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. 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 (SCC) 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 SCC (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.

Representing these sources of inequality is key to better incorporate the growing evi-

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

dence 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 capital and labor damages lead to more persistent damages, and to small but sustained growth effects at the regional level, which result in sizeable output losses through compounding effects. In addition, our results show that the allocation of the burden of channel-specific damages across the income distribution has strong impacts on inequality and on the livelihoods of the future poor. We rely on the existing empirical literature to find a plausible range for the income-elasticities of damages. We find that the growth effects of damages hitting the capital stock and labor productivity dominate the distributional effects on the social cost of carbon at low levels of regressivity. The opposite is true at higher regressivity levels: the social cost of carbon is then much 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 SCC. 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. Initial capital and output levels are calibrated using Penn World Table data. The trajectory of total factor productivity is then calibrated to match the "Middle of the road" Shared Socioeconomic Pathways (SSP) scenario. Resulting baseline output per capita and growth are shown in Figure A3.

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 Λ_{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 SCC 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 δ (the model has ten year time-steps)

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

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. Population grows according to UN population projections (United Nations, 2019).

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

[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.

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 α 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

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

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 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 A1 displays the input data for labor and capital income distribution.

To account for the future evolution of the income distribution, we follow the inequality projection in the "Middle of the road" Shared Socioeconomic Pathways (SSP) scenario, SSP2 (Rao et al., 2019). In this scenario, historical trends are continued. Income inequality is assumed to persist or slowly improve, and development trends remain heterogeneous (Fricko et al., 2017).

These trends describe the evolution of total income inequality, so we use the Gini decomposition method introduced by Rao (1969) and Kakwani (1977) to project inequality by income type. With equal ranking between income components and total income, the total income Gini is given by the sum of the income component Gini coefficients weighted with the share of this component in total income. The change in the total income Gini is

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

then given by

$$\frac{dlog(G_I)}{dt} = \frac{\Delta G_I}{G_I(t)} = \frac{\Delta(\sum_{i=1}^{I} s_i G_i)}{G_I(t)} = \frac{\alpha \Delta G_K + (1-\alpha)\Delta G_L}{G_I(t)} \tag{2.2.6}$$

We decompose changes by assuming that the change in the Gini for total income is equal to the sum of the change in the Gini for capital income and the change in the Gini for labor income, each weighted by the factor income shares (α and $1-\alpha$). Then, the absolute change of an income channel Gini equals the absolute change of the total income Gini:

$$sh_{i_{\Delta G_I}} = \frac{\frac{s_i \Delta G_I}{G_I(t)}}{\frac{dlog(G_I)}{dt}} = \frac{s_i \Delta G_i}{\Delta G_I}, sh_{i_{\Delta G_I}} = s_i \rightarrow \Delta G_i = \Delta G_I \tag{2.2.7}$$

The resulting evolution of capital and labor income shares in each region are depicted in Figure A2. Consistent with evidence on factor income distribution, our calibration features a more unequal distribution of capital income than labor income in most regions.

Income is more unequally distributed than consumption (e.g. World Bank (2016)) because of consumption smoothing, redistribution and consumption of public goods, etc. To capture this expected discrepancy, we estimate an elasticity of consumption share with respect to income share for each region from our calibrated income shares and World Income Inequality Database consumption shares for 2019.

2.3 Aggregate damages

Damages from climate change on gross output result from a temperature increase above the pre-industrial level. We model the global temperature response with the Finite Amplitude Impulse Response model (FaIR, v2.0.0) developed by Leach et al. (2021). The FaIR model is a simplified climate model estimating radiative forcing and temperature increase from greenhouse gas emissions such as CO_2, CH_4, and others. The main advantage of the FaIR model compared to the RICE climate model previously used in the NICE model is the state dependency of the model. The FaIR model represents state dependency through feedback loops in the carbon cycle. Feedback loop implementation is necessary to obtain radiative forcing estimates close to those of more complex Earth system models. We use the Julia implementation from Errickson et al. (2022) based on the default model by Leach et al. (2021). As in Errickson et al. (2022), we assume that non-CO_2 emissions follow the SSP2-45 scenario. Recent assessments of the SCC deploy the FaIR model to estimate the global temperature increase (e.g. Rennert et al. (2022); Hänsel et al. (2020); Rode et al. (2021); Barrage and Nordhaus (2023)).

Damages from the resulting global temperature increase are assumed to follow a quadratic function with temperature

$$D_{rt} = \lambda_{1r}(T_t - \bar{T}_{1986-2005}) + \lambda_{2r}(T_t - \bar{T}_{1986-2005})^2 \tag{2.3.1}$$

with λ_{1r} and λ_{2r} the region-specific damage parameters, T_t the temperature anomaly with respect to preindustrial levels, and $\bar{T}_{1986-2005}$ the average temperature anomaly of the period 1986 to 2005 with respect to preindustrial levels. We calibrate λ_{1r} and λ_{2r} based on the regional COACCH damage functions and employ the results from the 50th quantile regression of a quadratic fit with optimal adaptation to sea level rise for the REMIND model (Van Der Wijst et al., 2023). Due to differences in the regional aggregation between the REMIND and the NICE model, we map the regional damage estimates to each country within a REMIND region. We then estimate new regional coefficients for the NICE regions based on a GDP-weighted regression. The COACCH damage function calculates damages for temperature increases above the global temperature increase between 1986 and 2005.

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, we consider that 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

$$(1 - D^G_{rt}) A_{rt} L^{1-\alpha}_{rt} K^{\alpha}_{rt} \tag{2.4.1}$$

can be rewritten as

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

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

$$K^N_{rt} = (1 - D^G_{rt})^{\frac{f_K}{\alpha}} K_{rt} \tag{2.4.3}$$

$$L^N_{rt} = (1 - D^G_{rt})^{\frac{f_L}{1-\alpha}} L_{rt}. \tag{2.4.4}$$

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. We parametrize the extent to which shocks to labor persist from one period to the next, with λ between 0 (full and instantaneous dissipation of the shock) and 1 (no dissipation of the shock). Given that labor grows at the same rate as population, we get:

$$L_{rt} = \left(1 - \lambda\left(1 - \frac{L^N_{r,t-1}}{P_{r,t-1}}\right)\right) P_{rt}. \tag{2.4.5}$$

When $\lambda = 0$, labor is equal to population in the region. When $\lambda = 1$, population in a region at time t is multiplied by the ratio of net labor to population in $t-1$.

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

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 ξ reflecting how proportional damages are with respect to the specific income distribution. ξ_i equivalently captures the income-elasticity of damages in absolute terms, and the elasticity between the quintile's share in income of type i, $sh^{Y_i}_q$ and the quintile's share in damages of type i, $sh^{D_i}_q$, i.e.

$$\xi_i = \frac{\partial \ln d^i_q}{\partial \ln y^i_q} = \frac{\partial \ln sh^{D_i}_q}{\partial \ln sh^{Y_i}_q}, \tag{2.5.1}$$

with $i \in \{L, K, Y\}$ and d^i_q the damages of type i hitting quintile q. An income-elasticity ξ 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 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).

Evidence for damage disproportionality indicates that the income-elasticity of climate damages 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 heat stress related income losses in Australia showed that the most expensive productivity loss in absolute value corresponded to the higher payed occupations, although 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 capital (or asset) damages, most of the available evidence concerns physical capital impacts, mainly through studies of natural disasters. To the best of our knowledge, very little is known about how climate change will impact financial assets. 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). Insurance take-up also tends to be lower (e.g. Kousky (2019)). 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

$$\begin{aligned} \mathrm{sh}_{rqt}^{Y^N} &= \frac{y_{rqt}^N}{Y_{rt}^N} && (2.5.4) \\ &= \frac{\left(\mathrm{sh}_{rqt}^Y - \mathrm{sh}_{rqt}^D D_{rt}^G\right) Y_{rt}^G}{(1 - D_{rt}^G) Y_{rt}^G} && (2.5.5) \end{aligned}$$

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 $\mathrm{sh}_{rqt}^{Y^N}$ with the income-to-consumption scaling factor β yields the share of quintile q in regional consumption

$$\mathrm{sh}_{rqt}^C = \frac{\beta_{rq} \mathrm{sh}_{rqt}^{Y^N}}{\sum_q (\beta_{rq} \mathrm{sh}_{rqt}^{Y^N})}. \quad (2.5.6)$$

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

2.6 The social cost of carbon

The SCC 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: η captures aversion to inequality (inter- and intra-generational) and ρ 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

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

The SCC 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).

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

The global SCC 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

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

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

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 ξ_Λ. Expanding the concept of a "World-Fair normalization" presented in Adler et al. (2017), the global SCC 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.

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 δ of 70%. $\delta = 0.7$ is equivalent to compounding approximately a yearly depreciation of 10%, which is the depreciation rate used in RICE. We also set the yearly persistence of labor to $\lambda = 0.5$, meaning that half of damages hitting labor do not dissipate from one year to the next.

We first quantify the effect of capital and labor damages on overall regional damages and persistence of output losses. Second, we report the distributional outcomes of channel-specific impacts and income-elasticities of damages. Finally, we assess how the stronger persistence of damages hitting labor productivity and capital damages and their distributive outcomes affect the the social cost of carbon (SCC).

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 100% of recurring and instantaneous damages on the capital and labor stocks. We define our counterfactual "unpersistent" case to be when there are no damages on either capital or labor but only direct output losses, i.e. $f_Y = 1$, or equivalently $f_L = f_K = 0$. In the rest of this section, we report total and persistent[5] damages as a share of gross output in this counterfactual case, which we call *unpersistent gross output*.

Table 1 displays the ranges of damages as a share of unpersistent gross output for the twelve regions and for different allocations of damages across the output, capital and labor channels. In the unpersistent case ($f_Y = 1$), regional damages as a share of gross

[5]The exact definition of persistent damages can be found in subsection 2.4.

output fall in the $3.2 - 13.8\%$ range . The most affected region is India, followed by Africa and the Other Asia region (Figure A4a). Next, we compare the effect of assigning 10% of all damages to the capital versus the labor channel. As shown in Table 1, for 10% channel-specific damages, capital damages have a stronger impact than labor damages on regional damage shares.

