. Panel a) shows the total damages in each regions, as a share of gross output in the counterfactual scenario with no persistence of damages. Panel b) shows the share of total damages which stem from the persistence of damages.

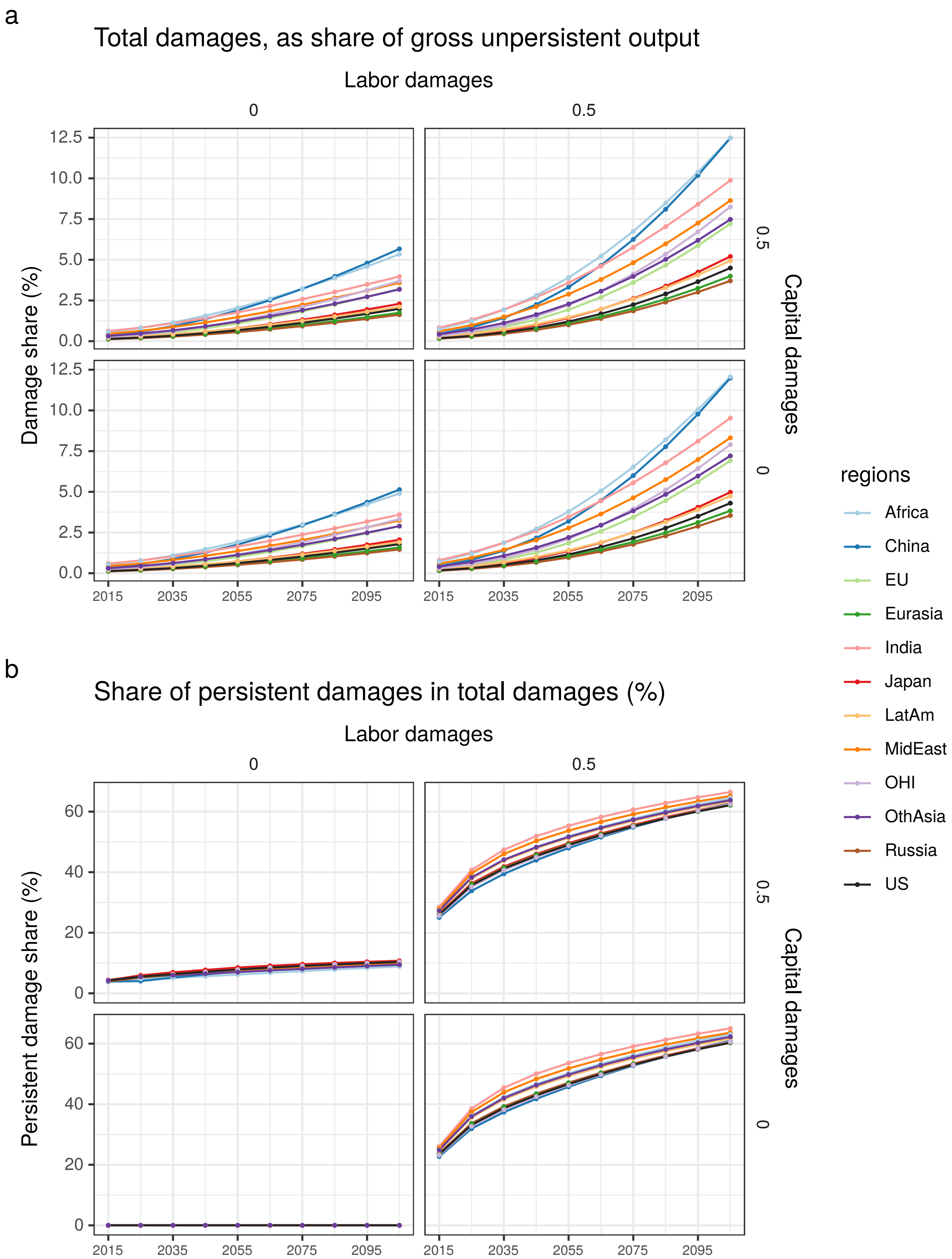


Figure 3: Regional output per capita and growth, with all damages falling on output ($f_L = 0$ and $f_K = 0$) or damages falling half on capital and labor ($f_L = 0.5$ and $f_K = 0.5$), $\delta = 0.8$

