Climate impacts on labor and capital: implications for growth, 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 introduce direct impacts on capital and productive labor stocks in a global integrated assessment model, resulting in endogenously persistent damages. To capture effects on sub-regional inequality, we calibrate the joint distribution of capital and labor income and connect it to damages hitting the stock of capital and productive labor.

We find that the share of labor damages hitting labor and the regressivity of labor damages are key determinants of outcomes at the bottom of the distribution. When damages fall on the factors of production rather than on output directly, global inequality increases. With half the damages hitting the capital stock and half hitting the labor stock, the social cost of carbon increases by a factor of four, through persistence and distributional effects.

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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 Nordhaus 2007 and Stern 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, Holmer, and Lemke 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 the social cost of carbon, 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, Hepburn, and Tol 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, Méjean, and Guivarch 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, Méjean, and Guivarch 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.

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, Oliva, and Walker 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, Tol, and Gay-Garcia 2015 analyze implicit persistence in IAMs and show that implied impact durations are not consistent with the available evidence on general output shocks. 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. Kikstra et al. 2021 introduce empirically estimated partial damage persistence through direct impacts on GDP growth and find strong effects on future GDP per capita and the social cost of carbon. 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 including labor and capital damages leads to persistent damages and growth effects, with heterogeneity across countries. 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. With slightly regressive income and labor damages, having half of the damages fall on the labor channel and half on the capital channel results in an increase in the global Gini, compared to the baseline with only direct output damages, of 5% in 2050 and 15% in 2100. We also show that labor damages and their distribution have a stronger negative impact than capital damages on income share and consumption at the bottom of the distribution. The growth and distributional effects of factor-specific damages result in an increased social cost of carbon (SCC). Compared to a baseline in which all damages fall directly on output, having half of the damages fall on capital and half on labor increases the SCC 3.4 times if damages are proportional to income, and at least 4 times if the burden fall disproportionally on the poorest households. We further disentangle the persistence and distributional channels of impacts on the SCC and explore the role of normative parameters.

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 in section section 4 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 formulation for the social cost of carbon (SCC).

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

$$Y_{rt}^G = A_{rt} K_{rt}^{\alpha} L_{rt}^{1-\alpha} \tag{2.1.1}$$

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

$$Y_{rt}^N = (1 - \Lambda_{rt})(1 - D_{rt}^G) Y_{rt}^G \tag{2.1.2}$$

with D_{rt}^G 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 yearly depreciation rate of δ

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

Regional aggregate consumption is then given by

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

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 discrepancies that arise when coupling aggregate outcomes to household level evidence,

2. We discuss this assumption in Section 4.

we build on the concepts and methods used in the construction of Distributional National Accounts (DINA)[3] (Alvaredo et al. 2016; Piketty, Saez, and Zucman 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:

$$Y^K_{rt} = \alpha Y^N_{rt} \tag{2.2.1}$$
$$Y^L_{rt} = (1-\alpha) Y^N_{rt} \tag{2.2.2}$$

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^K_{rqt} (resp. y^L_{rqt}) capital (labor) income of quintile q and $\mathrm{sh}^{Y^K}_{rqt}$ (resp. $\mathrm{sh}^{Y^L}_{rqt}$) quintile q's share in capital income (resp. labor income), pretax income of quintile q writes

$$y_{rqt} = y^K_{rqt} + y^L_{rqt} = \mathrm{sh}^{Y^K}_{rqt} Y^K_{rqt} + \mathrm{sh}^{Y^L}_{rqt} Y^L_{rqt} \tag{2.2.3}$$
$$= \left(\alpha \mathrm{sh}^{Y^K}_{rqt} + (1-\alpha)\mathrm{sh}^{Y^L}_{rqt}\right) Y^N_{rqt} \tag{2.2.4}$$

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

$$\mathrm{sh}^Y_{rqt} = \frac{y_{rqt}}{Y^N_{rqt}} = \alpha \mathrm{sh}^{Y^K}_{rqt} + (1-\alpha)\mathrm{sh}^{Y^L}_{rqt} \tag{2.2.5}$$

We calibrate capital income distribution using wealth distribution data from the Credit Suisse Global Wealth databooks (Davies, Lluberas, and Shorrocks 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, Goupille-Lebret, and Piketty 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 of the "Middle of the road" 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, Gini index for total income G_Y is given by the sum of the Gini coefficients for each income component (G_i) weighted with the share of this component in total income (sh^Y_i). With total income being the sum of capital and labor income and the factor share being equal

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

to the respective output elasticity (as in equation 2.2.1 and 2.2.2), the change in the total income Gini is given by

$$\frac{\Delta G_Y}{G_Y(t)} = \frac{\Delta(\sum_{i=1}^{n} sh_i^Y G_i)}{G_Y(t)} = \frac{\alpha \Delta G_K + (1-\alpha)\Delta G_L}{G_Y(t)} \tag{2.2.6}$$

The contribution of an income component to the change in the total income Gini is

$$sh_i^{\Delta G_Y} = \frac{\frac{sh_i^Y \Delta G_i}{G_Y(t)}}{\frac{d\log(G_Y)}{dt}} = \frac{sh_i^Y \Delta G_i}{\Delta G_Y} \tag{2.2.7}$$

We decompose changes of the total income Gini by assuming that $sh_i^{\Delta G_Y}$ is equal to its factor income share sh_i^Y. The absolute change of an income channel Gini is then the absolute change of the total income Gini ($\Delta G_i = \Delta G_Y$). 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 below 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 factors such as greenhouse gas emissions (e.g. CO_2, CH_4), land use, 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. Hänsel et al. 2020; Rode et al. 2021; Rennert et al. 2022; Barrage and Nordhaus 2023).

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

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

with ψ_{1r} and ψ_{2r} the region-specific damage parameters, T_t the temperature anomaly with respect to pre-industrial levels, and $\bar{T}_{1986-2005}$ the average temperature anomaly of the period 1986 to 2005 to pre-industrial levels. We calibrate ψ_{1r} and ψ_{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.

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 of the myriad of ways in which climate change manifests, it misses some of the endogenous economic responses. In the RICE and the NICE 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 (Acevedo et al. 2020; Heal and Park 2020; Dasgupta et al. 2021; Parsons et al. 2021; Somanathan et al. 2021). Impacts on labor productivity can be long-lasting, for instance through reductions in educational outcomes (Park, Behrer, and Goodman 2021) and health (Hallegatte et al. 2020).

Second, climate change also impacts the capital stock. The increased frequency and magnitude of extreme events, such as, for instance cyclones, floods, landslides, or fires, leads to more damages on physical capital such as plants or infrastructure (IPCC 2023). 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 the 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. Full persistence of labor shocks would be an extreme assumption. Instead, we control the dissipative dynamic of the shocks through a persistence parameter λ, between 0 (full and instantaneous dissipation of the shock) and 1 (no dissipation of the shock). This specification is close to that of Piontek et al. 2019 for a one-time shock and exogenous labor productivity growth, adapted to our specification with repeated shocks. Given that labor grows at the same rate as population, we get:

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

When $\lambda = 0$, all labor damages from the previous period dissipate, and labor is equal to population in the region. When $\lambda = 1$, the shock fully persists and the rate of population increase is applied to the region's net-of-damage labor from the previous period.

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 in a model with ten-year time-steps, 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 of capital (Estrada, Tol, and Gay-Garcia 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_q^i 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 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 income elasticity 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 (Hallegatte and Rozenberg 2017; Islam and Winkel 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 do not necessarily translate into the largest share at the national and regional scale, because the income of the poor makes 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-paid 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

$$\mathrm{sh}^{Y^N}_{rqt} = \frac{y^N_{rqt}}{Y^N_{rt}} \tag{2.5.4}$$

$$= \frac{\left(\mathrm{sh}^Y_{rqt} - \mathrm{sh}^D_{rqt} D^G_{rt}\right) Y^G_{rt}}{(1 - D^G_{rt}) Y^G_{rt}} \tag{2.5.5}$$

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 elasticity β_r yields the share of quintile q in regional consumption

$$\mathrm{sh}^C_{rqt} = \frac{\left(\mathrm{sh}^{Y^N}_{rqt}\right)^{\beta_r}}{\sum_q \left(\mathrm{sh}^{Y^N}_{rqt}\right)^{\beta_r}}. \tag{2.5.6}$$

We estimate the elasticity β_r based on a log-log model with income shares as calculated in eq. (2.2.5) and country-level consumption shares from the latest release of the World Income Inequality Database (WIID) (UNU-WIDER 2022) aggregated to regional quintiles.[4] 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 social cost of carbon (SCC) represents the present loss of consumption that is as costly as the discounted stream of future consumption losses due to the emission of an additional ton of carbon. We do not compute the SCC along the model's optimal emissions pathway, but instead along an emissions trajectory calibrated on the "Middle of the road" Shared Socio-economic Pathway (SSP2). SSP2 continues historical trends in socio-economic variables. This has two consequences. First, it allows us to compare values of the SCC on the same baseline emissions pathway when varying the main parameters of our model. This would not be possible with an emissions trajectory achieved through optimization, because a change in parameters would also lead to a change in the emissions pathways. Second, the SCC values computed along SSP2 trajectories will not be equal to the optimal carbon price[5]. We calibrate the model using a descriptive approach and perform a normative evaluation of damages on labor and capital.

To evaluate 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 assuming 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

$$W^G = \sum_{t=0}^{T} \frac{P_t}{(1+\rho)^t} \frac{c_t^{1-\eta}}{(1-\eta)} \tag{2.6.1}$$

4. We use consumption data from 2019 if available, otherwise we use data from the closest year to 2019. In case no consumption data is available, we take net income data (41 out of 190 countries) or income data labelled "net/gross" (12 countries).

5. The SCC is equal to the optimal carbon price if marginal damages are measured along the optimal emissions trajectory.

The global SCC 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 the first period (Nordhaus 2014),

$$SCC_G = \frac{\sum_{t=j}^{T} \Delta C_t \frac{\partial W^G}{\partial C_t}}{\frac{\partial W^G}{\partial C_0}}, \tag{2.6.2}$$

with ΔC_t the change in global consumption due to an additional ton of carbon. The global SCC uses aggregate consumption at the world level, and thus cannot reflect inter- and sub-regional impacts of climate change.