$f_K \backslash f_L$	0	0.1	0.5	0.7
0	3.2-13.8%	3.6-15.4 %		
0.1	5.7-22.4%	6-23.8%		
0.3				11.9-39.5%
0.5			14.6-43.4%	

Table 1: Range of regional damages as a share of regional unpersistent gross output, for different channel-specific impacts, 2100, $\delta = 0.7$, $\lambda = 0.5$.

We also find that the increase in overall output loss from labor and capital damages occurs proportionally to baseline damages in each region. Figure A4a shows total damages as a share of gross unpersistent output differentiated by region. 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 effect of channel-specific damages on total damages and on the persistence of damages depends on the depreciation rate of capital δ and on the persistence of labor damages λ. Figure A5 displays the percentage share of total damages in gross unpersistent output (panel a) and the percentage share of persistent damages in total damages (panel b), for a range of decadal depreciation and persistence of labor damage values. Reducing the decadal depreciation rate δ, or increasing the rate of persistence of labor damages λ, increases the total damage share in every region (Figure A5a), as well as the share of persistent damages in total damages (Figure A5b). A decadal capital depreciation rate of 0.8 (approximately equivalent to a compounded yearly depreciation rate of 0.15) and a labor damage persistence rate of 0.3 result in a share of persistent damages in total damages of 72-80% between 2040 and 2100, whereas a decadal depreciation of 0.6 (approximately equivalent to 0.09 yearly) and a labor damage persistence of 0.7 result in a share of persistent damages of 82-90% between 2040 and 2100.

Compared to the results in Piontek et al. (2019), our findings differ in two main aspects. First, our overall damage levels are larger. This can be explained by the update in the damage function from the standard DICE function (Nordhaus, 2014) to a regional COACCH damage function (Van Der Wijst et al., 2023). Second, contrary to what we find, Piontek et al. (2019) show labor and productivity damages have a stronger impact than capital damages on output losses. This is likely due to differences in the capital depreciation rate, the (implicit or explicit) persistence level of shocks to productive labor, and to compounding effects of different time steps.

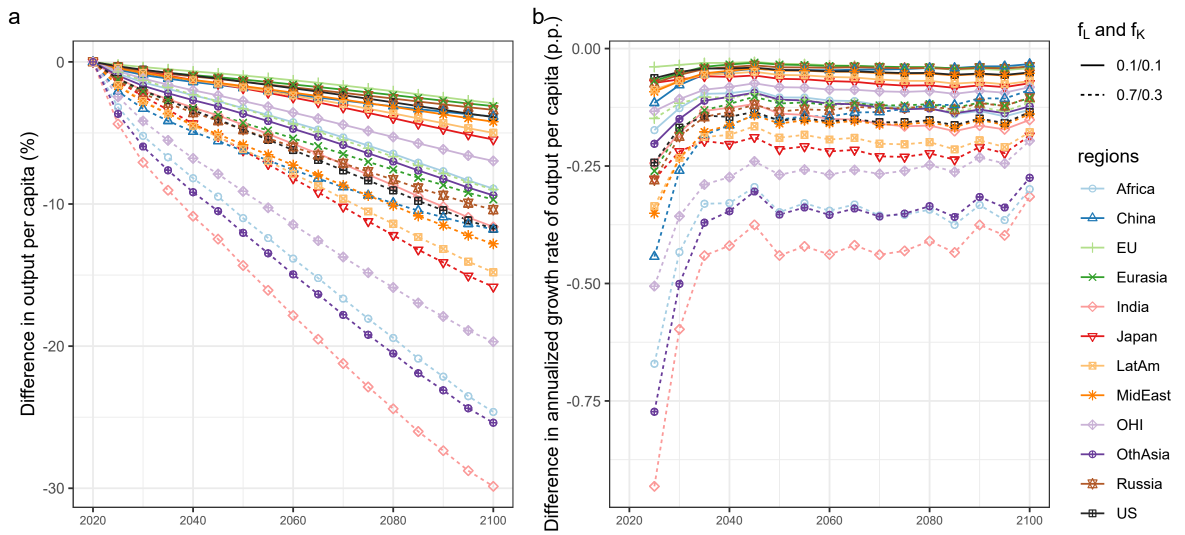
Next, we find that channel specific damages result in both level and growth effects on per capita output. Figure 1a shows the difference in regional output per capita with respect to the baseline case with damages falling only on output, and Figure 1b shows the difference in annualized growth of per capita output.

First, a damage composition with 10% on the capital channel and 10% on the labor channel results in continuously increasing level effects, with a reduction in regional output per capita between 3 and 12% in 2100. India, Africa and the Other Asia regions are the most affected, with reductions greater than 9%. In term of growth effect, this case with $f_L = 0.1$ and $f_K = 0.1$ results in long term reductions in annualized growth of less than 0.25 percentage points.

Second, we assign 100% of damages to the factor-specific channels, keeping the damage composition proportional to the production factor shares. This results in a level effect of over 9% in all the regions, with India, Africa and the Other Asia regions suffering an output per capita loss of over 24%. Growth effects are larger in the first periods and converge during the century to reductions in annualized regional growth rates approximately between 0.1 and 0.3 percentage points. The regional variation in level and growth effects reflects regional heterogeneity in overall climate change damages, with India, Africa and the Other Asia regions more affected by climate damages (Figure A4a).

Moore and Diaz (2015) introduce growth effects in the DICE model by calibrating reductions on total factor productivity growth and capital depreciation with empirical estimates of temperature impacts on GDP growth. In comparison to their findings, our scenario with 100% of damages falling on capital and labor channels in proportion to factor shares results in lower level and growth effects. For poor regions, they find a reduction of 40% in per capita output, and a reduction in the growth rate of 0.8 percentage points on average. For richer regions, our results are much closer, as they also find a level effect of around 10%.

Figure 1: Difference in regional output per capita level and growth, compared to the case with damages falling on output only ($f_L = 0$ and $f_K = 0$), $\delta = 0.7$ and $\lambda = 0.5$.



3.2 Distributional impacts of labor and capital damages

We now explore how channel-specific impacts affect inequality and income levels of the most vulnerable populations. We analyze the sub-regional distributional impacts from damages on labor and capital, as well as the role of the labor income elasticity of labor damages, ξ_L and capital income elasticity of capital stock damages, ξ_K. We first focus on the damage distribution with the Suits index, and then turn to impacts on global and regional inequality as well as the effect on the poorest within regions.

3.2.1 Suits index of progressivity of climate damages

The distribution of damages overall can be synthesized by applying the Suits index (Suits, 1977) to the damage shares (2.5.2)

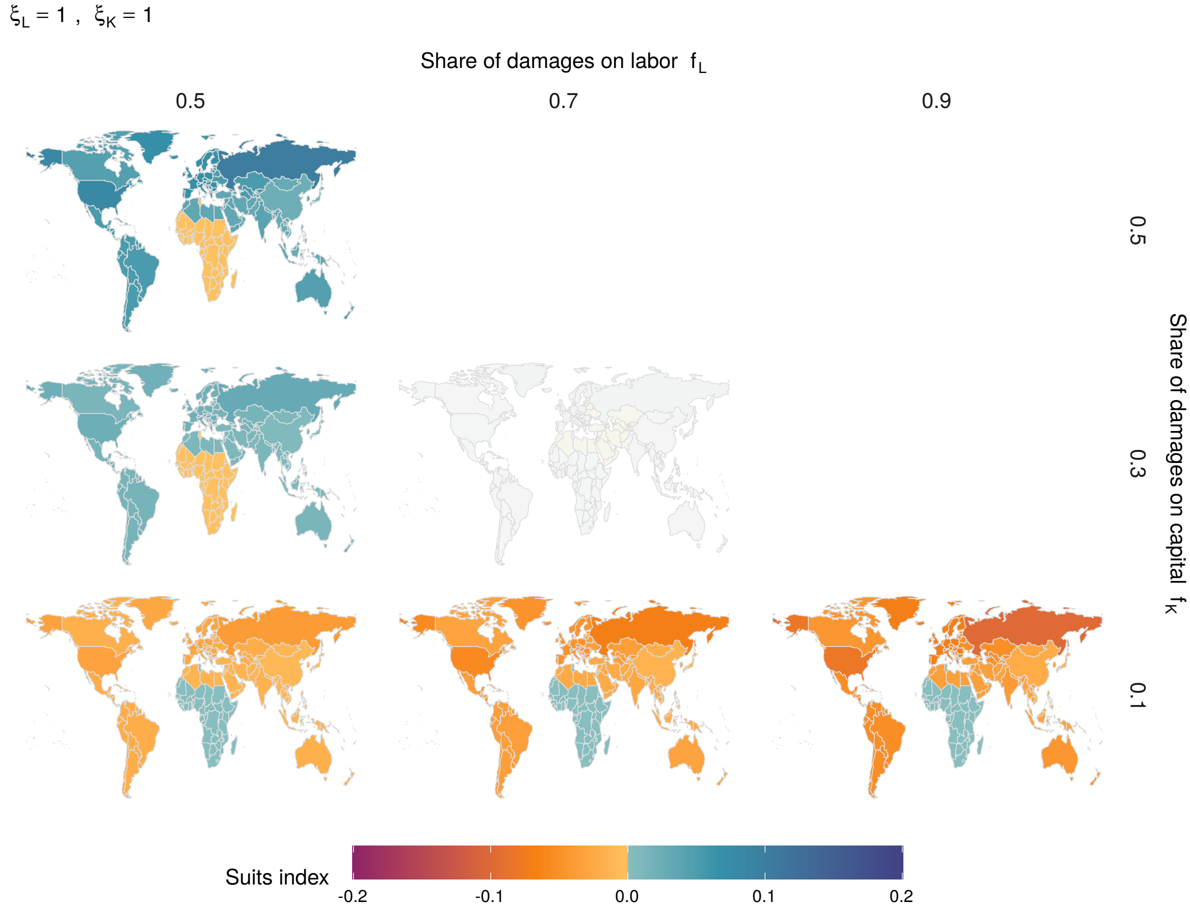
$$S_D \approx 1 - \frac{1}{0.5}\left[\sum_{i=1}^{5} \frac{1}{2}\left(\sum_{q=0}^{i} sh_q^D + \sum_{q=0}^{i-1} sh_q^D\right) sh_i^Y\right]. \tag{3.2.1}$$

The Suits index is based on the Lorenz curve for damage shares. Negative values indicate a regressive distribution of damages, with -1 the most regressive case (the poorest quintile bears the entire damage loss), and positive values indicate a progressive distribution, with 1 the most progressive case (the richest quintile bears the entire damage loss). A value of zero reflects damages with the same distribution as total income. There are three determinants of the regressivity of climate damages in our approach: a) the composition of damages between capital and labor damages, b) the income-elasticities of capital and labor damages and c) the pre-damage income inequality.