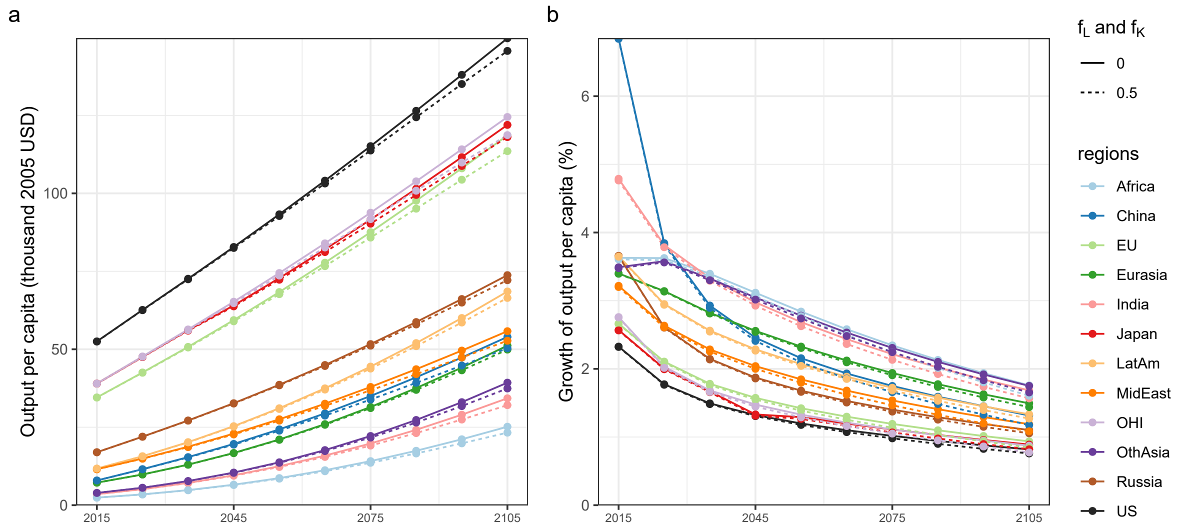
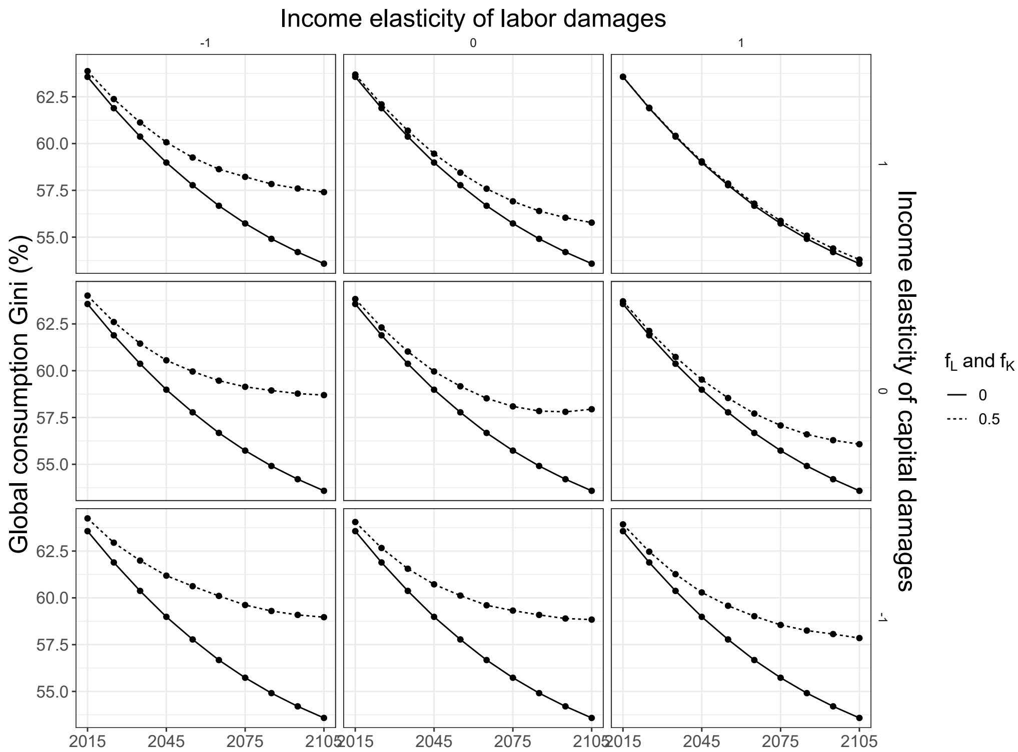



Figure 4: Global consumption Gini index for different levels of channel-specific damages and elasticities, with $\delta = 0.8$




in the lower end of the distribution. We find that the decline in inequality when damages are proportionally distributed is due to a reduction in inequality between regions, while more regressive damages implies a significant increase in within region inequality (Figure 5).