As our analysis accounts for the distribution of impacts across regions and quintiles, we turn to a welfare function with regional quintile consumption to compute the SCC. We use a welfare function with disentangled inter-temporal (η) and intra-temporal (γ) inequality aversion (Anthoff and Emmerling 2019). With $c_{trq} = \frac{C_{rqt}}{P_{rt}/5}$ consumption per capita for quintile q in region r, the social welfare function is

$$W^Q = \sum_{t=0}^{T} \frac{P_t}{(1+\rho)^t} \frac{1}{1-\eta} \left(\sum_r \sum_q \frac{P_{rqt}}{P_t} c_{rqt}^{1-\gamma} \right)^{\frac{1-\eta}{1-\gamma}} \tag{2.6.3}$$

If not stated otherwise, we assume as in Dennig et al. 2015 that inter- and intra-temporal inequality are equal[6], i.e. $\eta = \gamma$, which results in the following social welfare function

$$W^Q = \sum_{t=0}^{T} \sum_r \sum_q \frac{P_{rqt}}{(1+\rho)^t} \frac{c_{rqt}^{1-\eta}}{1-\eta} \tag{2.6.4}$$

The SCC translates the welfare effect of a marginal ton of emissions into an equivalent change in present consumption, in monetary units. This change in consumption represents the present welfare benefit from the marginal emission, or equivalently the present welfare cost of mitigating the additional unit of emission. When consumption is aggregated at the global level with a unique representative agent, the normalization can be based on global average consumption. However, when consumption is disaggregated, a choice becomes necessary over the entity whose present marginal welfare will serve as normalization.

Picking a specific region for this normalization amounts to considering that the costs of mitigation are borne only by that region. In addition, choosing a richer region mechanically results in a higher SCC (e.g., Adler et al. 2017; Anthoff and Emmerling 2019) because foregoing present consumption has a lower welfare cost for a richer region. Consistent with our normative approach and the assumption of a globally impartial decision-maker, we assume instead that the cost of mitigation is shared globally across all quintiles. We expand the concept of a "World-fair normalization" (Adler et al. 2017) to quintile level consumption. The present cost of a marginal emission reduction is borne by regions in proportion to their share in global consumption, and by quintiles within regions in proportion to their share in regional consumption weighted by the consumption-elasticity of mitigation costs ξ_Λ. The quintile level social cost of carbon with quintile world-fair normalization then writes

$$SCC_Q = \frac{\sum_{t=0}^{T} \sum_r \sum_q \Delta C_{trq} \frac{\partial W^Q}{\partial C_{trq}}}{\sum_r \sum_q \pi_{rq} \frac{\partial W^Q}{\partial C_{0rq}}} \tag{2.6.5}$$

6. In the results section we test the sensitivity of the SCC to changes in the inter- and intra-temporal inequality aversion as in Anthoff and Emmerling 2019. We assume that within- and between-region inequality aversion is equal.

with π_{rq} the weight of quintile q in region r such that

$$\pi_{rq} = \frac{C_{0r}}{C_0} \frac{\left(\frac{C_{0rq}}{C_{0r}}\right)^{\xi_\Lambda}}{\sum_q \left(\frac{C_{0rq}}{C_{0r}}\right)^{\xi_\Lambda}}$$

with ξ_Λ the consumption-elasticity of mitigation costs. Under the assumption that current mitigation efforts would be distributed proportionally to consumption ($\xi_\Lambda = 1$), the normalization weight of each quintile reduces to the share of quintile consumption in world consumption, $\pi_{rq} = \frac{C_{0rq}}{C_0}$.

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 labor damage persistence to $\lambda = 0.5$ per year, meaning that half of the 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 the persistence of output losses. Second, we report the distributional outcomes of channel-specific impacts and income elasticities of damages. We then assess how the stronger persistence of damages hitting labor productivity and capital damages and their distributive outcomes affect the social cost of carbon (SCC) and test the sensitivity of the SCC to the key parameters.

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, the 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[7] 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 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 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).[8] 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.

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

7. The exact definition of persistent damages can be found in subsection 2.4.

8. The regional heterogeneity in the unpersistent case follows from the calibration to the COACCH regional damage functions.

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

$f_K \backslash f_L$	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%	

damages scale up the baseline damages but do not affect the ordering of regions according to the 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 difference can be explained by the use of distinct damage functions. Piontek et al. 2019 use the standard DICE function (Nordhaus 2014), whereas we apply the 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 savings rate and production function, in the capital depreciation rate, the (implicit or explicit) persistence level of shocks to productive labor, and to compounding effects of different time steps.

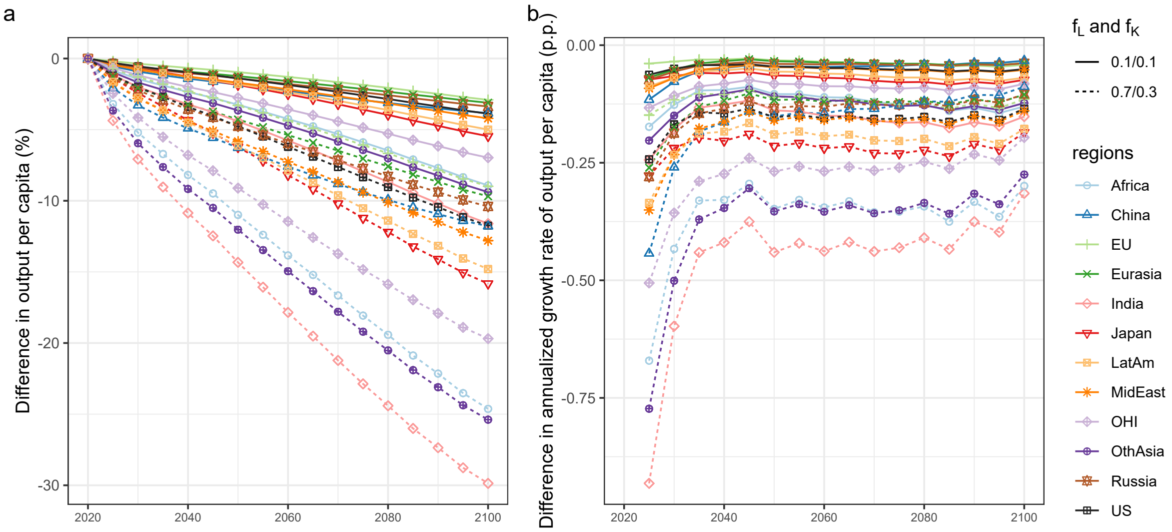
Next, we find that channel-specific damages result in both level and growth effects on per capita output. Figure 1a shows the difference in regional output per capita with respect to the baseline case with damages falling only on output, and Figure 1b shows the difference in annualized growth of per 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 Other Asia are the most affected regions, with reductions greater than 9%.[9] In terms 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

9. LatAm stands for Latin America, MidEast for Middle East, OHI for Other High Income countries, and OthAsia for Other Asia.

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



composition proportional to the production factor shares. This results in a level effect of over 9% in all the regions, with India, Africa, and Other Asia 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 Other Asia being 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 in 2100, and a reduction in the average annual growth rate of 0.8 percentage points. For richer regions, our results are closer, as they also find a level effect of around 10% and a growth rate reduction of 0.1 percentage points.

Kikstra et al. 2021 implement growth effects through explicit damage persistence calibrated to match empirical evidence. With the central estimate of damage persistence of 50%, they also obtain heterogeneous GDP growth reductions across regions. In Africa, they find larger reductions (0.5 to 1 percentage points in the 21st century) than we do. In the EU, they find an increase of around 0.1 percentage points compared to a scenario with zero persistence. Our model does not allow for a growth increase caused by climate change damages, but our estimate for the growth reduction in the EU is the one closest to zero. Our results coincide with the results from Kikstra et al. 2021 in terms of a large regional heterogeneity, with poorer regions more strongly affected.

3.2 Distributional impacts of labor and capital damages

We now explore how channel-specific impacts affect inequality and income levels of the poorest within regions. We analyze the sub-regional distributional impacts of 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)

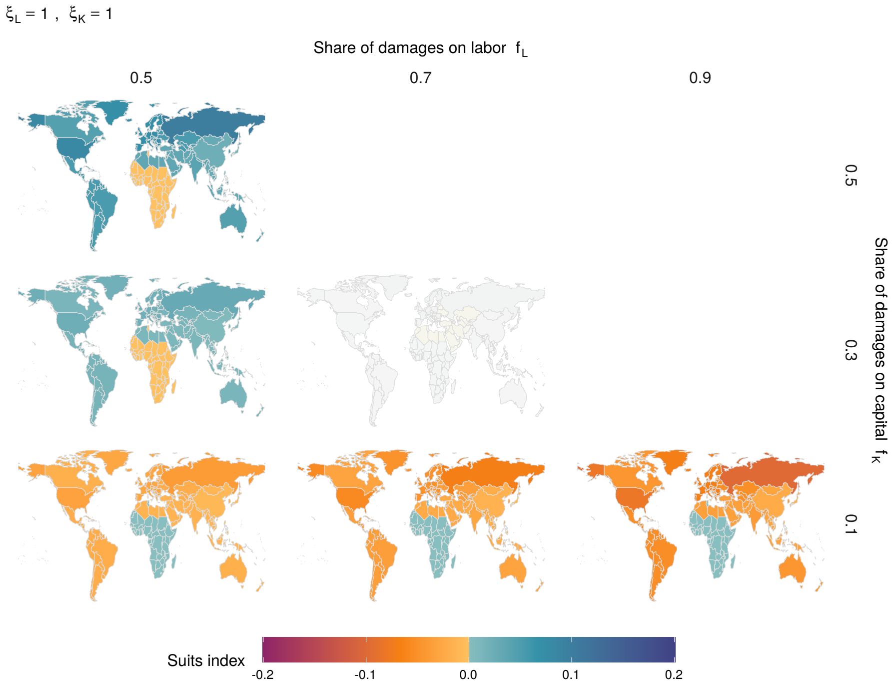
$$S_D \approx 1 - \frac{1}{0.5}\left[\sum_{i=1}^{5} \frac{1}{2}\left(\sum_{q=0}^{i} sh_q^D + \sum_{q=0}^{i-1} sh_q^D\right) sh_i^Y\right]. \tag{3.2.1}$$

The Suits index is based on the Lorenz curve for damage shares. Negative values indicate a regressive distribution of damages, with -1 being the most regressive case (the poorest quintile bears the entire damage loss), and positive values indicate a progressive distribution, with 1 being 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 labor and 30% on capital, as in the central panel of Figure 2, damages are exactly proportional to income (Suits index equal to zero). This damage distribution reflects 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 index increases. Since capital income is more unequally distributed than labor income, 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.