Figure 2 displays the impact of the composition of damages on the Suits index in 2020, with income-elasticities of 1. When 70% of damages fall on labour and 30% on capital, as in the central panel of Figure 2, damages are exactly proportional to income (Suits index equal to zero). This reflects the fact that aggregate income is distributed according to factor shares, with $(1-\alpha) = 0.7$ the labor share. When the composition of damages shifts towards a larger capital share, damages are distributed more progressively and the Suits increases. This is because capital income is more unequally distributed than labor income, so shifting damages toward capital with an income-elasticity of one shifts the burden of climate damages towards the richer quintiles. The opposite is true when the composition of damages shifts towards a larger labor share. This pattern occurs in every region except in Africa. For this region, our calibration resulted in very high levels of both capital and labor Ginis, and, contrary to other regions, in a labor income Gini slightly higher than the capital income Gini.

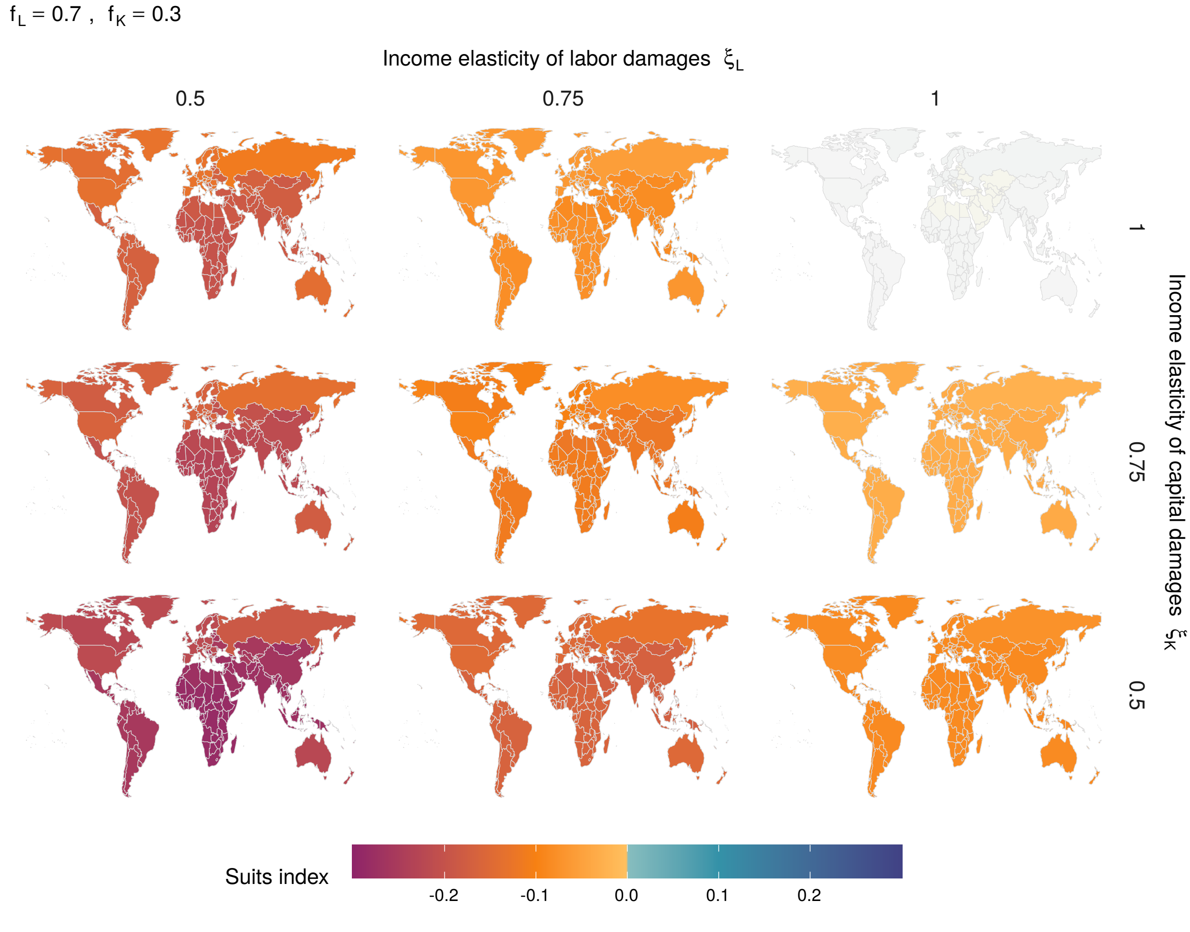
Figure 3 displays the effect of the income-elasticities of labor and capital damages (ξ_L and ξ_K), for labor and capital damages shares fixed and proportional to the labor and capital share in income ($f_L = 0.7$ and $f_K = 0.3$). Damages are proportional to total income when both elasticities are equal to one. A decrease of ξ_L or ξ_K from 1 towards 0.5 results in more regressive damages in all regions. Finally, Figure 3 shows, for labor and capital damage shares proportional to the aggregate income shares, that the income-elasticity of labor damages ξ_L has a stronger regressive effect than the income-elasticity of capital damages ξ_K. The stronger impact on the Suits index reflects that labor income makes up a larger share of the income of poorer households.

Figure 2: Impact of capital and labor damage shares on regressivity of climate damages, 2020



Note: white values are approximately equal to zero with a tolerance level of 1e-15.

Figure 3: Impact of capital and labor income elasticities of damages on regressivity of climate damages, 2020



Note: white values are approximately equal to zero with a tolerance level of 1e-15.

3.2.2 Global and regional inequality

We start by computing the global Gini index by pooling together all quintile consumption at the world level. Figure A6 shows the global Gini index in the unpersistent case ($f_Y = 1$). In the absence of any channel-specific impact, the Gini index decreases from around 56% in 2020 to 40% in 2100, i.e. a decrease of 16 percentage points (p.p.) (Figure A6). This reduction in the baseline global Gini is due to differential growth between regions, with partial convergence, and to changes in the regional inequality driven by the SSP scenario projections.

Figure 4 displays the change in global consumption Gini for different combinations of channel-specific damages and income-elasticities of damages, compared to the unpersistent case. First, half of total damages are assigned to the channel-specific damages ($f_Y = 0.5$). For damages proportional to income in both channels ($\xi_L = \xi_K = 1$), the global Gini increases by around 1 p.p.. Having damages fall disproportionately on the bottom of the distribution increases the global Gini with respect to the case with damages on output. The global Gini index increases by 2 p.p. for income elasticities of capital and labor damages of 0.75, and by 3 p.p. for income elasticities of capital and labor damages of 0.5.

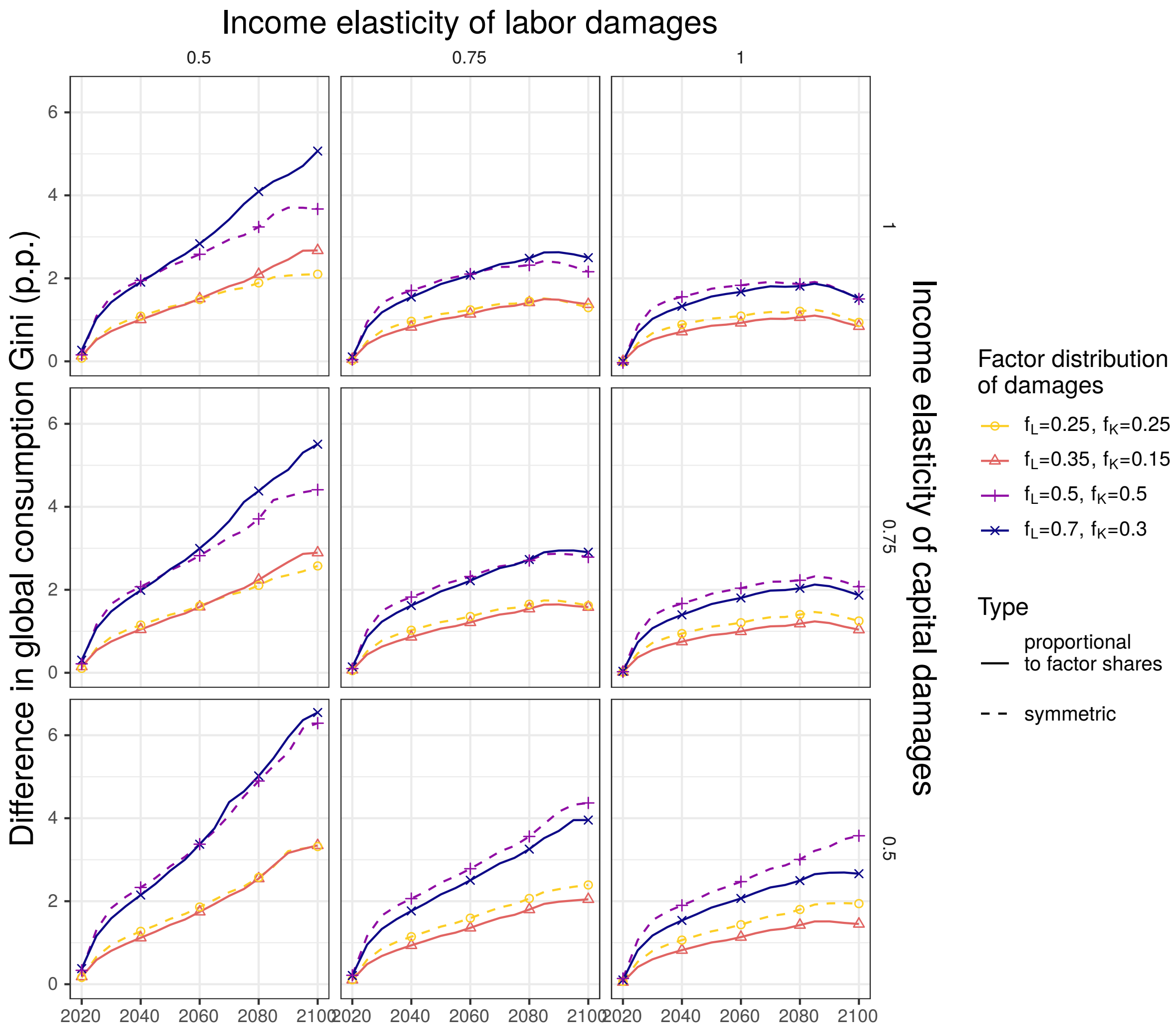
Second, we assign 100% of total damages to the channel-specific damages ($f_Y = 0$). As a result, the global Gini increases compared to the unpersistent case, by around 1.75 p.p. for proportional damages and up to around 6.5 p.p. for disproportionate damages with $\xi_L = 0.5$ and $\xi_K = 0.5$, in 2100 (Figure 4). Hence, for damages falling fully on the labor and capital channels, and regressive damages with channel-specific income-elasticities between 1 and 0.5, around a fifth to a third of the baseline decrease in the global Gini is offset.