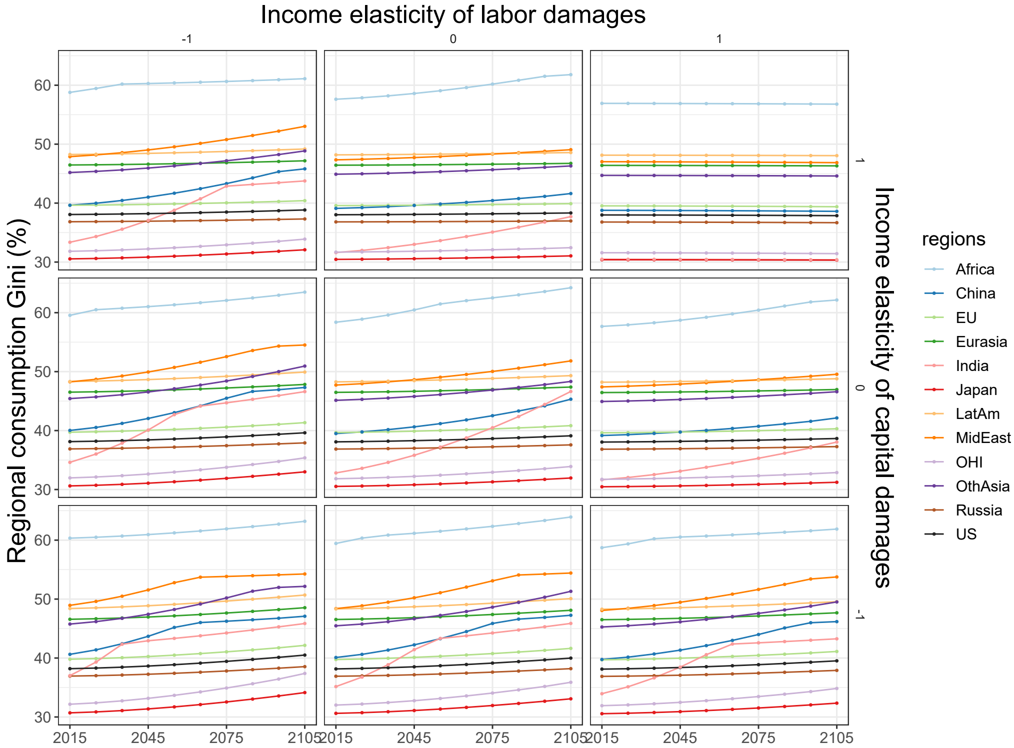
Next, we focus on the regional Gini index. At the regional level, inequality is not affected by aggregate patterns of growth, because the distribution of gross income is assumed constant across time. For a given level of labor and capital damages, regional Gini indices are more sensitive to changes in factor-specific elasticities than the global Gini index, with important regional heterogeneity (Figure 6). Regions that witness the largest change in the Gini are those who are most affected by climate change damages, and subsequently see the largest output losses due to persistent impacts (Figure 2a). Heterogeneous rates of increase in the Gini across regions leads to a re-ordering of countries accprding to within-region inequality. A striking example is India which goes from a low inequality (Gini of around 30-35%) to levels close to or above those of regions such as the US, EU or Russia (Gini of around 40%). Kinks appear in the evolution of the Gini index, for the most affected regions and with more regressive impacts. These kinks correspond to periods when current damages get sufficiently large to exceed the pre-damage income at the lower end the distribution. Although the impacts of unmitigated climate change continue to build up thereafter, consumption at the bottom of the distribution has reached a lower bound, which is reflected in the lower rate of increase in the regional Gini after the kink.

Figure 5: Global Theil L index, GE(0), for different elasticities, with $f_K = 0.5$ and $f_L = 0.5$, and $\delta = 0.8$


### 3.2.2 Distributional impact on the bottom quintile

We turn to the analysis of distributive outcomes at the quintile level, and in particular the impacts of channel-specific damages on consumption levels of the first—or "bottom", i.e. the poorest—quintile.

Figure 6: Regional consumption Gini index for different elasticities with half the damages on capital and half on labor ($f_K = 0.5$ and $f_L = 0.5$) and decadal depreciation $\delta = 0.8$