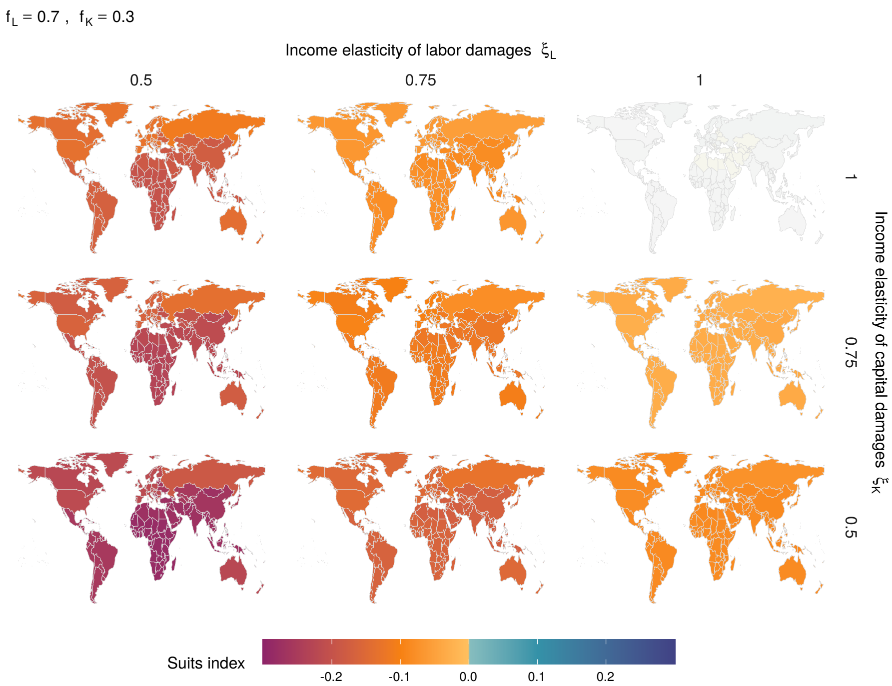
Figure 3 displays the effect of the income elasticities of labor and capital damages (ξ_L and ξ_K), for labor and capital damages shares fixed and proportional to the labor and capital share in income ($f_L = 0.7$ and $f_K = 0.3$). Damages are proportional to total income when both elasticities are equal 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 more pronounced impact on the Suits index reflects that labor income makes up a larger share of the income of poorer households.

Figure 2: Suits index of the damage distribution for different levels of capital and labor damage shares, 2020.



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

Figure 3: Suits index of the damage distribution for different levels of capital and labor income elasticities of damages, 2020.



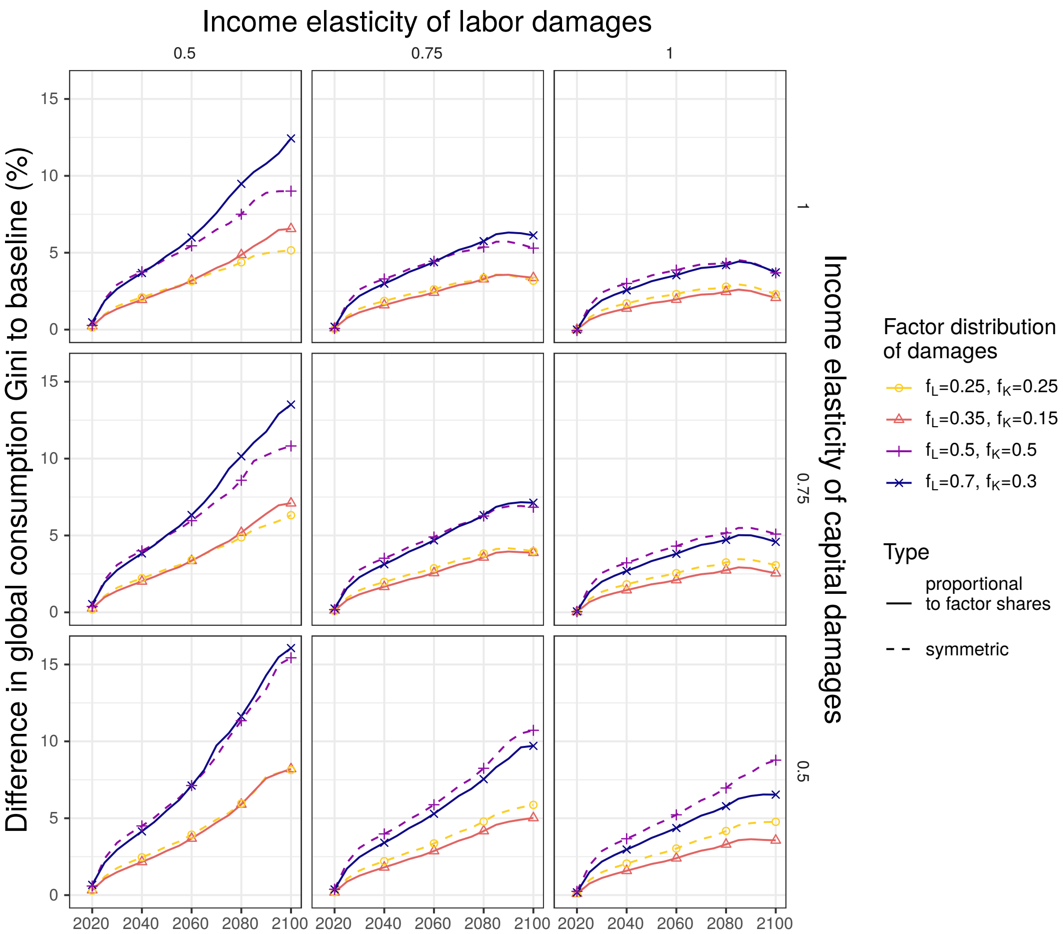
Note: white values are approximately equal to zero with a tolerance level of 1e-15.

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.). 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 2.5% in 2100. Having damages fall disproportionately on the bottom of the distribution raises the global Gini with respect to the case with damages on output. By 2100, the global Gini index increases by 4% for income elasticities of capital and labor damages of 0.75, and by 7.5% for income elasticities of capital and labor damages of 0.5.

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



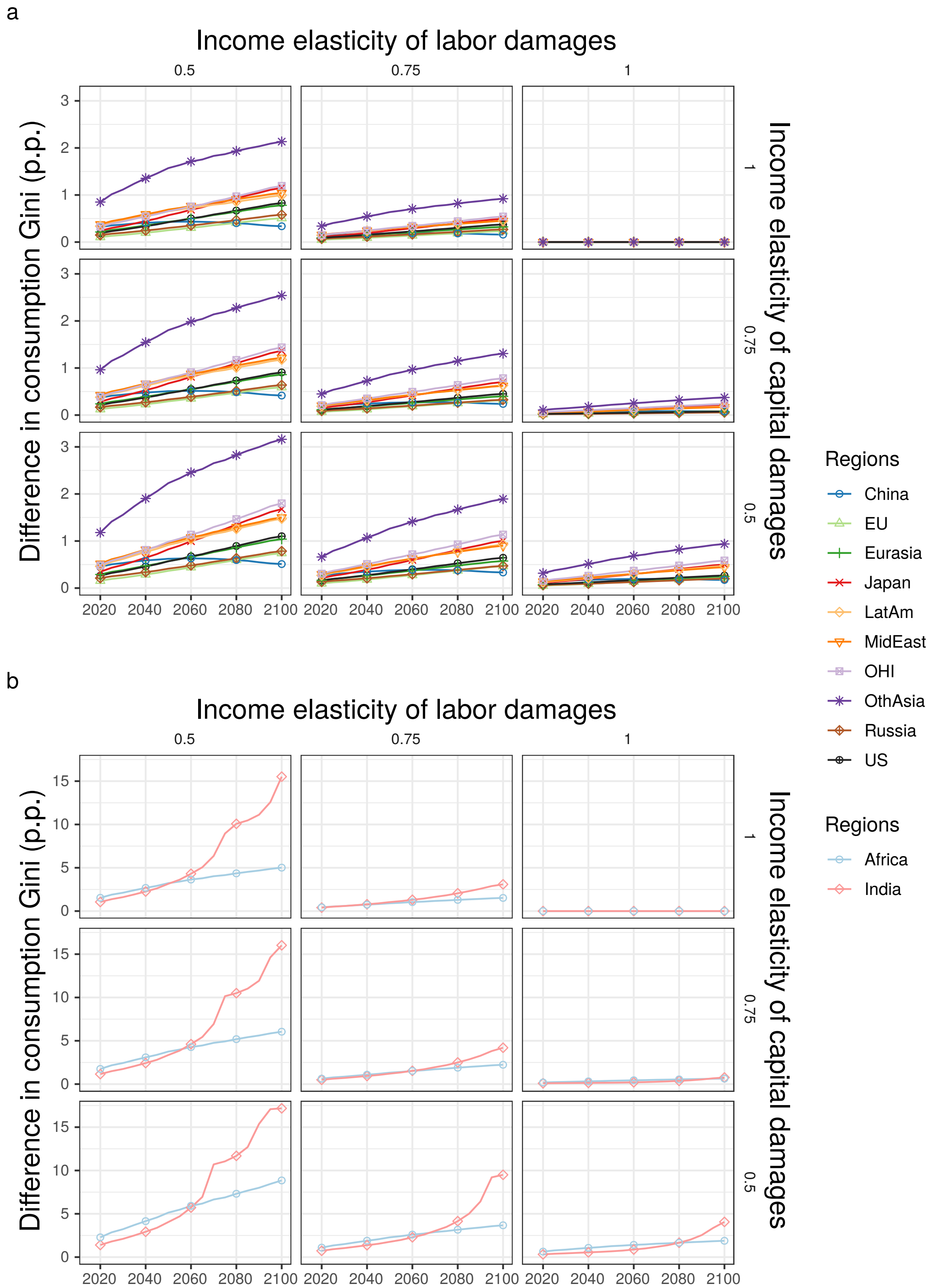
Second, we assign 100% of total damages to the channel-specific damages ($f_Y = 0$). As a result, the global Gini increases compared to the unpersistent case, by around 3.5% for proportional damages and up to around 15% for disproportionate damages with $\xi_L = 0.5$ and $\xi_K = 0.5$, in 2100 (Figure 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 4 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 the 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 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 around 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 loss in consumption per capita 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 reductions of 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 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 slightly increases the income share of the first quintile (Figure 7b). This increase 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 does not occur 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 effect can be seen by the larger income share loss from disproportional labor damages than from 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 dependent on the share and regressivity of climate damages hitting labor productivity.