In addition, we explore the role of damage composition across the labor and the capital channels by assigning the damages in two ways, symmetric (e.g. $f_K = f_L = 0.5$ for a total of 100% of channel-specific damages) or proportional to factor shares (e.g. $f_K = 0.3$ and $f_L = 0.7$ for a total of 100% of channel-specific damages). Figure 4 shows that the impact on the difference in global Gini to the baseline is small when the labor and capital income-elasticities of damages are equal, and up to 1 p.p. when $\xi_L = 0.5$ and $\xi_K = 1$.

Next, we focus on the regional Gini index. Figure A7 depicts the regional Gini index with unpersistent damages based on quintile consumption ($f_Y = 1$) following the calibration to the SSP2 scenario. India experiences a large increase in the regional Gini index and becomes the most unequal region at the end of the century (Gini around 35% in 2020 and 50% in 2100). Regions with less pronounced increases or relatively stable Gini index are the US, Russia, Eurasia, EU, Japan, and OHI. In the other regions, the regional consumption Gini decreases. China, the region with the most pronounced decrease, becomes the most equal region at the end of the century in the baseline scenario (Gini around 35% in 2020 and 20% in 2100).

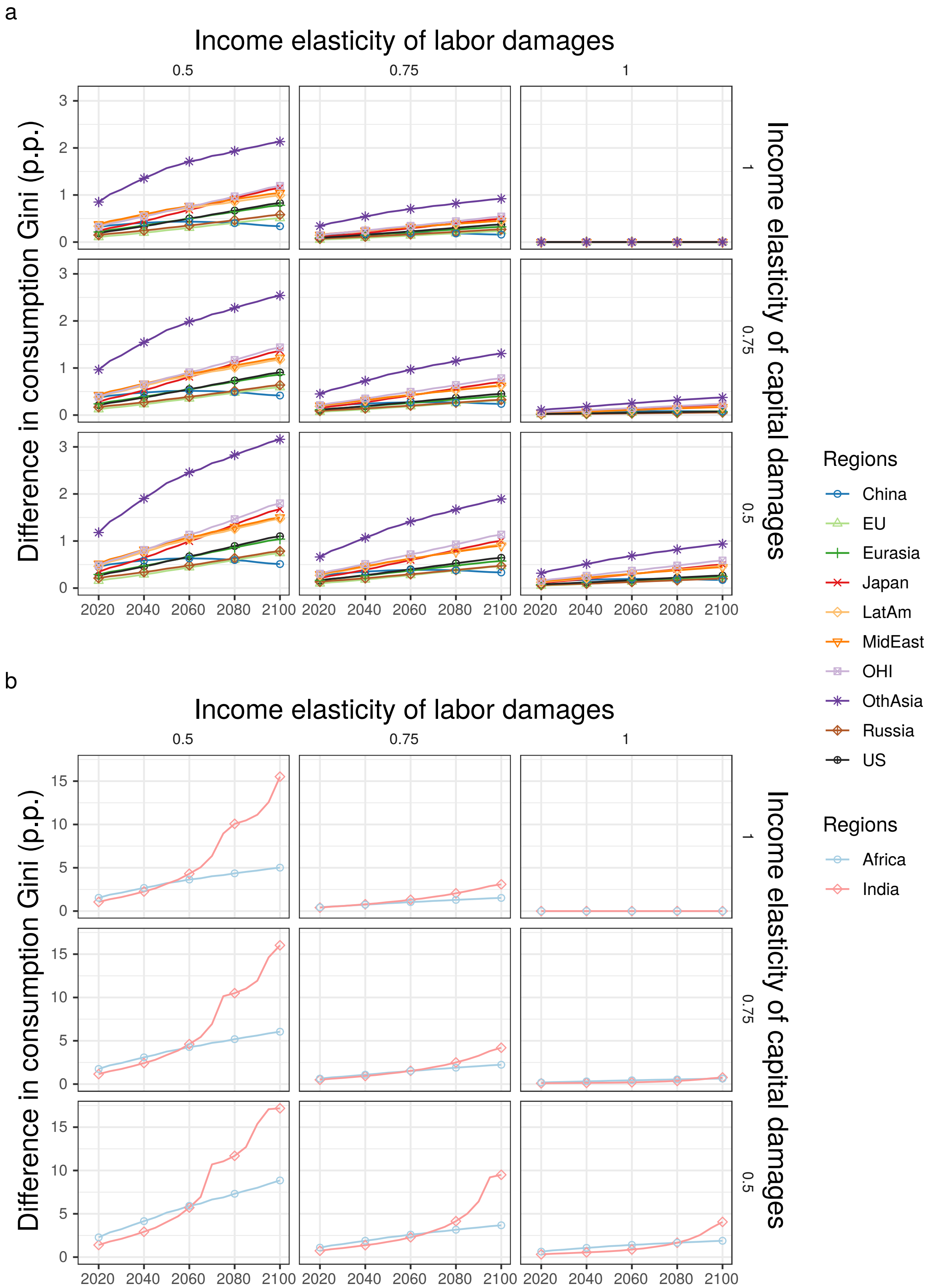
Figure 5 shows the difference in the regional Gini index to the unpersistent case for labor and capital damages proportional to the labor and capital share in income ($f_L = 0.7$ and $f_K = 0.3$) and with different income elasticities of damages. Regressively distributed damages lead to increases in the regional Gini up to 3 p.p. compared to the unpersistent case, with important regional heterogeneity. Regions that witness the largest change in the Gini are those that are most affected by climate change damages (Figure A4a). Despite being affected by larger regional damages, India initially experiences a smaller change in the Gini index than Africa in most income elasticity combinations and then overtakes Africa in the second half of the century. As India is first more equal and becomes more unequal in the second half of the century than Africa, this showcases the

Figure 4: Difference in global consumption Gini index for different levels of channel-specific damages and elasticities, with $\delta = 0.7$, $\lambda = 0.5$.



role of pre-existing inequality in the regressivity of climate damages.

Figure 5: Difference in the regional consumption Gini index for different elasticities with damages on capital and labor in proportion to production factor shares ($f_K = 0.3$ and $f_L = 0.7$), $\delta = 0.7$, $\lambda = 0.5$.



3.2.3 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 quintile (or "bottom" quintile).

Figure 6 displays the difference in consumption per capita compared to the unpersistent case for two groups of regions, with different combinations of labor and capital damage shares and income-elasticities. We find extreme effects in India, and strong effects in other regions. For the first group of regions (Figure 6a), consumption per capita in the bottom quintile is projected to be at least 7-13% lower at the end of the century with 25% damages on the labor and capital channels, and around 12-20% lower if damages fall 50% each on labor and capital. The range increases to 8-15% and 15-25% with lower values for the income elasticities of damages. For the second group of regions, the decrease in consumption per capita is larger, with reduction over 13% in 2100. The decrease is most pronounced with regressive channel-specific damages. In India, the reduction amounts to 100% after 2080 with income elasticities of damages of 0.5. Consumption per capita in the first quintile plummets to near-zero under these scenarios in India. Capital and labor damages elasticities produce relatively symmetrical impacts, with slightly larger effects for regressive labor damages than for regressive capital damages.

Next, Figure 7 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 income elasticities of damages of 1 or 0.75. First, when damages are strictly proportional to factor income shares ($\xi_L = \xi_K = 1$), a larger portion of the damages falling on capital produces a slight increase in the income share for the first quintile (Figure 7b). This is because the first quintile hardly earns any capital income (Figure A2). For $\xi_L = \xi_K = 1$, having damages fall 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. The effect is less visible in Africa, where our calibration results in a slightly more unequal labor income distribution than capital income distribution (Figure A2).

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 disproportional labor damages than disproportional capital damages (Figure 7a and c), as well as the strongest gradient along the labor damage axis when both capital and labor damages are distributed with an elasticity of 0.75 (Figure 7c). The distributive impacts at the bottom of the distribution are thus more dependant on the share and regressivity of climate damages hitting labour productivity.