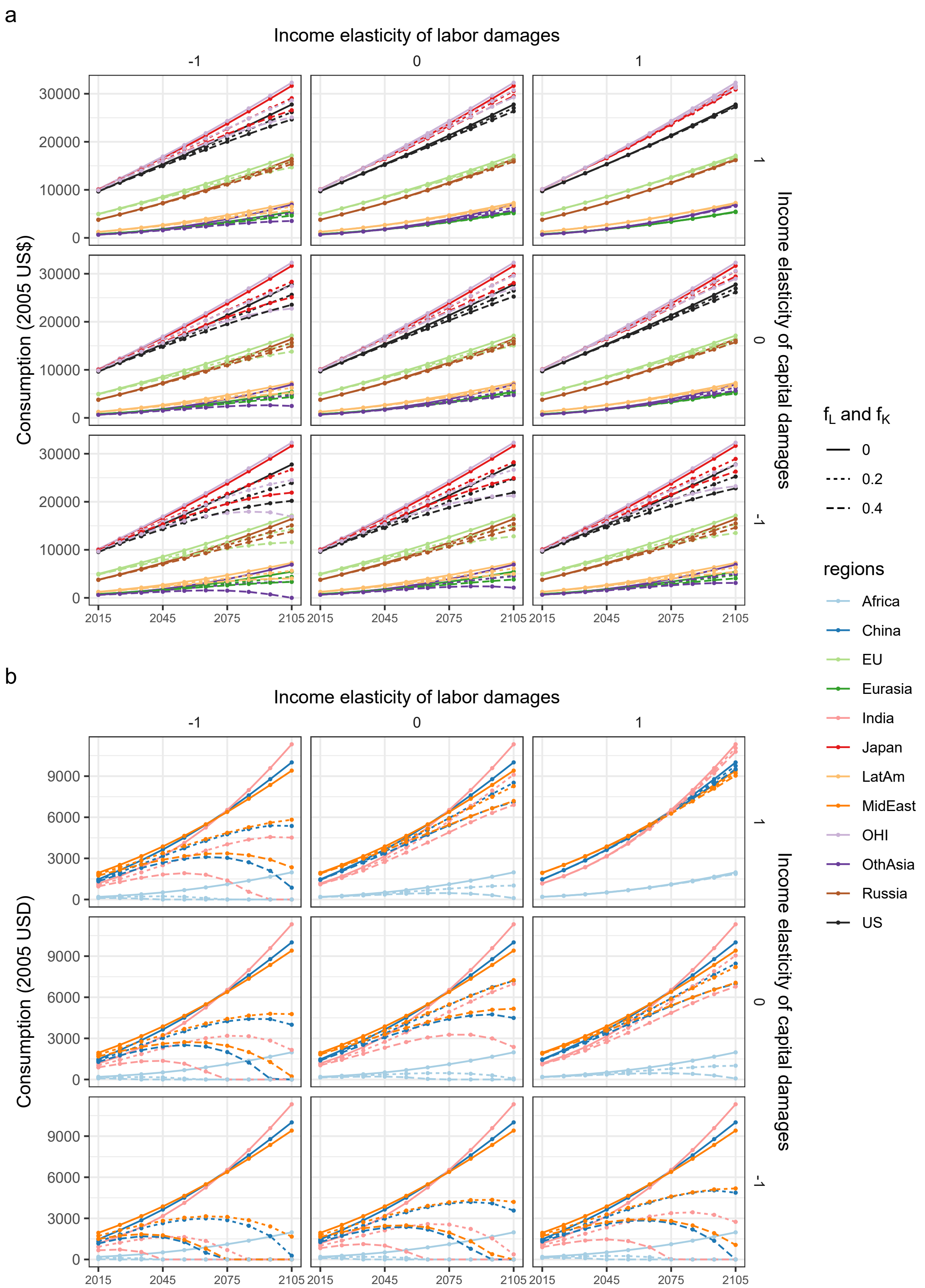



Starting with the consumption of households in the bottom quintile, we find very strong effects in four regions, and milder effects for the bottom quintile in other regions. Figure 7 displays consumption per capita for the two groups of regions, with different combinations of labor and capital damage shares and income-elasticities. For the first group of regions (Figure 7a), consumption per capita in the bottom quintile is projected to at least double by the end of the century. Although consumption is significantly reduced under more pessimistic scenarios (i.e. more channel-specific damages and lower elasticity), the future poor are generally found to be better-off than the current poor.

By contrast, in Africa, China, India, and the Middle East, which are the regions poised to suffer the most damages (Figure 2b), consumption per capita plummets to near-zero under a number of scenarios. With a respective share of capital and labor damages of 40% ($f_L = 0.4$ and $f_K = 0.4$), consumption starts declining before the end of the century when both labor- and capital- income elasticities are equal or below zero (Figure 7b, panels under the $\xi_L = 0$ and $\xi_K = 0$ diagonal). That is to say, when damages are equally split among quintiles ($\xi = 0$) or inversely proportional ($\xi = -1$).

Capital and labor damages elasticities do not produce symmetrical impacts. Regressive capital damages reduce consumption more rapidly and strongly than regressive labor damages (e.g. compare top left and bottom right panels of Figure 7b). Capital income is more unequally distributed than labor income. With an elasticity of damages zero or lower, the gap between the original distribution and the elasticity-transformed distribution is wider when the original distribution is more unequal. Thus, a given level of elasticity (when zero or lower) implies a larger damage burden borne by the poorest quintiles when it applies to capital damages than to labor damages. Elasticities also produce heterogeneous impacts across regions, reflecting different joint distributions of labor and capital income.

Figure 7: Consumption per capita of the first quintile for different levels of channel-specific damages and elasticities, $\delta = 0.8$



To disentangle the different determinants of the distributional impacts from labor and capital incomes, damages and elasticities, we take a closer look at the engine of distribution in our model: the net income distribution mechanism (eq. 2.5.5). Pre- damage and abatement labor and capital income distributions are assumed constant across time. We can thus investigate the effect on the net income share of labor and capital damages. Figure 8 shows the change in the net income share of the first quintile in the four most affected regions, for different levels of labor and capital damage shares, and focusing on damages elasticities of 1 or 0.5. Elasticities of 0.5 yield a damage share between the original income share and a fifth of the damages.

First, when damages are strictly proportional to the share in the corresponding factor-income ($\xi_L = \xi_K = 1$), a larger portion of the damages falling on capital produces a slight increase in the income share for the first quintile (Figure 8b). This is because the first quintile hardly earns any capital income (Figure 11). In this case of proportionality, having damages falling on the capital stock instead of directly on output, transfers part of the damage burden to the capital earners i.e. away from the first quintile.

Second, for this range of elasticities labor damages have a stronger impact on the income share loss than capital damages. This can be seen by the stronger income share loss from disproportionate labor damages than disproportionate capital damages (Figure 8a and c), as well as the strongest gradient along the labor damage portion when both have an elasticity of 0.5 (Figure 8c). Labor productivity damages are thus both more persistent and more damageable to the more vulnerable.