Figure 6: Difference in consumption per capita of the first quintile for different levels of channel-specific damages and elasticities, $\delta = 0.7$, $\lambda = 0.5$.

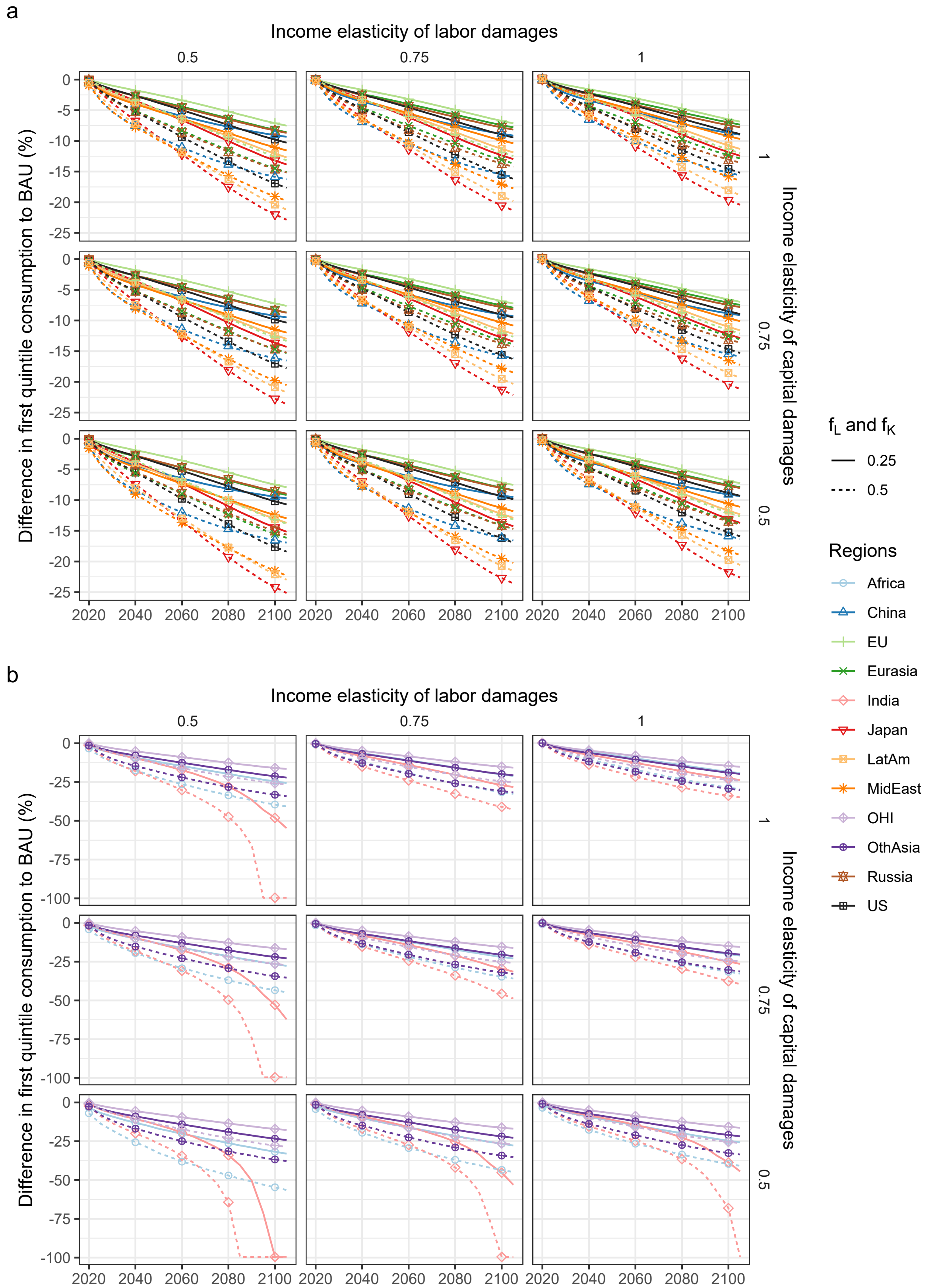
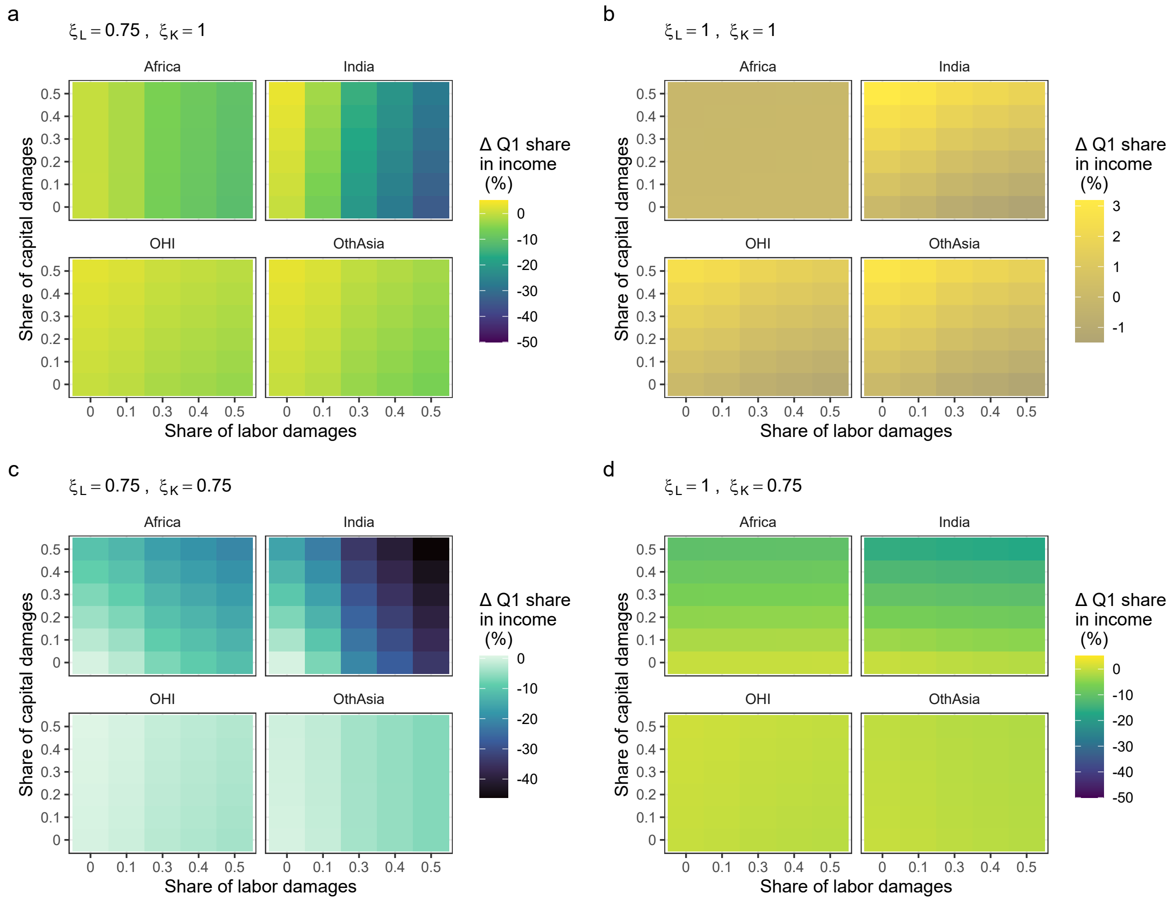


Figure 7: Change in the income share of the first quintile, from pre-damage to net income distribution, for different levels of channel-specific damages and elasticities, 2105, $\delta = 0.7$, $\lambda = 0.5$.

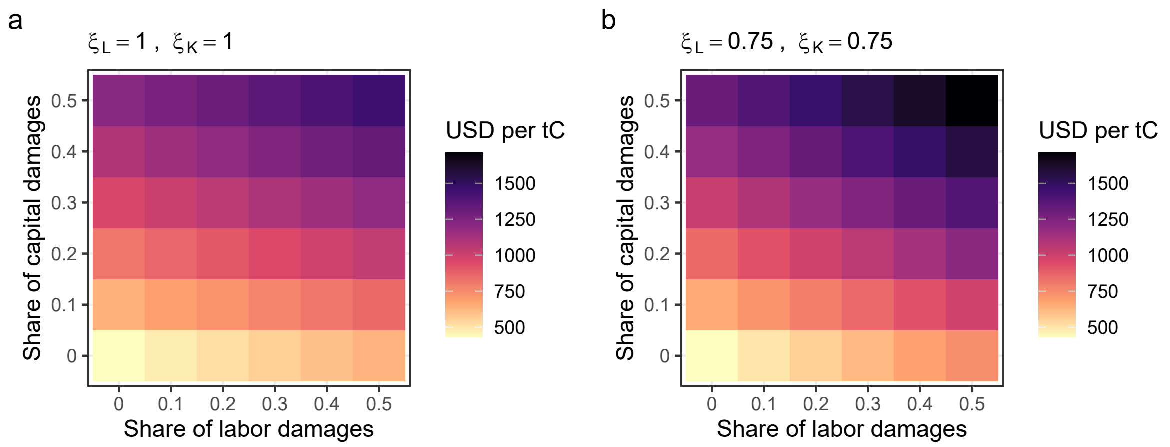


3.3 Social cost of carbon

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 generations[10] ($\eta = \gamma = 2$) and a rate of time preference of $\rho = 0.015$.

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 a), and detailed in Table A1a. With all damages falling directly on output, the SCC is 432 dollars per ton of carbon. If damages fall completely on capital and labor (with a share of 50% respectively), the SCC is 1452 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.