Figure 6: Consumption per capita of the first quintile for different levels of channel-specific damages and elasticities, $\delta = 0.7$

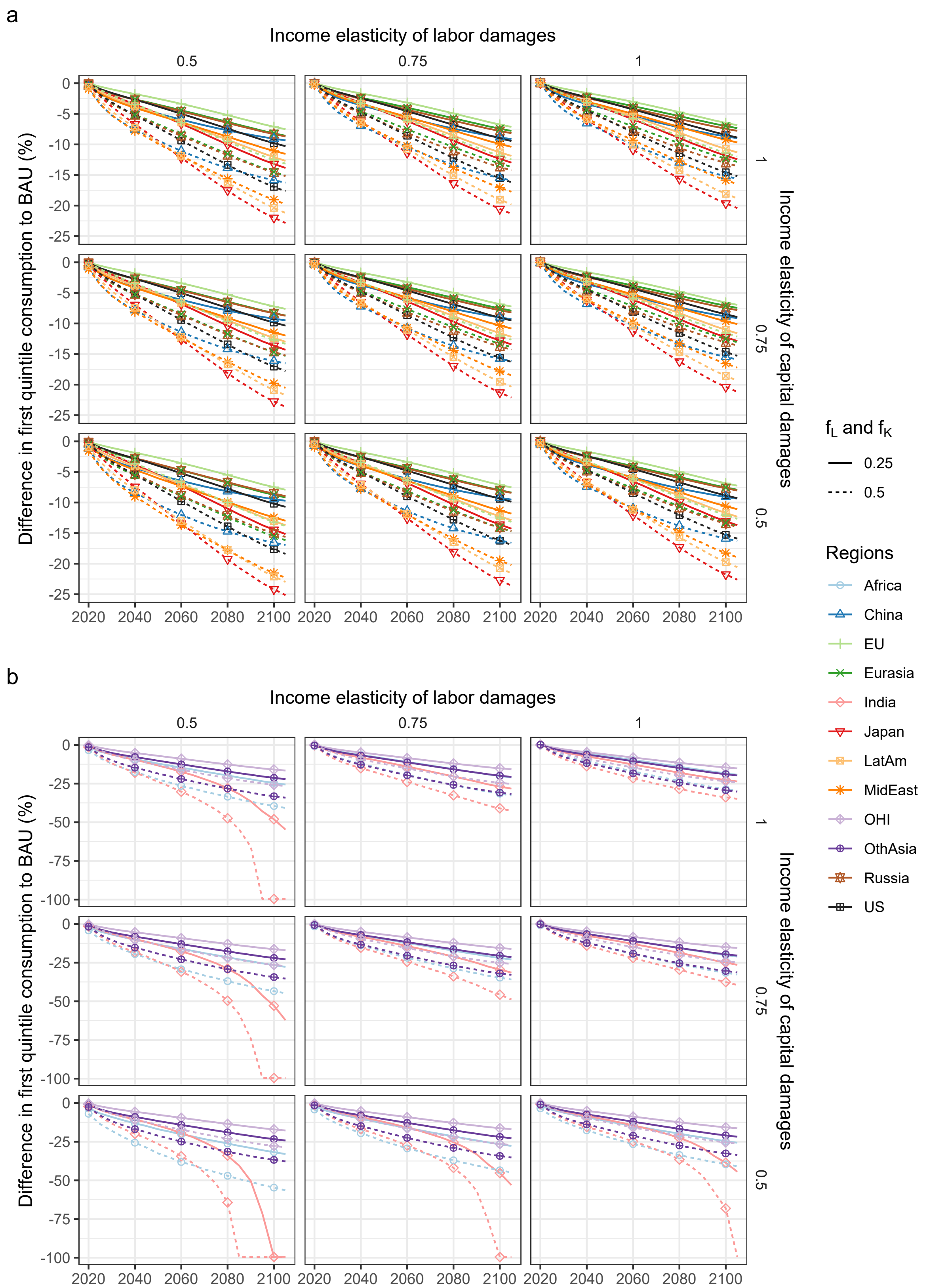
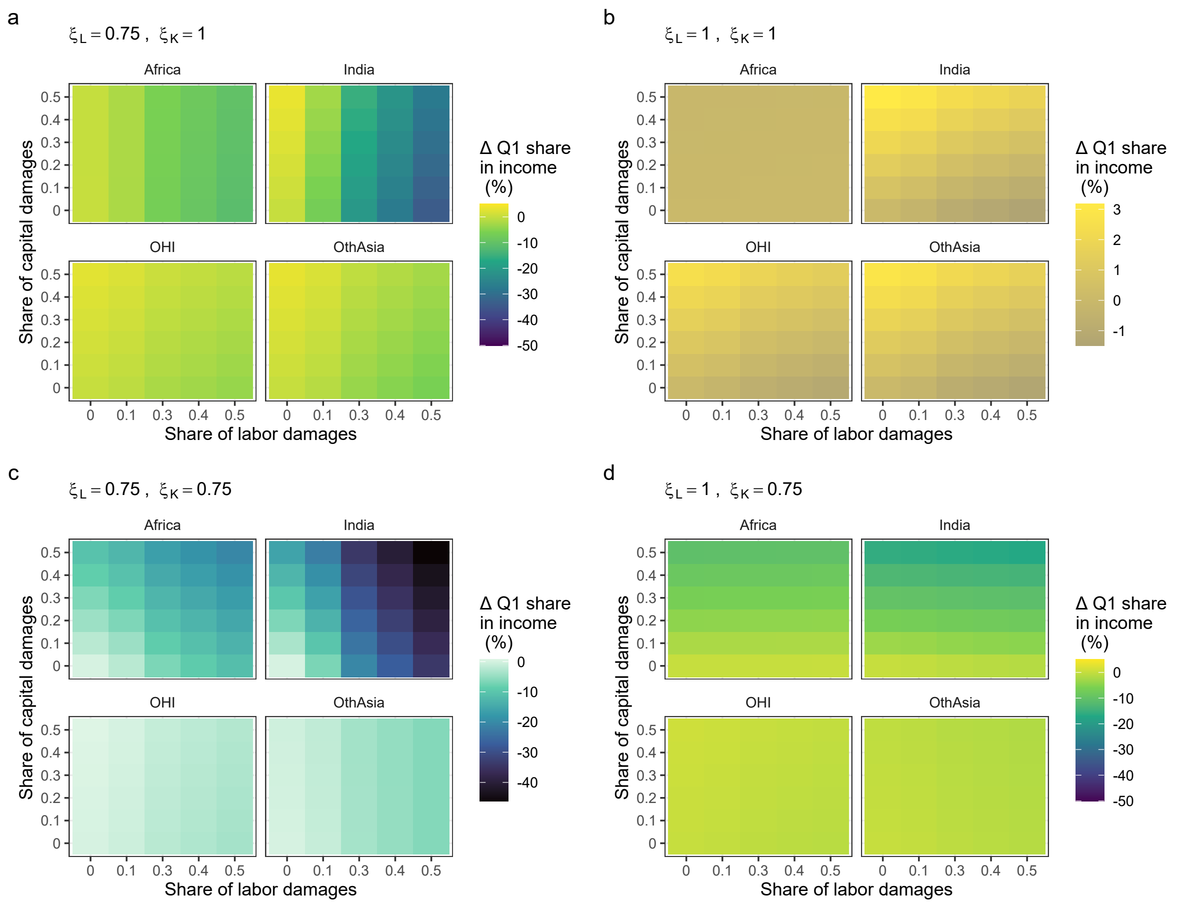


Figure 7: Change in the income share of the first quintile, from pre-damage to net income distribution, for different levels of channel-specific damages and elasticities, 2105, $\delta = 0.7$



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

We now analyze the effect of channel-specific damages and the resulting distributional impacts on the social cost of carbon (SCC) based on quintile consumption per capita. We evaluate the SCC with the same inequality aversion within and across regions ($\eta = 2$) and a rate of time preference of $\rho = 0.015$.[6]

Figure 8 displays the SCC based on quintile consumption per capita for 2023, for varying damage shares and different combinations of labor and capital income-elasticities of damages.

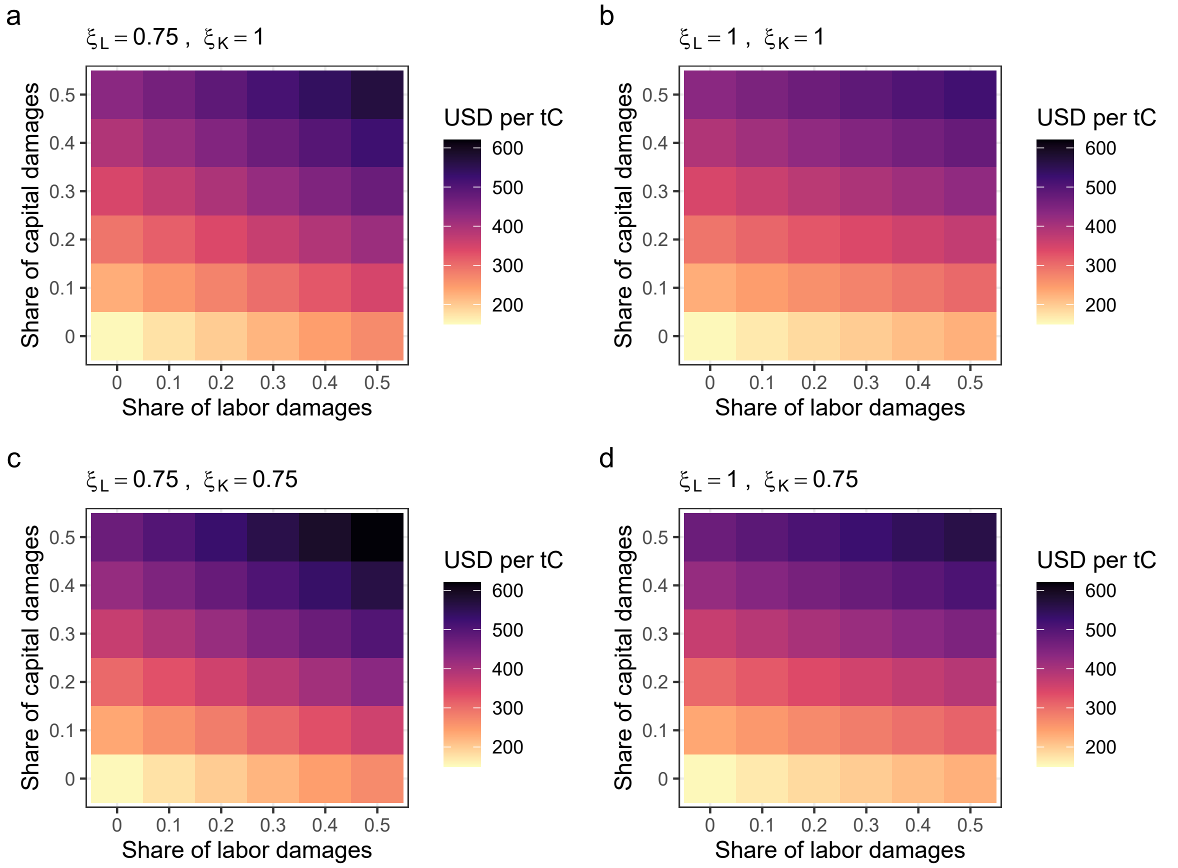
We first focus on the results for damages proportional to income shares ($\xi_K = \xi_L = 1$) which are shown in Figure 8 panel b), and detailed in Table A9a. With all damages falling directly on output, the SCC is around 155 dollars per ton of carbon. If damages fall completely on capital and labor (with a share of 50% respectively), the SCC 520 dollars per ton of carbon, i.e. 3.4 times larger. With a capital and labor damage share of 0, a rise from 0 to 0.5 in the labor damage share yields a 47% increase in the SCC, while a rise to 0.5 in the capital damage share yields a 180% increase. Hence, for proportional damages, damages hitting the capital stock have a stronger impact on the SCC than damages hitting labor productivity.