## 3.3 Impact of capital and labor damages and their distribution on the social cost of carbon

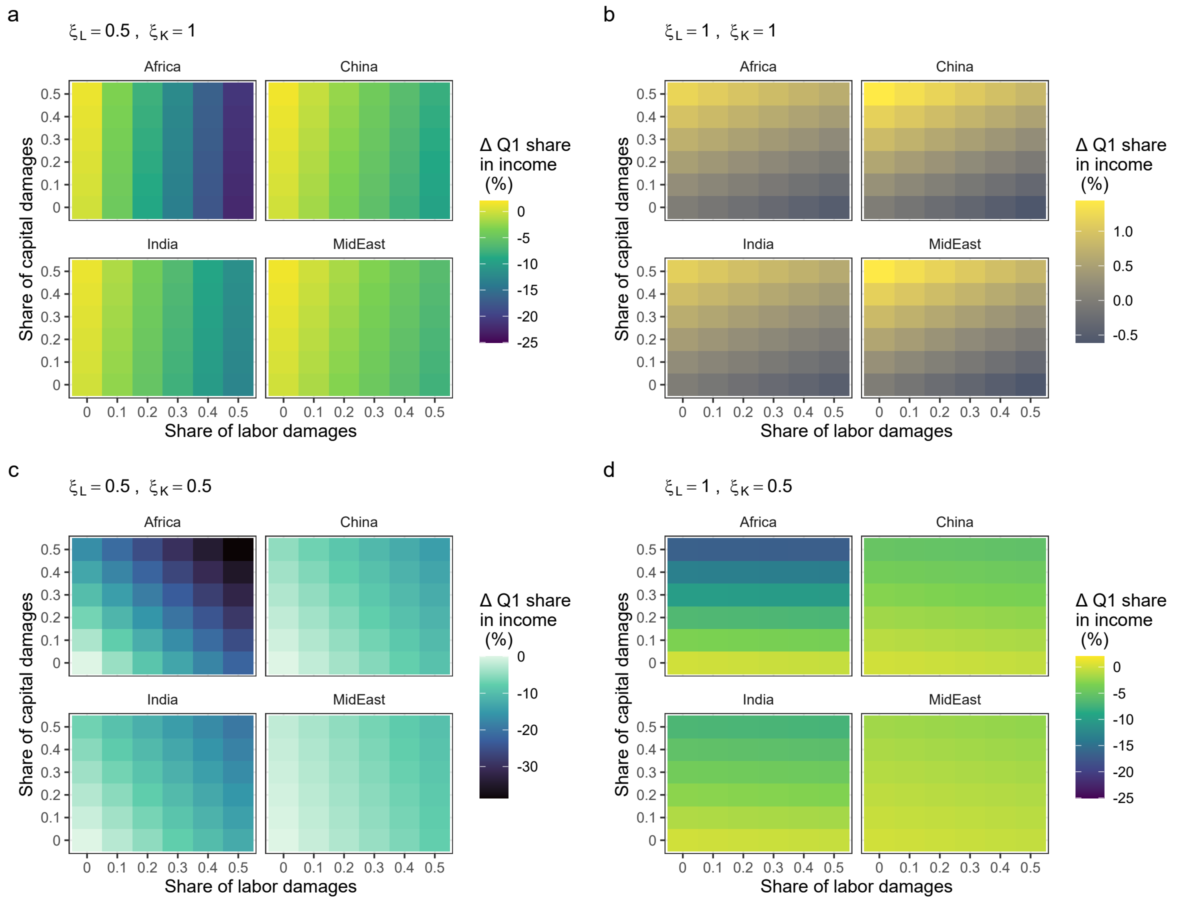
We now analyze the influence of the channel-specific damages and the resulting distributional impacts on the social cost of carbon (SCC) based on global and quintile consumption per capita (CPC).

Table 2 summarizes the results for the two SCCs in 2025. The SCC based on global CPC without damages on capital nor labor is around 51 dollars. If damages fall completely on capital and labor (with a share of 50% respectively), the SCC is 2.2 times larger. With a capital (labor) damage share of 0, a rise of the labor (capital) damage share from 0 to 0.5 yields a rise of 113% (6%) in the SCC based on global CPC. In line with the results in Table 1, an increase in the labor damage share has a larger impact on the SCC based on global CPC than a similar increase in the capital damage share because of the higher persistence of labor damages.

| $f_K \backslash f_L$ | 0 | | 0.5 | |
|---|---|---|---|---|
| | $SCC_G$ | $SCC_Q$ | $SCC_G$ | $SCC_Q$ |
| 0 | 51 | 42 | 109 | 101 |
| 0.5 | 54 | 38 | 112 | 96 |

Table 2: Social cost of carbon with global consumption per capita ($SCC_G$) and quintile consumption per capita ($SCC_Q$) for different channel-specific impacts (2025), in 2005 PPP USD and with $\delta = 0.8$, $\rho = 0.015$, $\eta = 2$.

Figure 8: Change in the income share of the first quintile, from pre-damage to net income distribution, for different levels of channel-specific damages and elasticities, 2105, $\delta = 0.8$



The evaluation of the SCC based on global CPC neglects between- and within-regional inequality. Therefore, we turn next to the analysis of the SCC based on quintile CPC within regions. We evaluate this SCC with the same inequality aversion within and across regions.