Figure 8: The social cost of carbon for different levels of channel-specific damages, 2023. 2017 PPP USD per tC, $\delta = 0.7, \eta = \gamma = 2, \rho = 0.015, \lambda = 0.5$



Next, we explore the results for damages falling slightly disproportionally on the poorer quintiles for the labor and the capital damages ($\xi_L = 0.75$ and $\xi_K = 0.75$) shown in Figure 8b. The SCC amounts to more than 1710 dollars per ton of carbon if damages fall fully on capital and labor, around 260 dollars per ton of carbon larger than with damages distributed proportionally to shares in factor income (see Table A1). With slightly regressive damages, the share of capital damages still has a stronger increasing effect on the SCC than the share of labor damages. However, regressive labor damages result in stronger increases in the SCC than regressive capital damages (comparing with SCC with proportional damages in Figure 8 and with the same damage shares). These results show 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

10. We relax this assumption further down.

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.

3.3.1 Disentangling the persistence and distributive channels

Capital and labor damages yield persistent output losses and distributive effects. To investigate the contribution of these two effects to the increase in the SCC, we compute SCC_{nodist}, the value of the social cost of carbon 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 A1b shows the SCC_{nodist} for different shares of capital and labor damages.

With a capital damage share of 0 and a labor damage share of 0.5, the SCC_{nodist} is 629 dollars per ton of carbon, a few dollars lower than the SCC with $\xi_L = \xi_K = 1$ (Table A1a). 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 A1b) is larger than the SCC_{nodist} (Table A1c). 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 more than 250 dollars higher than the SCC_{nodist}, a 17% increase.

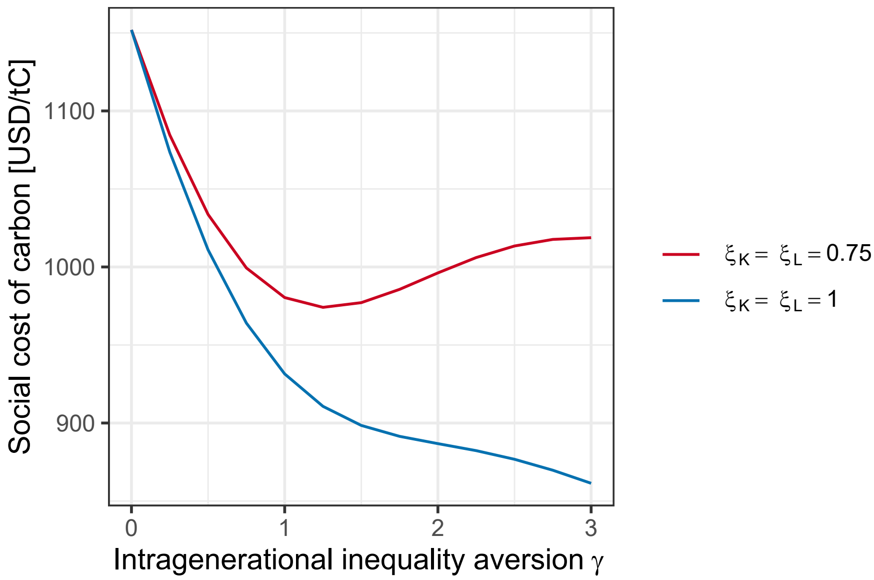
The impact of the distributive channel on the SCC depends on the normative evaluation of damages and mitigation costs. Figure 9 illustrates the relationship between the SCC and the intra-generational inequality aversion γ, keeping the inter-generational inequality aversion η fixed ($\eta = 2$). We fix $f_K = 0.15$ and $f_L = 0.35$ and look at two scenarios: a first with damages distributed proportionally, and a second with damages distributed regressively to income shares. In the absence of intra-generational inequality aversion ($\gamma = 0$), the two curves overlap and the distribution of damages is irrelevant. As γ increases above zero, the SCC first experiences a decline in both scenarios. With proportionately distributed damages, the SCC falls continuously. With regressively distributed damages, the SCC decreases initially until in reaches a minimum value at γ slightly larger than one, then increases.

The result on the SCC under proportional damages is similar to that in Anthoff and Emmerling 2019. The authors find that the SCC declines with increasing γ. However, they use a poor region for the normalization of the SCC, whereas we implement a "World-fair" normalization assuming proportional distribution of mitigation costs. An increase in γ has two opposing effects[11]. On the one hand, it increases the current welfare cost of mitigating a marginal unit of emission at the expense of the poor, which tends to

11. These correspond to the effects of γ on the denominator and the numerator of the SCC, see subsection 2.6.

decrease the SCC. On the other hand, it increases the welfare costs of disproportionate climate damages from a marginal unit of emissions, which tends to increase the SCC. In addition, baseline global inequality falls over time while average consumption grows, so in the baseline scenario the future world has richer poor and is more equal. When damages fall proportionally ($\xi_L = \xi_K = 1$), an increase in γ thus results in a larger increase in the welfare costs of today's mitigation costs than in the welfare costs of future damages, so the SCC decreases with γ. When damages fall disproportionately on the poor ($\xi_L = \xi_K = 0.75$), the effect on the welfare cost of future damages[12] dominates at larger values of γ, so the SCC increases with γ at these larger values.

Figure 9: The social cost of carbon for different levels of intra-generational inequality aversion γ and income elasticity of damages ξ_L and ξ_K, 2023.
2017 PPP USD per tC, $\delta = 0.7, \lambda = 0.5, \eta = 2, \rho = 0.015, f_K = 0.15, f_L = 0.35$.



3.3.2 Sensitivity analysis

We test the sensitivity of the SCC to the key parameters of the models. We first focus on the income elasticity of damages. Figure A8 in the Appendix 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 more than 4700 dollars per ton of carbon with capital and labor damages, a fourfold increase compared to the SCC with proportionate capital and labor damages and the same factor-specific damages.

In a number of capital and labor damage combinations, damages exceed income for at least one quintile – specifically, the poorest quintile in India, as can be seen in Figure 6b. As a result, consumption in these quintiles has to be bounded by zero or some positive value. Our CRRA utility function, commonly used in integrated assessment models, features infinite marginal utility at the origin. This implies that the SCC is either unbounded

12. In this case, the reduction in global inequality over the century is lower than in the proportionate case, see Figure 4.

if minimal consumption is set to zero, or is unstable and very sensitive to the boundary value if minimal consumption is set to a positive value[13]. This issue can be related to the debate on the welfare evaluation of catastrophic outcomes sparked by Weitzman's "dismal theorem" (Weitzman 2009). As Millner 2013 points out, technical problems surrounding the sensitivity of welfare computations to the behavior of the utility function at low consumption levels are in fact ethical questions regarding how to socially value catastrophic outcomes, such as a quintile losing all means of subsistence in our setting. Given that our current framework is not equipped to address questions of population ethics, we chose not to compute the SCC when the income share of a quintile falls to zero, and instead mark theses cases in grey in Figure A8. The proportion of greyed labor and capital damage combinations is large with a labor income elasticity of damages of 0.5 (Figure A8a and c), indicating the potential for regressive labor damages to result in catastrophic outcomes for the poorest.

Finally, Figure A9 displays the sensitivity of the social cost of carbon to the main parameters. We modify one parameter value at a time while keeping the other parameters at their central value. The SCC amounts to around 1000 USD/tC with our central choice of parameter values. Figure A9 indicates a strong sensitivity of the SCC to the normative parameters η (inter-temporal inequality aversion) or ρ (pure rate of time preference). For low values of η or ρ, the SCC reaches more than 23000 and 3000 USD/tC, respectively, but can also fall to around 500 USD/tC for high values of η or ρ. The SCC is also very sensitive to the value of the labor damage elasticity ξ_L as already observed in Figure A8. We mark the range for ξ_L as unbounded at the upper end because the income share of the poorest quintile in India falls to the lower bound of zero with $\xi_L = 0.5$. Finally, the persistence of labor damages λ and the capital and labor damage share f_K and f_L also have a significant impact, albeit smaller than the parameters mentioned above. The SCC is least sensitive to changes in the capital damage elasticity ξ_K, the capital depreciation δ, and the intra-temporal inequality aversion γ.

4 Discussion

Our results remain conditional on a number of assumptions. In the section, we discuss our choices of a fixed savings rate and a constant factor share.

We keep the savings rate fixed as in the original NICE[14] (Dennig et al. 2015). This assumption could lead to larger impacts of factor-specific damages, as we are missing a possible readjustment channel. Piontek et al. 2019 show that for a large one-time shock followed by a recovery, a fixed savings rate leads to larger damages in the case of a capital shock and to a lesser extent in the case of an output shock, and to smaller damages in the short run followed by slightly larger damages in the long run in the case of a labor shock[15]. They also show that the savings rate responds less with a Cobb-

13. Alternatively, Kikstra et al. 2021 implement a convergence system to the boundary value to ensure that an additional ton of carbon yields additional consumption loss even when the consumption level is close to the boundary. With our model, the SCC become unstable and very sensitive to marginal changes in the labor and capital damages shares. Yet another option would be to bound utility directly, which leads to similar issues.

14. In the NICE, the fixed saving rate is derived following Golosov et al. 2014, as the optimal rate chosen by private savers. Under a set of assumptions, the endogenous savings rate will be fixed and a function of the capital share α and the pure rate of time preference, ρ.

15. They show that for a capital or output shock, the endogenous savings rate increases which hastens the recovery, while for a labor shock, the drop in labor results in overcapitalization with respect to the

Douglas production function. So endogenizing the savings rate while keeping an elasticity of substitution of one would not necessarily result in a strong readjustments.

Turning next to recurring and anticipated shocks, as in our setting, Fankhauser and Tol 2005 highlight the ambiguous effects of capital damages on an endogenous savings rate: although savers would want to compensate for the loss of capital with an increased savings rate, they also factor in the lower returns on capital investments. In this case, Piontek et al. 2019 show that using a fixed instead of an endogenous savings rate results in larger welfare and growth rate reductions for the capital channel, but has very small effects on the output and labor channels. These findings indicate that the assumption of a fixed savings rate in our setting could be resulting in larger and more persistent damages from the capital channel, leading to an over-estimation of the impact of growth effects with respect to distributional effects on the SCC. The effect is likely to be smaller through the output and labor channel. Finally, the response of an endogenous savings rate to simultaneous damages on labor and capital would likely be ambiguous in the short to medium run and depend on the respective shares of output, labor and capital damages, given that labor damages would tend to decrease the savings rate while capital damages would tend to increase it.