Next, we explore the results for damages falling slightly disproportionally on the poorest quintile for the labor damages, the capital damages or both ($\xi_L = 0.75$ and/or $\xi_K = 0.75$). First, for $\xi_L = \xi_K = 0.75$ (Figure 8c), the SCC amounts to more than 600 dollars per ton of carbon if damages fall fully on capital and labor, around 100 dollars per ton of carbon larger than with damages distributed proportionally to shares in factor income (see Table A9). Second, to investigate whether the labor or the capital damage elasticity has more impact on the SCC, we now compare he results for a scenario with regressive damages on labor income and proportional to capital income (Figure 8a) and a scenario with mirrored elasticities (Figure 8d). In both panels, the share of capital damages still has a stronger increasing effect on the SCC than the share of labor damages. However, regressive labor damages and proportional capital damages (Figure 8a) result in stronger increases in the SCC (comparing with SCC with proportional damages in(Figure 8b)), than proportional labor damages and regressive capital damages (Figure 8d). This shows that the income-elasticity of labor damages tends to have a stronger impact on the SCC than the income-elasticity of capital damages, but that the effect on the value of the SCC is of second order compared to the impact of the share of damages falling on capital. This finding is in line with the result presented in section 3.2 on the stronger effect of labor elasticity on inequality or on consumption of the bottom quintile.

Capital and labor damages yield persistent output losses and distributive effects (see subsections 3.1 and 3.2). To investigate the contribution of these two effects to the increase in the SCC, we compute SCC_{nodist}, the value for the social cost of carbon from quintile level consumption per capita for which we neutralize the redistributive effects of channel-specific damages by distributing damages at the quintile level proportionally to total quintile income. That is, quintile income shares remain unaffected by climate change damages by assumption in the computation of SCC_{nodist}. Table A9b shows the SCC_{nodist} for different shares of capital and labor damages.

[6]The effect of intra-generational inequality on 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).

Figure 8: The social cost of carbon based on global consumption per capita (CPC) and quintile CPC welfare function for different levels of channel-specific damages, 2023, 2017 PPP USD, $\delta = 0.7, \eta = 2, \rho = 0.015, \lambda = 0.5$



With a capital damage share of 0 and a labor damage share of 0.5, the SCC_{nodist} is 226 dollars per ton of carbon, a few dollars lower than the SCC with $\xi_L = \xi_K = 1$ (Table A9a). On the other hand, with a labor damage share of 0 and a capital damage share of 0.5, the SCC_{nodist} is a few dollars larger than the SCC value. Thus, for proportional damages, the output loss and growth effects of channel-specific damages tend to dominate the within-region distributional effect on the SCC. The distributive effect of capital damages decreases the SCC, whereas the distributive effect of labor damages increases the SCC, which is consistent with the findings in subsection 3.2 that for damages proportional to income shares, a larger portion of damages on capital slightly increases the income share of the first quintile whereas it decreases with a larger portion of labor damages (see Figure 7b).

Furthermore, with regressive damages ($\xi_L = \xi_K = 0.75$) and damage shares of 0.5 on the labor or the capital channel, the SCC (Table A9b) is larger than the SCC_{nodist} (Table A9c). It implies that, for regressive damage distributions, the distributive and the growth effects of damages increase the SCC for labor and capital damages. For half of damages on labor and half on capital, the SCC with regressive damages is close to 100 dollars higher than the SCC_{nodist}.

Finally, the SCC and how it reacts to changes in channel-specific damages and damage regressivity hinges on the assumptions over the income-elasticity of damages, and over the depreciation rate of capital and the persistence of labor damages. Figure A8 shows the SCC for varying damage shares and more disproportionately distributed damages than in Figure 8 (elasticities of 1 and 0.5 instead of 0.75). When the income-elasticities of labor and/or capital damages are 0.5, the SCC reaches values of several thousand dollars per ton of carbon with capital and labor damages, implying a fivefold to tenfold increase. In many of these scenarios, the income share of the poorest quintile in India would fall below zero and needs to be bounded. The SCC becomes very sensitive to small differences in the share of labor and capital damages, in the cases where a marginal unit of emission can trigger a drop in consumption of the poorest.

Figure A9 displays, for different depreciation and labor damage persistence rates, and over a range of damage shares and income-elasticities of damages, the percentage share of SCC values in the top 20% highest values. It shows that decreasing the depreciation rate or increasing the persistence of labor damages results in an increased share of SCC values among the highest values.

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 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 0.5—labor damages are more regressive than capital damages. Overall, we find that damages that hit labor productivity tend to lead to more regressive outcomes, while damages hit the capital stock tend to lead to more persistent aggregate output losses. A slight disproportion (income-elasticity of 0.5) in the damages is sufficient to increase the SCC by one order 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.

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 Appendix

Figure A1: Maps of input data for inequality

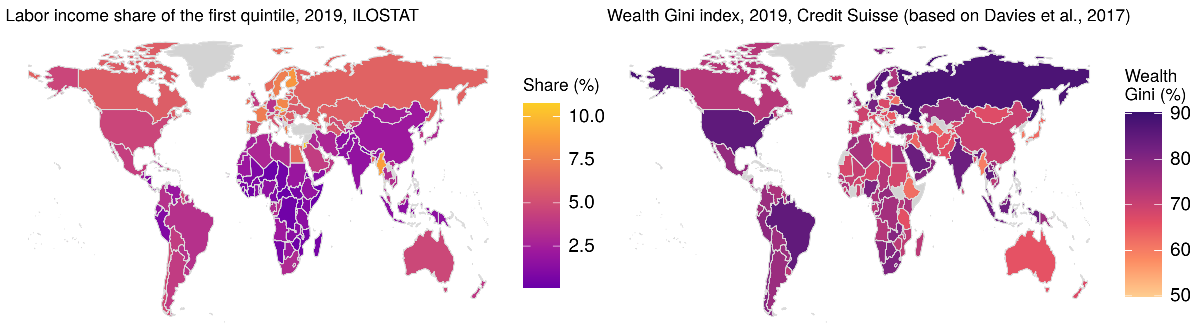

Figure A2: Calibrated distributions for capital income and labor income

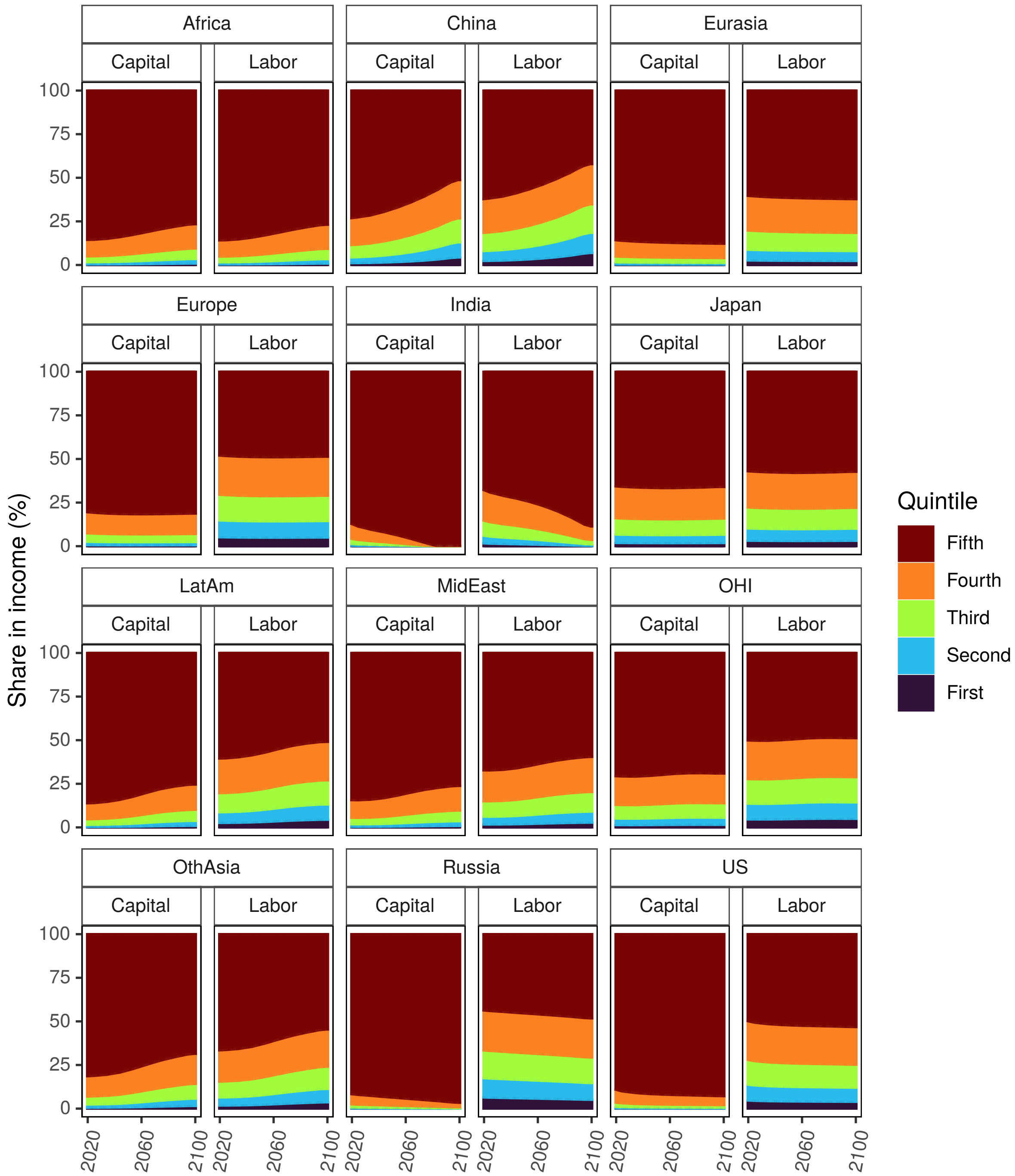

Figure A3: Regional output per capita and growth with output damages only, $\delta = 0.8$