Comparing the quintile consumption SCC with the SCC based on global CPC without damages on the input factors in Table 2, the SCC is almost 18% smaller when derived based on quintile CPC.[7] If damages fall on the input factors, the SCC based on quintile CPC shows, in general, a similar behavior as the SCC based on global CPC. The SCC reacts more strongly to a change of the labor damage share (140% increase) than to a change of the capital damage share (10% decrease). .

Focusing on the relative increase of the SCC, the quintile CPC based SCC reacts more to 50% damages on labor than the SCC based on global CPC. With 50% damages on capital, the quintile CPC based SCC is lower, whereas the SCC based on global CPC is higher compared to the case without damages on labor or capital. This is caused by the change in the income distribution observed in Figure 8b. As damages are assumed to fall proportionally with income shares, poorer quintiles suffer from an increased (lower) portion of damages if the damage share of labor (capital) is higher. In turn, this leads to a rise (decrease) of the SCC additional (contrary) to the impact of the channel-specific persistence effect on total damages observed with the global SCC.

We now extend the analysis to a range of labor and capital damage shares between 0 to 0.5. Figure 9 displays the SCC based on global and quintile CPC.[8] The figure shows that the two methods yield, in general, a similar pattern for the SCC over the analyzed range. For both methods, the labor share is more influential than the capital share. In addition, the effect of an increase of the labor share is positive for both SCC. For the capital share, however, the effect is slightly positive (negative) for the SCC based on global (quintile) CPC.

In the previous evaluation, we assume proportionality of the damage distribution. We now consider combinations of channel-specific elasticities of $\xi = 1$ and $\xi = 0.5$. Figure 10 displays the SCC based on quintile CPC for varying damage shares and the different combinations of channel-specific elasticities.

To investigate whether the labor or the capital damage elasticity has more impact on the SCC, we first compare panels a and d. Figure 10a shows the results for a scenario with regressive damages on labor income and proportional on capital income, panel d for a scenario with mirrored elasticities. In line with the findings in Figure 8 on the effect of elasticities on the net income distribution, labor productivity damages are more important for the SCC. We find a more pronounced effect of a regressive distribution of labor income damages combined with a proportionate distribution of capital income damages on the SCC with increasing labor damage share (panel a) than for the mirrored elasticities with increasing capital damage share (panel d). We see the same result in panel c with regressive distribution of damages on both income factors. An increase in the labor damage share has a more pronounced impact on the SCC than a rise in the capital damage share.

A rise in the capital damage share increases the SCC if capital damages are regressive

[7]Whether taking into account intra-generational inequality decreases or increases the SCC, depends on damages and mitigation cost distribution, growth assumptions, and normative assumptions— inequality aversion and the pure rate of time preference—(Budolfson et al., 2017).

[8]The contribution of each effect is contingent upon the choice of the normative parameters, inequality aversion and pure rate of time preference.

Figure 9: The social cost of carbon based on global consumption per capita (CPC) and quintile CPC welfare function for different levels of channel-specific damages, 2025, $\delta = 0.8, \eta = 2, \rho = 0.015$