The constant factor share results from applying a Cobb-Douglas production function, a special case of the constant elasticity of substitution production function when the elasticity of substitution is equal to one. Instead, the factor share could be interpreted in a neo-classical fashion as reflecting relative factor prices, as in Piontek et al. 2019 and Tsigaris and Wood 2019. In this vein, a shock on the stock of either capital or productive labor would increase the relative price of the shocked input. Depending on the elasticity of substitution, the shock would affect the share of this factor in income and ultimately earnings (distributive effect). In Piontek et al. 2019, the change in the factor share of capital and productive labor compared to the case without climate change damages is most pronounced with impacts on capital. Following from their assumption of an elasticity of substitution of 0.5, the capital income share increases in this scenario. With an elasticity larger than one, the capital income share would decrease with impacts on capital.[16]

To obtain these endogenous changes in the factor income share, the elasticity of substitution needs to be different from one. Piontek et al. 2019 and Tsigaris and Wood 2019 show that the elasticity of substitution also alters the ability of the economy to cope with climate change damages. In Tsigaris and Wood 2019, a higher elasticity of substitution reduces the deviation from the path without climate damages, no matter which damage type. In Piontek et al. 2019, the impact depends on the damage type. A higher elasticity reduces the average GDP per capita growth rate more strongly with output and capital damages but less so with labor damages. Our findings could be mitigated or amplified, depending on the magnitude of the aggregate and the distributive effect of an elasticity of substitution different from one.

steady state level, leading initially to a decrease in the savings rate.

16. Another approach would be to attribute the net share of income to capital owners as in Tsigaris and Wood 2019, given by $(\frac{\partial Y}{\partial K} - \delta) * \frac{K}{Y_{net}}$. Even with a Cobb-Douglas production function, the share of income to capital would then depend on the capital to income ratio.

5 Concluding Remarks

We study how introducing channel-specific damages and composition of income affects 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 parameterize 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 find that including damages that fall directly on the factors production results in level and growth impacts on per capita output and in increased inequality, with heterogeneity across regions. With all damages falling on the labor and capital stocks proportionally to factor shares, regional annualized growth rates fall by 0.1 to 0.3 percentage points. The heterogeneity of damages across regions, combined with regressive impacts within regions, leads to an increase in the global Gini with respect to the baseline case with damages falling only on output. With half of damages falling on the capital channel and half on the labor channel, the global Gini increases by 5% in 2050 and 15% in 2100 relative to the baseline. We show that labor damages and their distribution are key to the outcomes of households at the bottom of the distribution.

We investigate the impact of channel-specific damages on the social cost of carbon. We find that the social cost of carbon increases four times if damages fall half on the capital and half on the labor channels and damages are slightly regressive, compared to a baseline in which all damages fall directly on output.

We further disentangle the persistence and distributional effects of factor-specific damages on the social cost of carbon by having damages fall on labor and capital while keeping the ex-post distribution of income fixed. Under our benchmark calibration with slightly regressive damages and the same inequality aversion within and between regions, we find that the growth channel accounts for the bulk of the effects on the SCC. With slightly regressive damages, the SCC increases by 17% compared to the SCC with neutralized distributional impacts.

Our results remain conditional on a number of assumptions. The basis for the distribution of damages could be developed by including further insights from the empirical literature on ongoing climate impacts. More research is needed to determine relevant parameters such as the persistence and the income elasticity of labor damages. Furthermore, our income decomposition remains a coarse approach to the many factors determining the distributional effects of climate policies. Future work could expand our framework of disentangled damages and inequality to include more dimensions of social heterogeneity, such as health, gender, or spatial inequalities. The role of adaptation in reducing or exacerbating the persistence and regressivity of climate damages could also be explored.

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A Appendix

Figure A1: Maps of input data for inequality

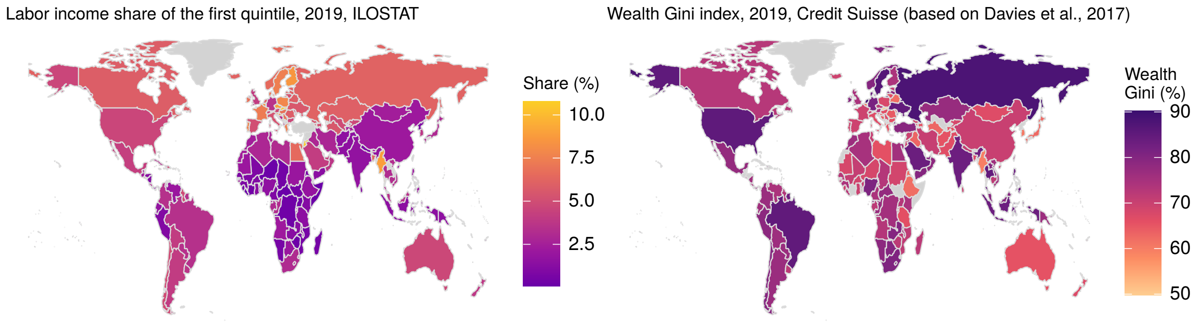


Figure A2: Calibrated distributions for capital income and labor income

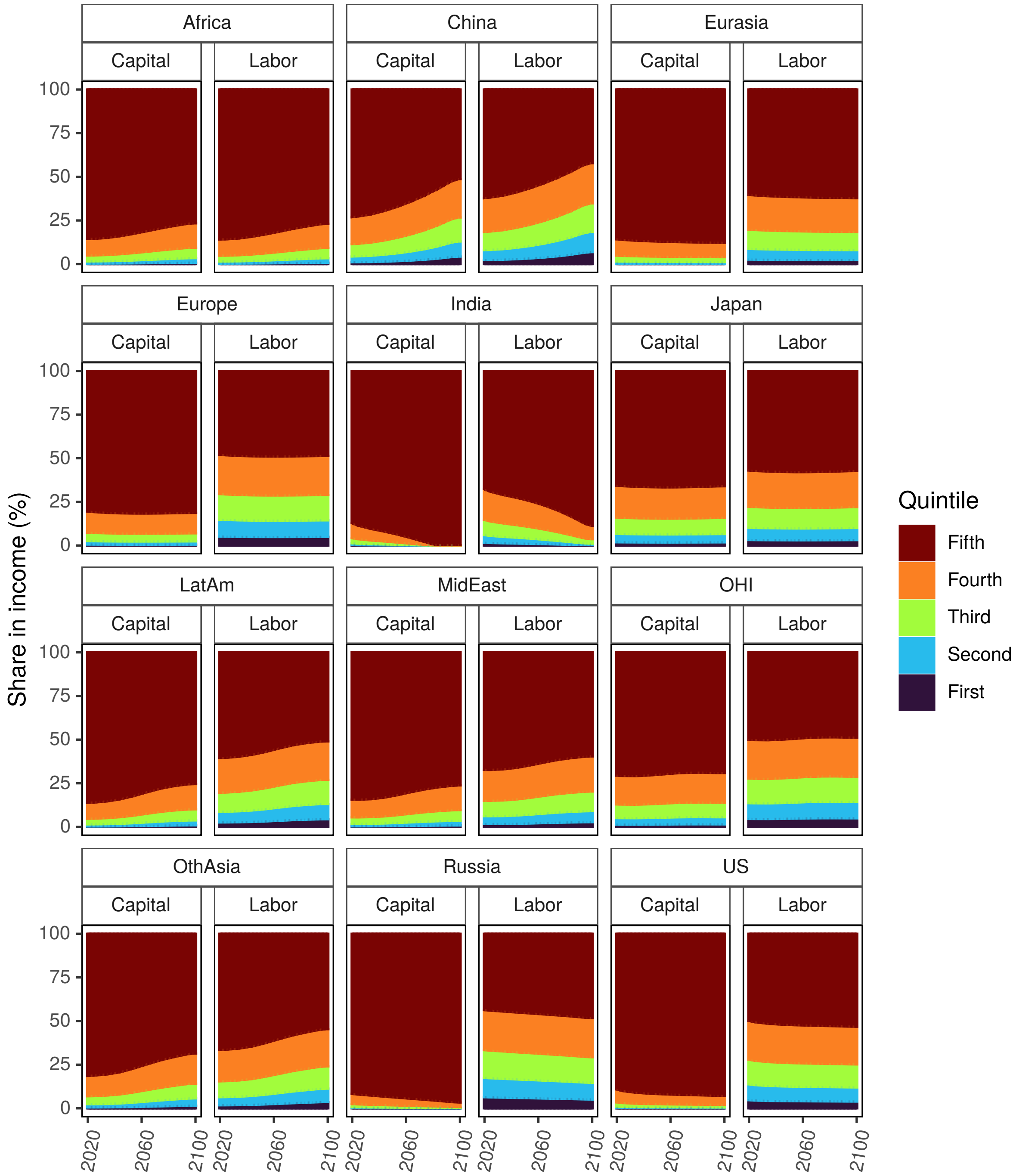


Figure A3: Regional output per capita and growth with output damages only, $\delta = 0.7$

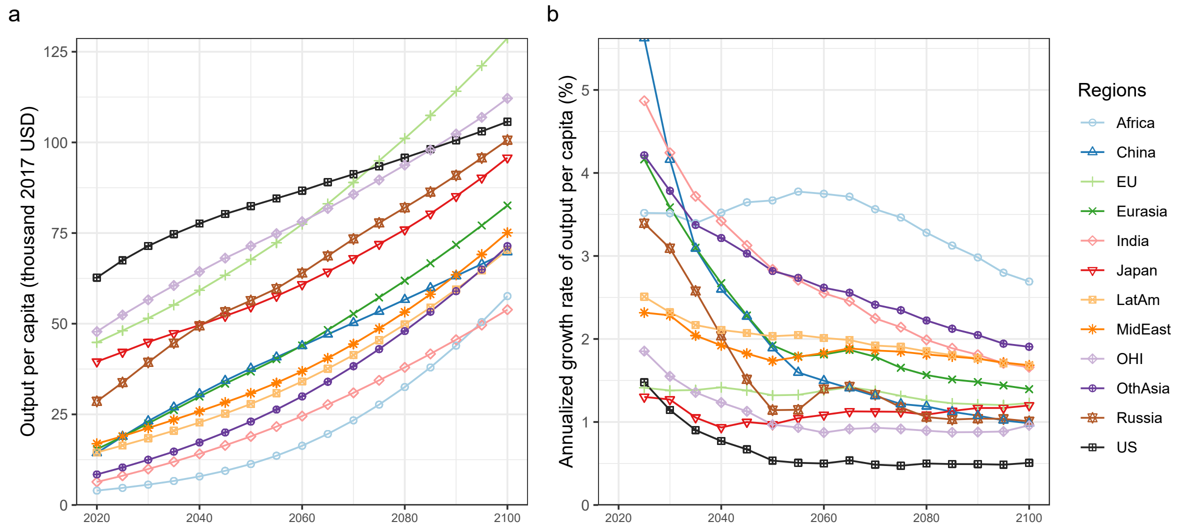


Figure A4: Impact of channel-specific damages on overall damages and on share of persistent damages, $\delta = 0.7$, $\lambda = 0.5$.