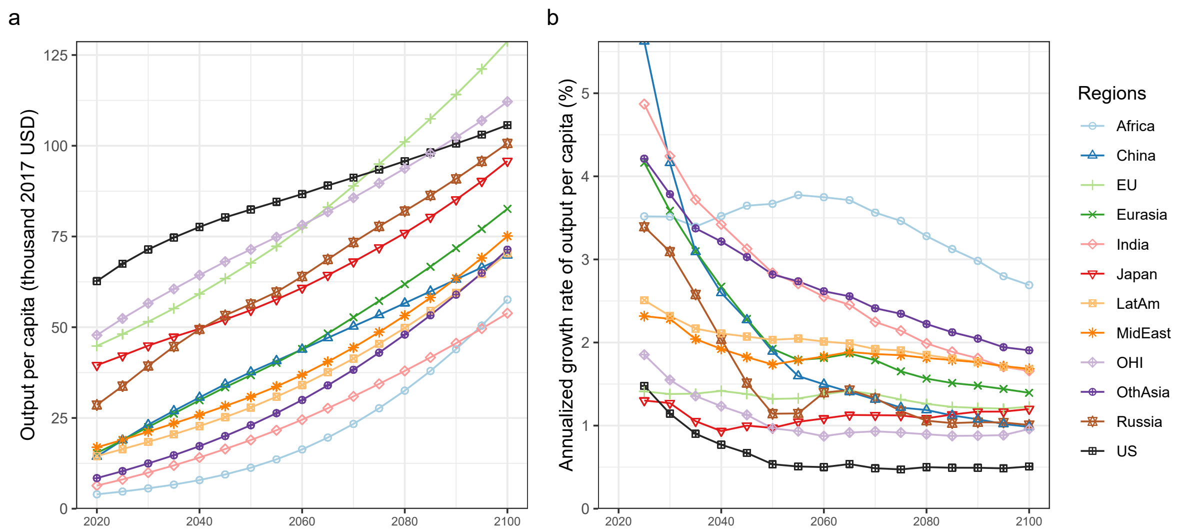

Figure A4: Impact of channel-specific damages on overall damages and on share of persistent damages, $\delta = 0.7$, $\lambda = 0.5$.
Panel a) shows the total damages in each regions, as a share of gross output in the counterfactual scenario with no persistence of damages. Panel b) shows the share of total damages which stem from the persistence of damages.

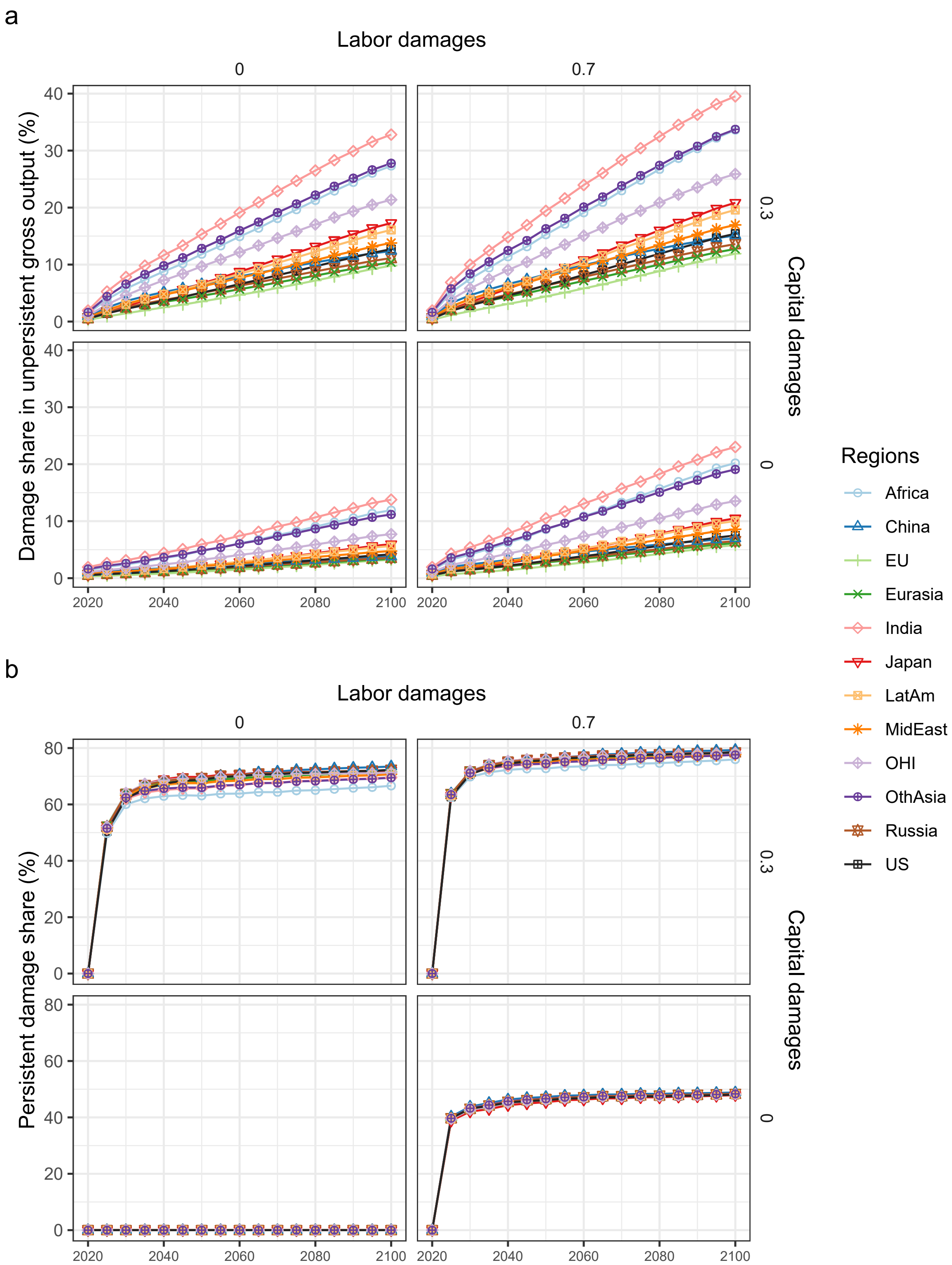

Figure A5: Share of total damages in gross unpersistent output (a) and Share of persistent damages in total damages (b), for different values of the decadal depreciation rate δ and of the persistence of labor damages λ, $f_K = 0.5$ and $f_L = 0.5$.
Note: In panel b) the share of persistent damages is shown starting in 2030 instead of 2020.

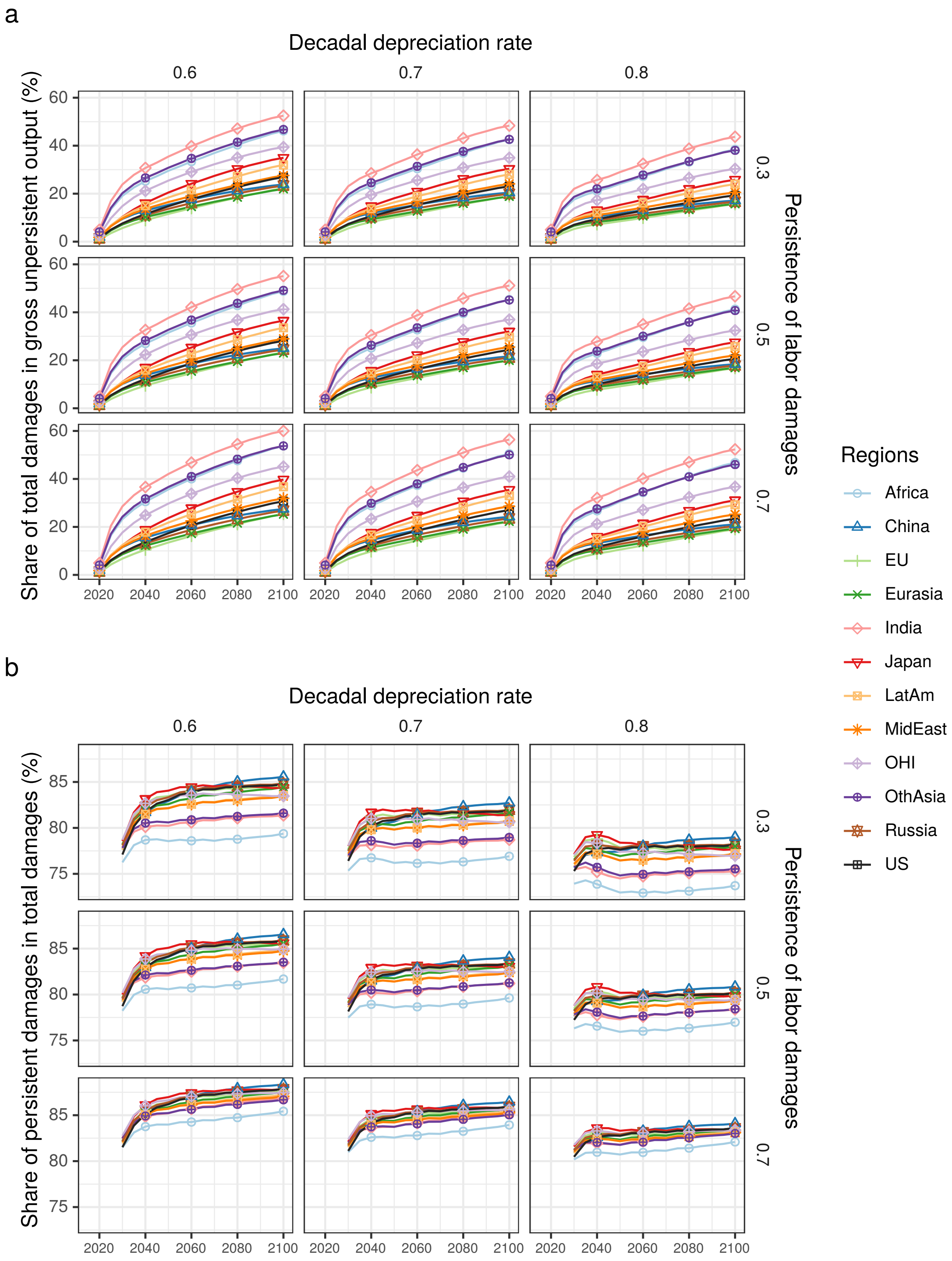

Figure A6: Global Gini index in the baseline case with all damages falling on output ($f_Y = 1$), $\delta = 0.7$, $\lambda = 0.5$.