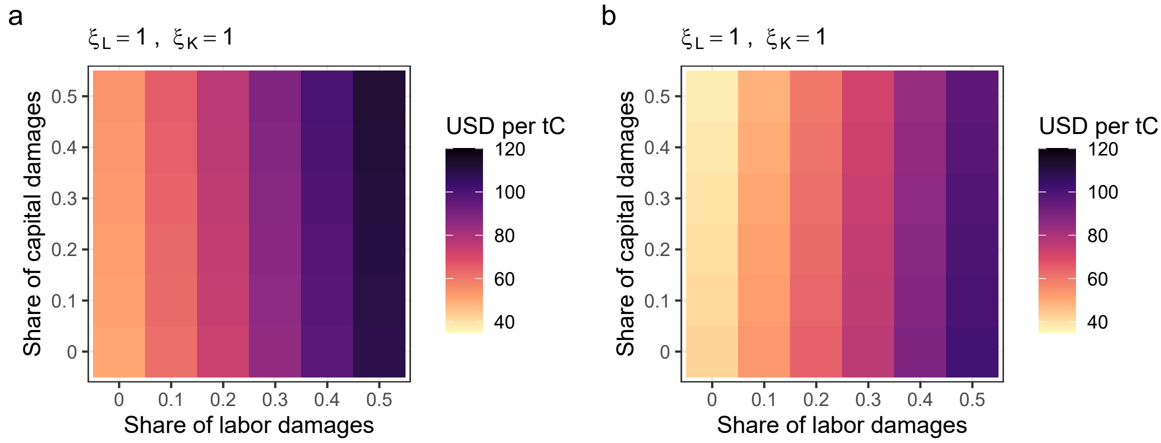
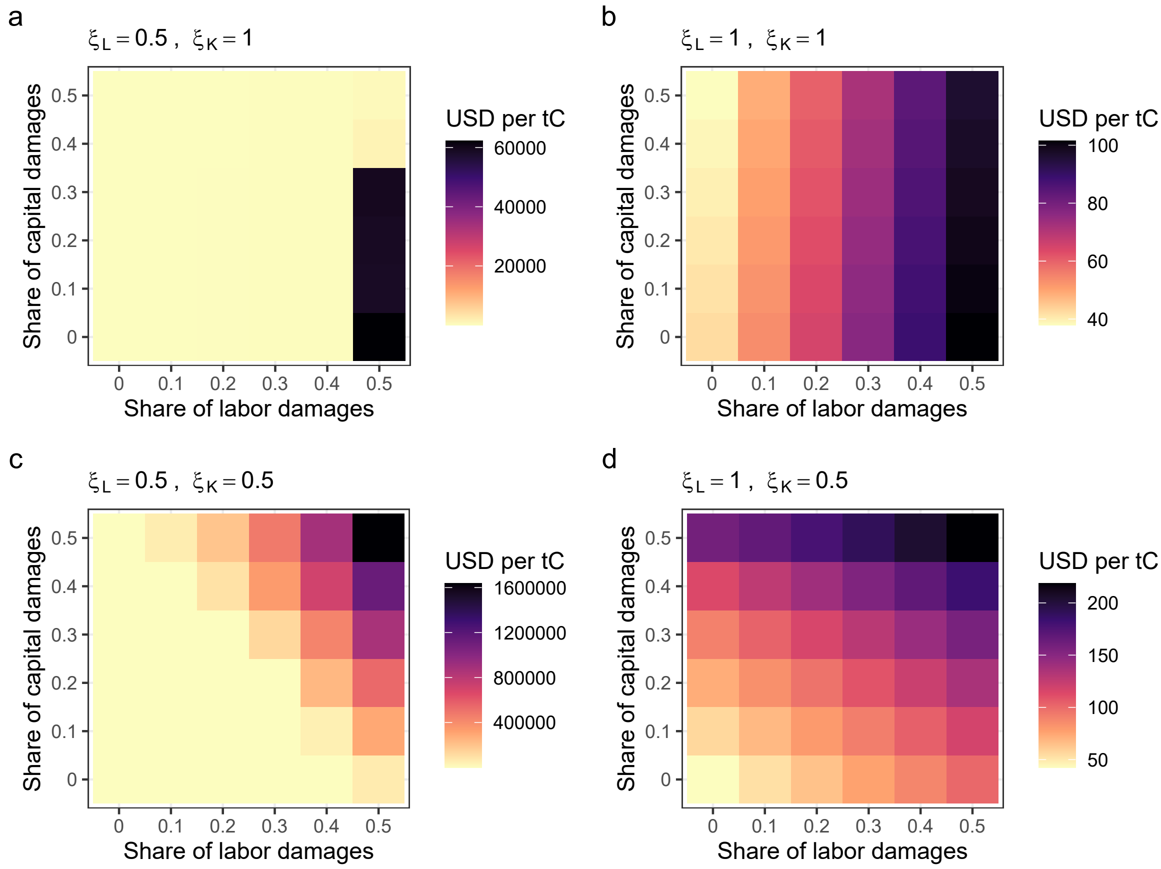



Figure 10: The social cost of carbon with quintile-level welfare function for different levels and elasticities of channel-specific damages, 2025, $\delta = 0.8$, $\eta = 2$, $\rho = 0.015$




(Figure 10c and d). This effect goes in the opposite direction than the one observed with proportionate capital damage distributions. It implies that, for sufficiently regressive capital damage distributions, the aggregate and the distributive effect of capital damages work in the same direction and increase the SCC.

In general, Figure 10 displays that the damage distribution is more important for the SCC than an increase of the capital or labor damage share. The SCC estimates are more than one order of magnitude larger if capital (labor) damages are regressive and damages fall partly on capital (labor) compared to the SCC with proportionate distribution of damages.

# 4 Concluding Remarks

We study how introducing channel-specific damages and composition of income impacts inequality, the well-being of the future poor, and ultimately the social cost of carbon. We split both income and damages into a capital and a labor component, and parametrize the proportionality of damages. As a result, the model encompasses damages that interact with the labor, capital, and total income distributions, and are endogenously persistent.

We show that the impact of capital and labor damages on inequality and the social cost of carbon is driven more by the income composition effect than by the persistence of damages. If the share of channel-specific damages falling on the poor is disproportionate without being inversely proportional—i.e. for an income-elasticity of damages between 0 and 1—labor damages are more regressive than capital damages. Overall, we find that damages that hit labor productivity tend to lead to more regressive outcomes and to be more persistent. A slight disproportion (income-elasticity of 0.5) in the damages is sufficient to increase the SCC by up to two orders of magnitude.

Our results remain conditional on a number of assumptions. The first set is needed to deal with the paucity of data on the source of incomes with global coverage and consistent definitions. We assume equal ranking across the consumption, labor income, and wealth distributions, as well as fixed factor share and consumption to income scaling factor. The constant factor share assumption could be revised in two ways. First, it could be interpreted in a neo-classical fashion as reflecting relative factor prices, as in Piontek et al. (2019). In this vein, a shock on the stock of either capital or productive labor would increase the relative price of the shocked input, the share of this factor in income, and ultimately earnings. Our findings could be mitigated or magnified, depending on whether the effect of the endogenous factor share is aligned or opposed to the effect from the damage distribution. Second, the labor share could be estimated from empirical data and projected based on variables in the shared socioeconomic scenarios (SSP). For instance, it could take into account the role of labor-enhancing versus capital-enhancing technical change for the labor share. This could affect the magnitude of our results depending on the distance to the baseline assumption of a 70% labor share. Next, the income scaling factor needed to capture the gap between income and consumption could be modeled with more precision. With estimates of the relative effect of differential savings versus tax and redistribution systems, an avenue of research on the role of consumption smoothing and welfare states in socioeconomic vulnerability could be opened.