Note: 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.

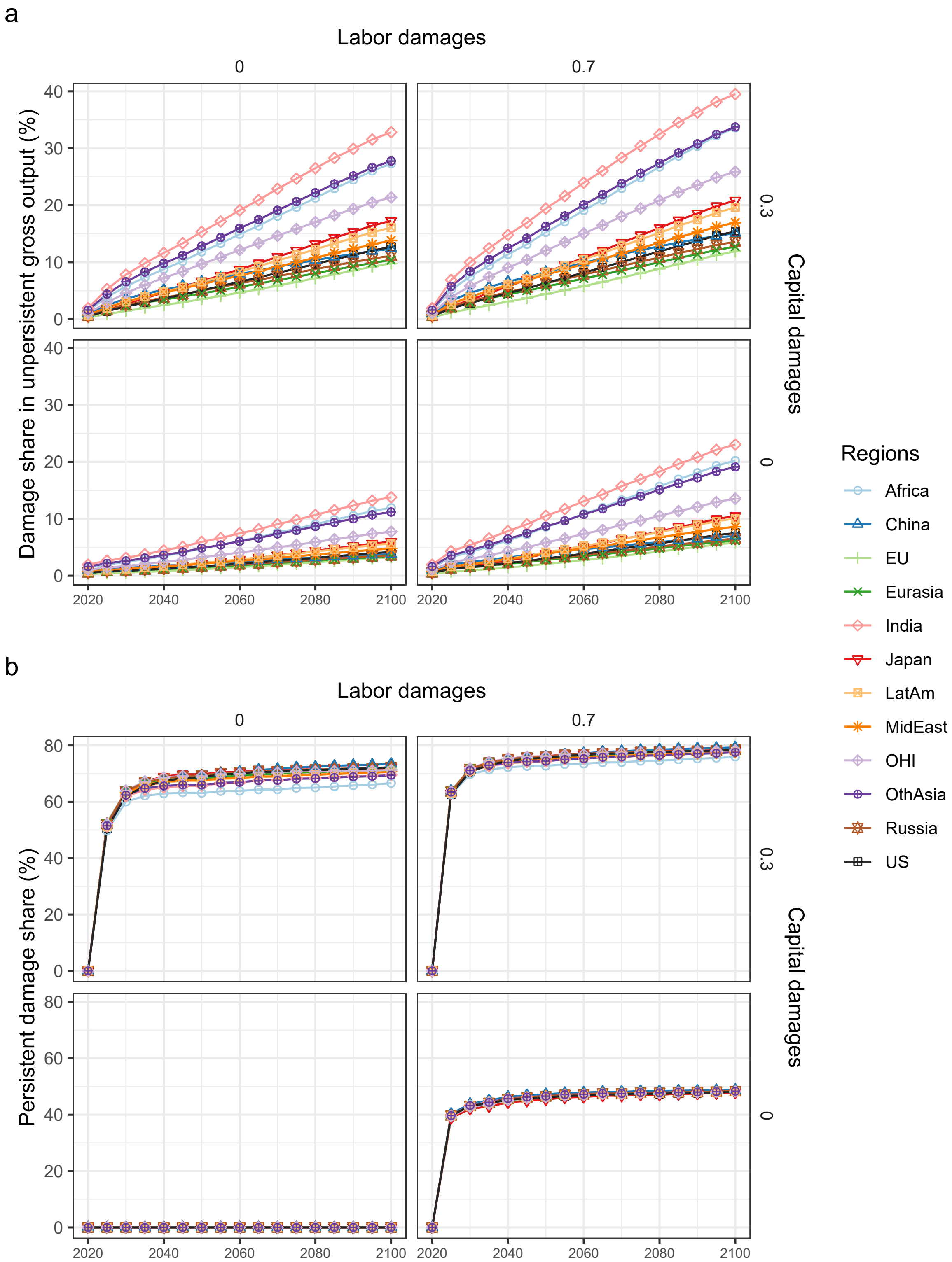


Figure A5: Share of total damages in gross unpersistent output (a) and Share of persistent damages in total damages (b), for different values of the decadal depreciation rate δ and of the persistence of labor damages λ, $f_K = 0.5$ and $f_L = 0.5$.

Note: In panel b) the share of persistent damages is shown starting in 2030 instead of 2020.

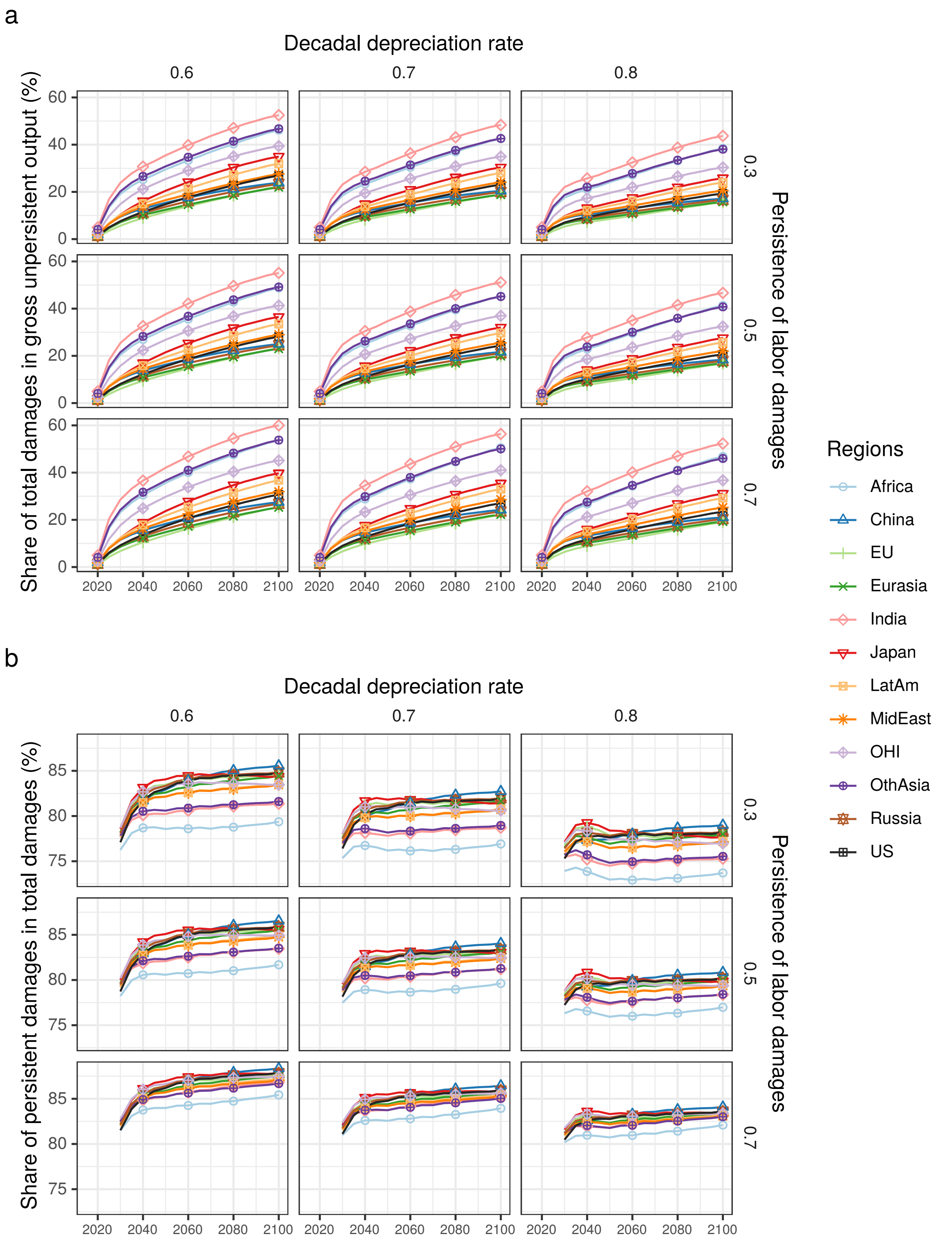


Figure A6: Global Gini index in the baseline case with all damages falling on output ($f_Y = 1$), $\delta = 0.7$, $\lambda = 0.5$.

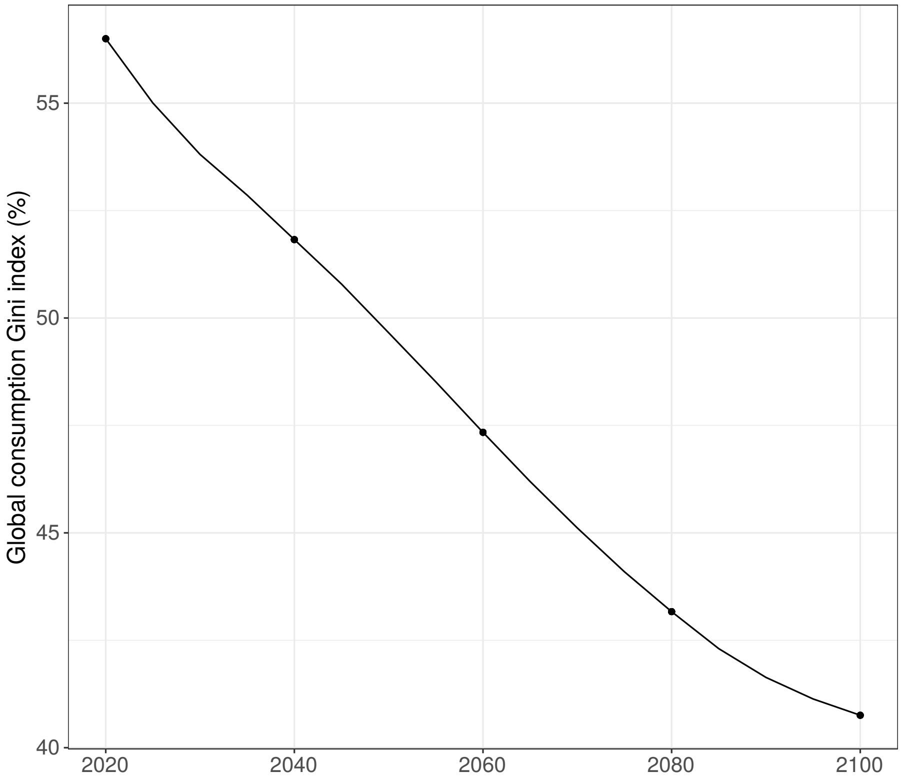


Figure A7: Regional Gini index in the baseline case with all damages falling on output ($f_Y = 1$), $\delta = 0.7$, $\lambda = 0.5$.