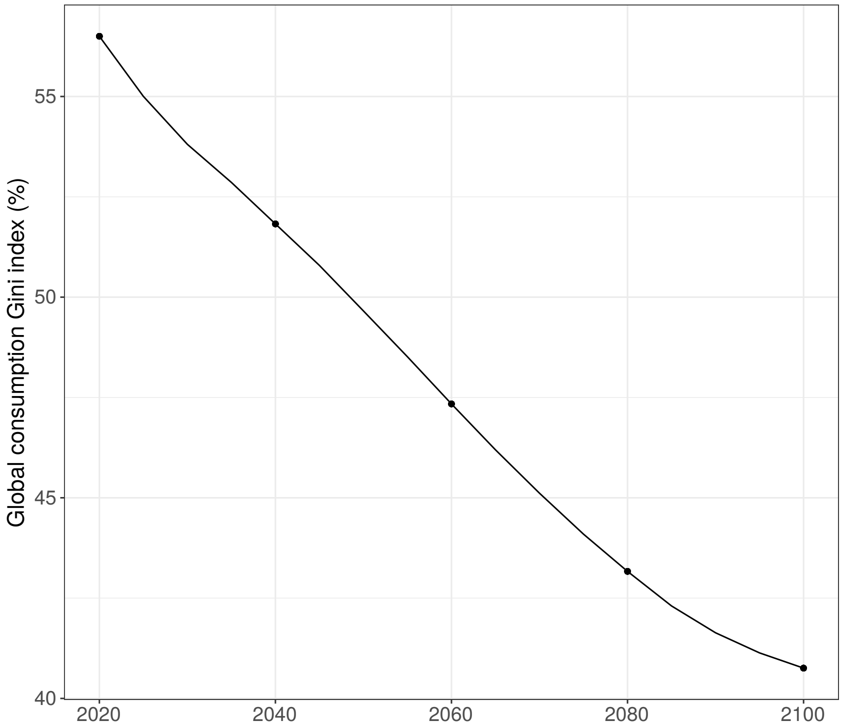

Figure A7: Regional Gini index in the baseline case with all damages falling on output ($f_Y = 1$), $\delta = 0.7$, $\lambda = 0.5$.

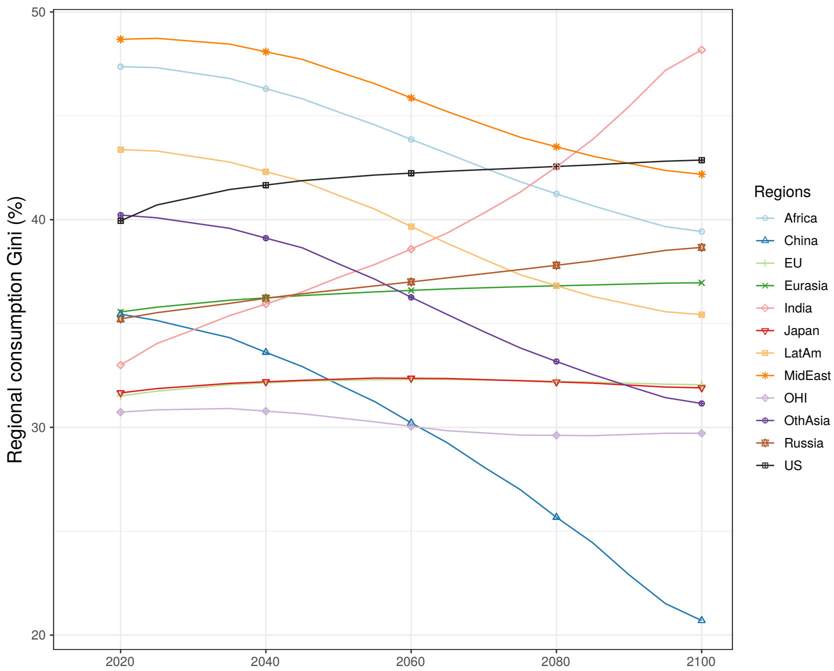

Figure A8: The social cost of carbon based on quintile CPC welfare function for different levels of channel-specific damages and combinations of elasticities ($\xi \in (0.5, 1)$), 2023, 2017 PPP USD, $\delta = 0.7, \eta = 2, \rho = 0.015, \lambda = 0.5$

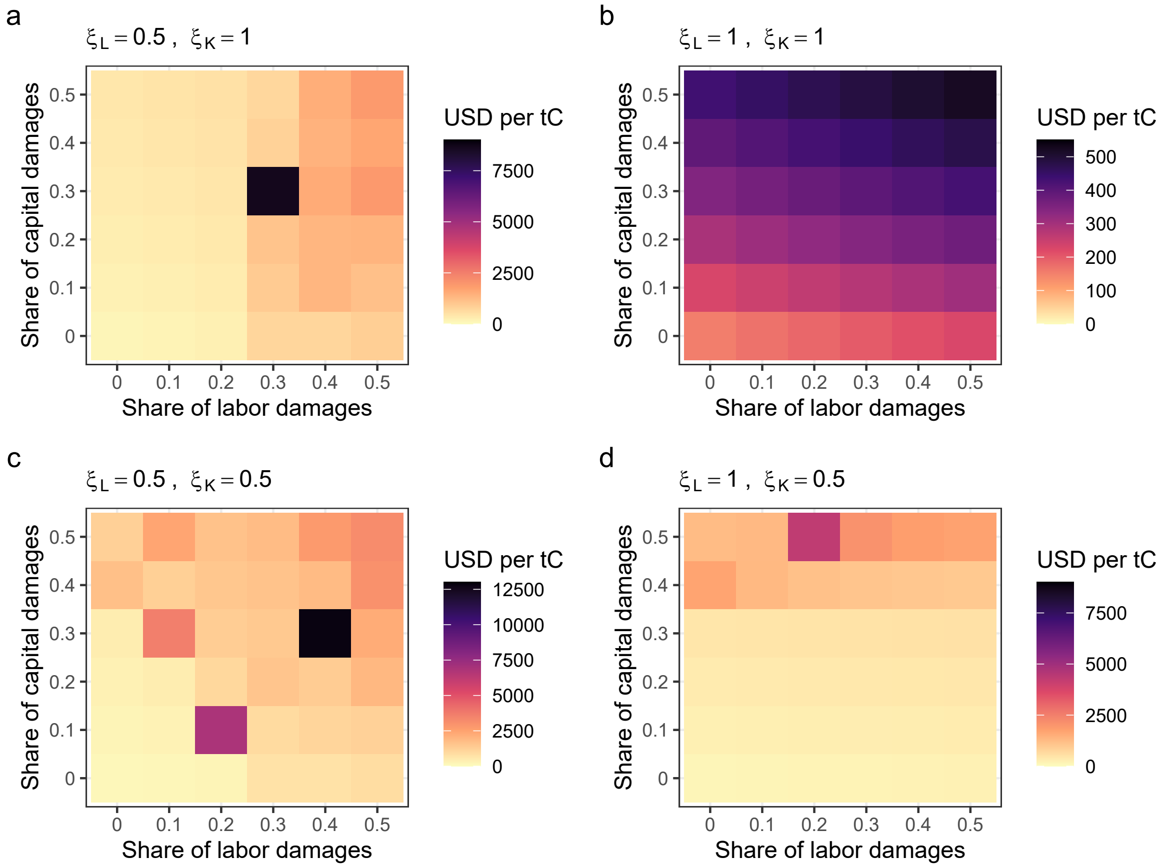

Figure A9: Percentage of runs for different levels of depreciation and labor damage persistence in the fifth social cost of carbon quintile, based on quintile consumption per capita welfare function, $\eta = 2$, $\rho = 0.015$, 2023

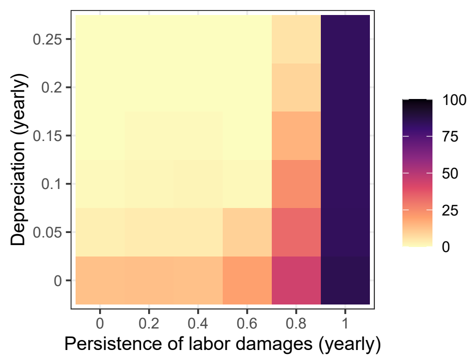

Table A9: Social cost of carbon with quintile consumption per capita, for different channel-specific impacts (2023) in 2017 USD per tC, $\delta = 0.7$, $\rho = 0.015$, $\eta = 2$.
SCC is the social cost of carbon from quintile consumption per capita, and SCC_{nodist} is the social cost of carbon from quintile consumption per capita with damages proportional to total income by assumption (distributional impact of channel-specific damages neutralized).

a)

SCC, $\xi_K = \xi_L = 1$

$f_K \backslash f_L$	0	0.5
0	155	228
0.5	434	520

b)

SCC, $\xi_K = \xi_L = 0.75$

$f_K \backslash f_L$	0	0.5
0	155	268
0.5	472	618

c)

SCC_{nodist}

$f_K \backslash f_L$	0	0.5
0	155	226
0.5	439	523