The second set of assumptions in our analysis relates to the distribution of future damages. First, our baseline inequality, which serves as basis for the damage distribution, is assumed constant across time. Although this assumption enables us to focus on the gap between pre- and post- damage distributions, introducing scenarios for future inequality would enrich the outcomes of the model. In particular, inequality could be projected following the SSP scenarios developed by Rao et al. (2019), with the use of additional assumptions for the evolution of the labor and capital income components. Second, the basis for the distribution of damages could be developed by including further insights from the empirical literature on ongoing climate impacts.

Our income decomposition remains a coarse approach to the many factors that determine the distributional effects of climate policies. Future work could expand our framework of disentangled damages and inequality to include these other factors, further improving policy advice based on Integrated Assessment Models.

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# A Additional Material

Figure 11: Calibrated distributions for capital income, labor income, total income and consumption

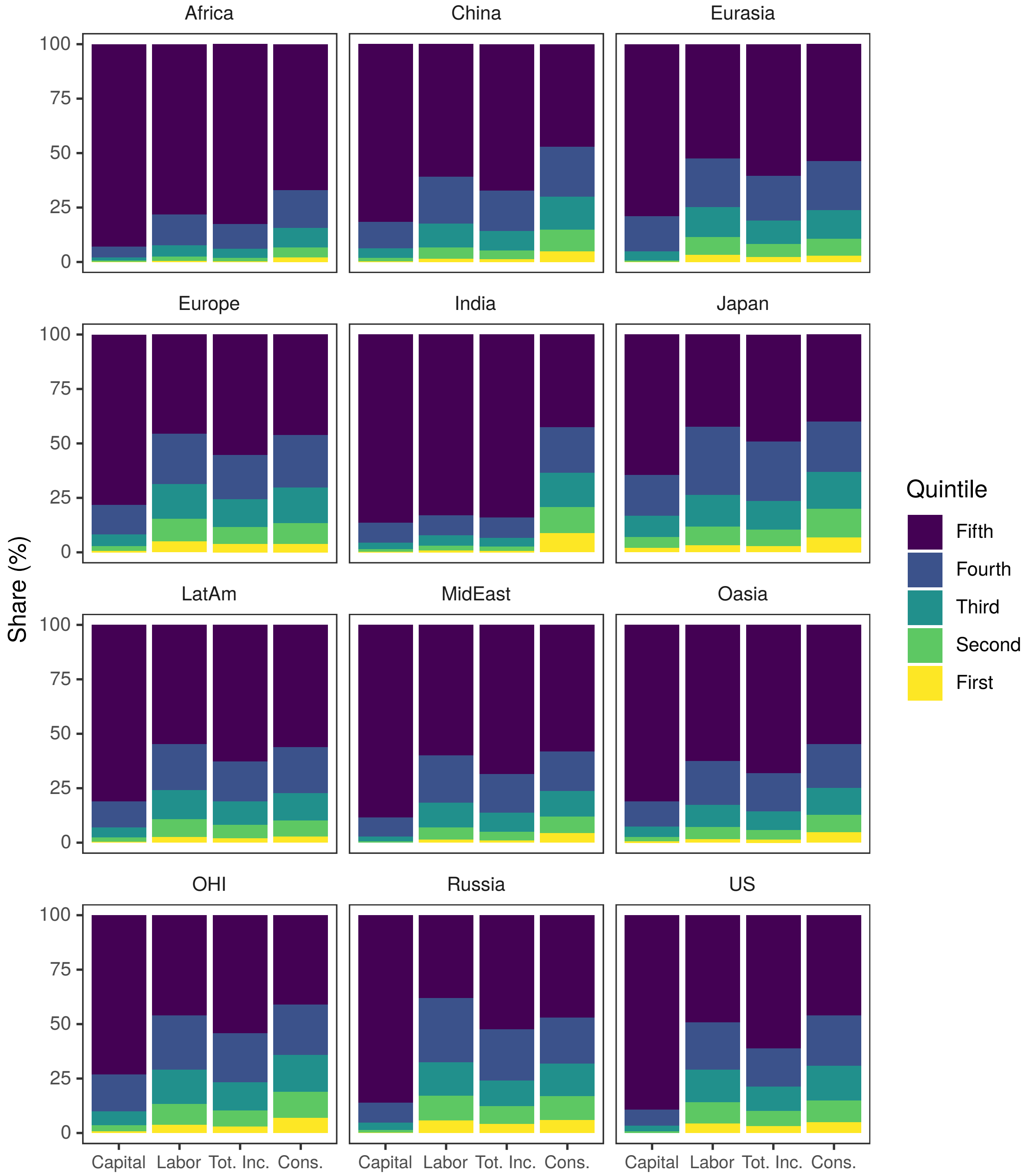

Figure 12: Capital damages and depreciation rates