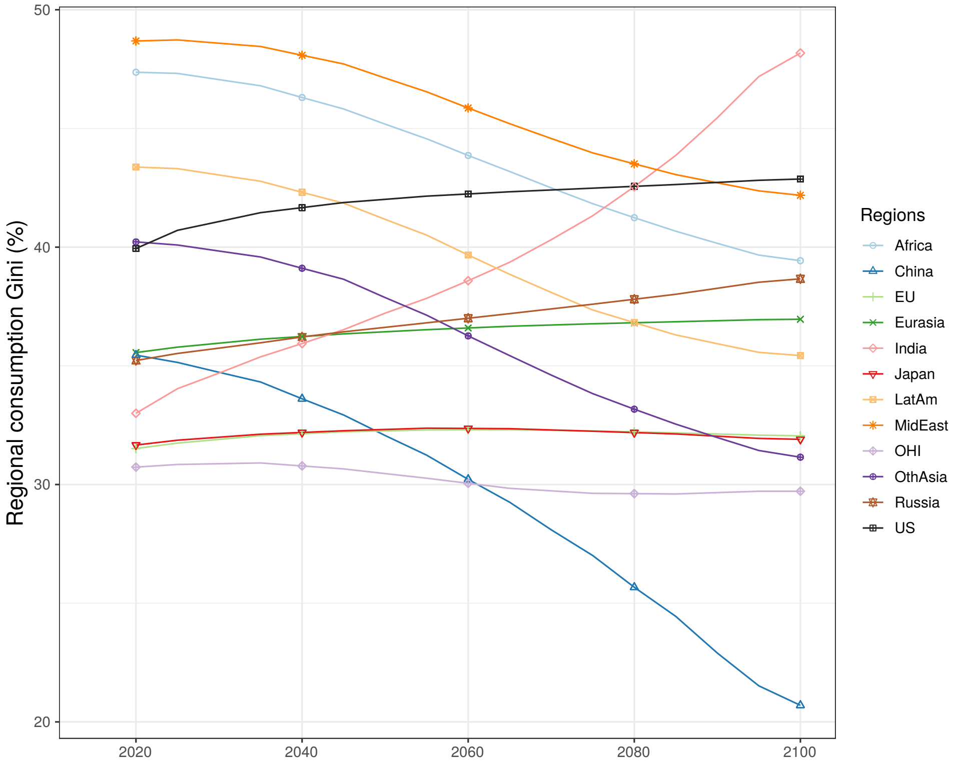
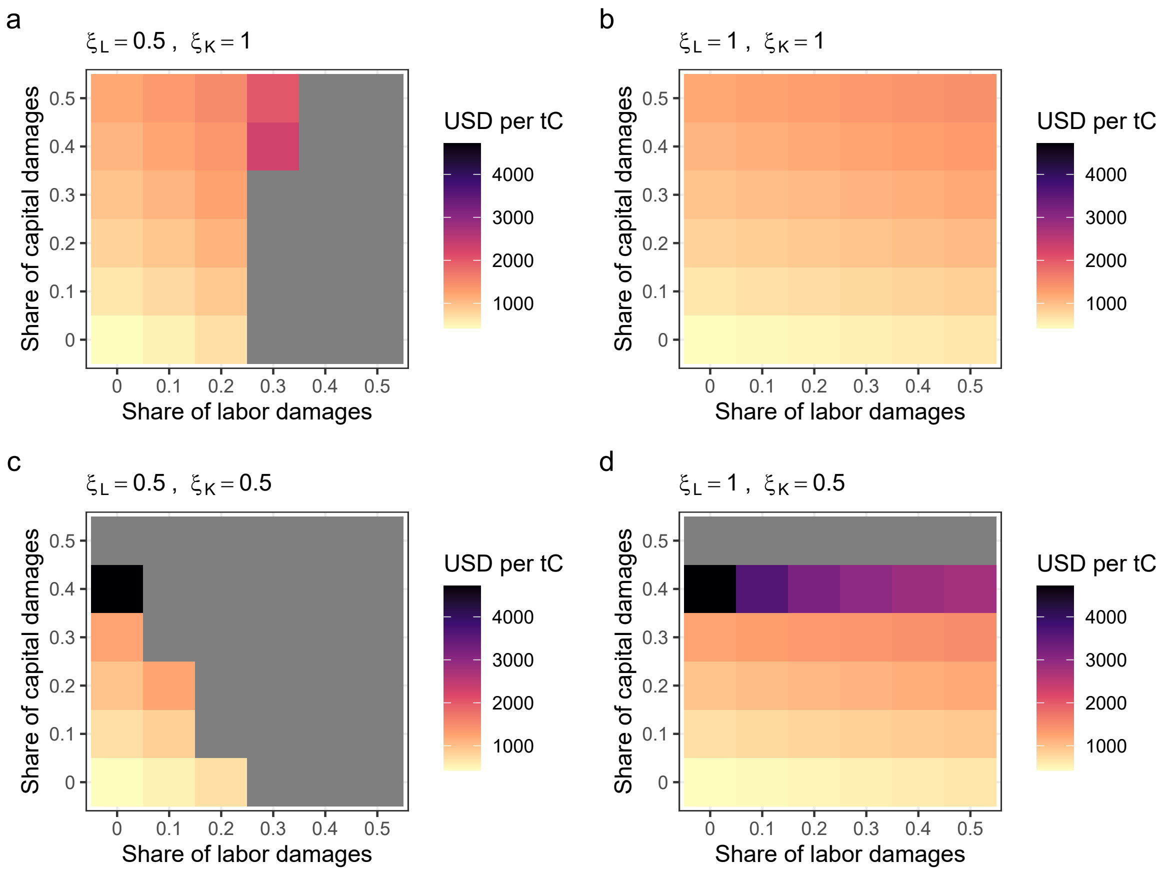
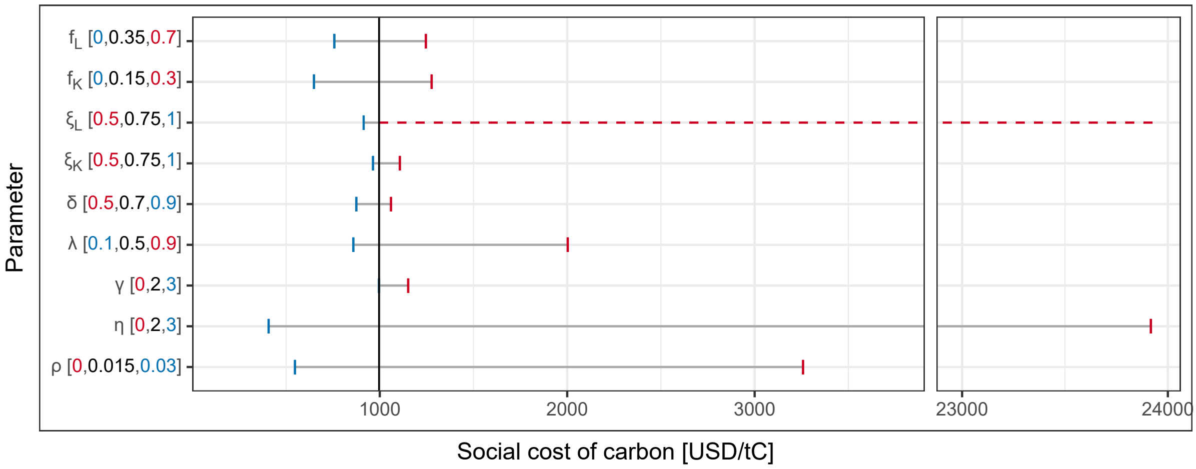


Figure A8: The social cost of carbon based on quintile CPC welfare function for different levels of channel-specific damages and combinations of elasticities ($\xi \in (0.5, 1)$), 2023, 2017 PPP USD, $\delta = 0.7, \eta = \gamma = 2, \rho = 0.015, \lambda = 0.5$



Note: The grey values indicate the combinations of capital and labor damages shares for which we do not compute the SCC because consumption drops to the boundary value of zero for a least one quintile.

Figure A9: Social cost of carbon based on quintile CPC welfare function for different levels of main parameters, holding all other parameters fixed at their central value, 2023.



Note: The SCC corresponding to the central parameter values (black) is marked by the vertical line. A blue (red) parameter value correspond to the lower (higher) SCC value. The x-axis is split at around 4000USD/tC.
With $xi_L = 0.5$ the income share of the poorest quintile in India reaches the boundary of zero.

Table A1: Social cost of carbon with quintile consumption per capita, for different channel-specific impacts (2023) in 2017 USD per tC, $\delta = 0.7$, $\lambda = 0.5$, $\rho = 0.015$, $\eta = \gamma = 2$.

a)

SCC, $\xi_K = \xi_L = 1$		
$f_K \backslash f_L$	0	0.5
0	432	634
0.5	1212	1452

b)

SCC, $\xi_K = \xi_L = 0.75$		
$f_K \backslash f_L$	0	0.5
0	432	744
0.5	1313	1710

c)

SCC_{nodist}		
$f_K \backslash f_L$	0	0.5
0	432	629
0.5	1223	1458

Note: 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).