

Inequality repercussions of financing negative emissions

Pietro Andreoni (✉ pietro.andreoni@eiee.org)

RFF-CMCC European Institute for the Economics and the Environment (EIEE) & Politecnico di Milano
<https://orcid.org/0000-0003-2487-1671>

Johannes Emmerling

RFF-CMCC European Institute on Economics and the Environment, Centro Euro-Mediterraneo sui
Cambiamenti Climatici <https://orcid.org/0000-0003-0916-9913>

Massimo Tavoni

European Institute on Economics and the Environment

Article

Keywords:

Posted Date: August 15th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1928418/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Inequality repercussions of financing negative emissions

Pietro Andreoni ^{*1,2}, Johannes Emmerling¹, and Massimo Tavoni^{1,2}

(1) RFF-CMCC European Institute for the Economics and the Environment, Milan, Italy

(2) Politecnico di Milano, Milan, Italy

* correspondence to pietro.andreoni@eiee.org

Abstract

Negative emission technologies are attracting the interest of investors in the race to make them effective and profitable. When deployed at scale, negative emissions will need to be financed through carbon tax revenues or issuing other taxes. Financing negative emissions could thus reduce the fiscal resources needed for a socially inclusive transition. Moreover, if negative emissions are privately owned their profits will disproportionately benefit investors and equity holders. We quantify the inequality repercussions of negative emission through an integrated assessment model which features within-country income heterogeneity and direct air capture of CO₂. We find that negative emissions technologies deployed by private actors contribute to more than half of the increase in income inequality observed in a 1.5°C scenario. The effects are concentrated around the time of net-zero and are higher in scenarios with carbon budget overshoot. We attribute regional variations to two main mechanisms, the revenue drying and private ownerships effects of negative emissions.

Main

In 2022 alone, almost 1 billion dollars have been pledged by foundations linked to private donors such as Google and Facebook to advance and sustain the research and development of negative emission technologies (NETs)¹. In a world of sluggish climate mitigation policies, these technologies can serve the critical function of speeding-up the decline of carbon dioxide emissions, they can offset hard-to-abate emissions and provide a “reverse switch” for global temperature².

While criticized because they are currently immature or speculative technologies^{3,4} and they might crowd out emission reductions⁵⁻⁷, there is consensus that NETs will be needed to achieve the Paris agreement targets given the delays in reducing emissions and technological and political inertias^{8,9}. Therefore, R&D on these technologies is a necessary step to reduce uncertainty about their cost, potential and scalability, and build an effective and efficient portfolio of options to reach 1.5°C. However, the fact that the main push for the development of NETs is pursued by the private sector poses additional challenges: the business model of this technologies relies (partially or entirely) on expensive public subsidies to operate at scale and on the profit expectations that these companies would collect in a high carbon price environment.

Under a uniform carbon price and up to net zero emissions, these subsidies are covered by carbon tax revenues. After that, unless intertemporal mechanisms like carbon funds have been put into place¹⁰, government budget must be altered to finance for the net-negative fraction of carbon removal either by increasing taxes, issuing debt, or cut spending¹¹.

Several studies found that NETs can shift part of the mitigation burden to countries with higher historical responsibility¹²⁻¹⁴. However, no existing literature considers the potential repercussions of negative emissions in shaping future inequality *within* societies. Two mechanisms suggest that privately-owned negative emission technologies can significantly influence the distribution of wealth. First, remunerating negative emissions reduces the amount of carbon tax revenues available to counterbalance the regressivity of climate policy or to tackle inequality and alleviate poverty¹⁵ (*revenue drying effect*). Second, if these technologies are privately owned their financing will benefit disproportionately the high end of the income distribution that owns companies which might be very profitable (*ownership effect*). Since the carbon tax is expected to produce mostly regressive outcomes¹⁵⁻¹⁷ and equity ownership is almost exclusively concentrated in the top of the income distribution, both mechanisms can lead to significant inequality which can erode the support and desirability of ambitious climate goals.

To explore and quantify these dynamics, we use an open-source, highly regionalized Integrated Assessment Model¹⁸. Featuring 57 independent regions, this model allows for a granular representation of income dynamics between-countries. We extend it by differentiating income groups within-countries into deciles¹⁹ and by introducing Direct Air Capture (DAC)²⁰ as a representative technology for NETs (see Methods for details). The representation of income heterogeneity is key for understanding the distributional implications of technological developments. Most models rely on representative agents²¹, though exceptions exist and have flagged important distributional concerns of climate strategies^{15,19}. Direct air capture is an example of NET which has catalyzed significant financial interest; it is considered to have significant deployment potential and smaller environmental and social trade-offs than biological NETs such as biomass and CCS^{3,22}.

We quantify the distributional effects of negative emissions in a 1.5°C scenarios under the assumptions of a global uniform carbon tax and private ownership of carbon removal companies. We analyze and quantify the within-country and global implications on inequality under different socio-economic and technological assumptions. Finally, we propose two possible layers of policy intervention, supported by our analysis, to mitigate the regressive potential of technology-based NETs.

Privately owned direct air capture in an IAM

We model the economic costs and gains of climate policy by six different components, summarized at the global level in Figure 1a: total mitigation costs (dotted blue line) are composed by the sum of abatement costs (red area) and NETs costs, that include investment and operational costs (green area).

The remaining components sum to zero for each timestep and country. The government receives the carbon tax revenues (brown area), which are used to pay NETs owners at the carbon price for their negative emissions (an effective subsidy) or redistributed through transfers to households (purple area). When NETs payments exceed carbon tax revenues, the government must raise other taxes (dark blue area) to balance the budget.

Since we don't consider the cost of public funds nor potential aggregate growth effects due to variations in the income distribution, these fluxes have no aggregate effect on the economy or

emissions but do influence the distribution of welfare because each flux impacts differently different income deciles (Figure 1b). Abatement costs and the carbon tax are assumed to be regressive for rich countries and progressive for developing countries, following empirical evidence¹⁵. Costs and revenues of our representative NET are calibrated to fall mostly on the richest two deciles of each country, because stocks and capital are owned by the rich. Because of data availability, we use wealth distribution as a proxy for equity ownership. This is a conservative assumption since equity ownership is more concentrated on the top of the income distribution than wealth. Furthermore, we assume that all capital is owned exclusively by each country's citizens. Finally, the redistribution of carbon tax revenues is designed to offset the regressivity of the carbon tax. To better isolate the inequality consequences of negative emissions, we don't consider progressive schemes for carbon tax recycling. If assumed, progressive recycling schemes would exacerbate the *revenues drying effect*. The other taxes raised after net-zero are progressive to reflect the structure of most taxation systems (see *Methods: calibration* for details). Even if less so than with carbon tax revenues, financing carbon removal revenues with the other taxes is regressive because NETs ownership is more skewed to the right of the income distribution than the households targeted by the tax (Figure 1b and *ANNEX B: calibration of elasticities* for details).

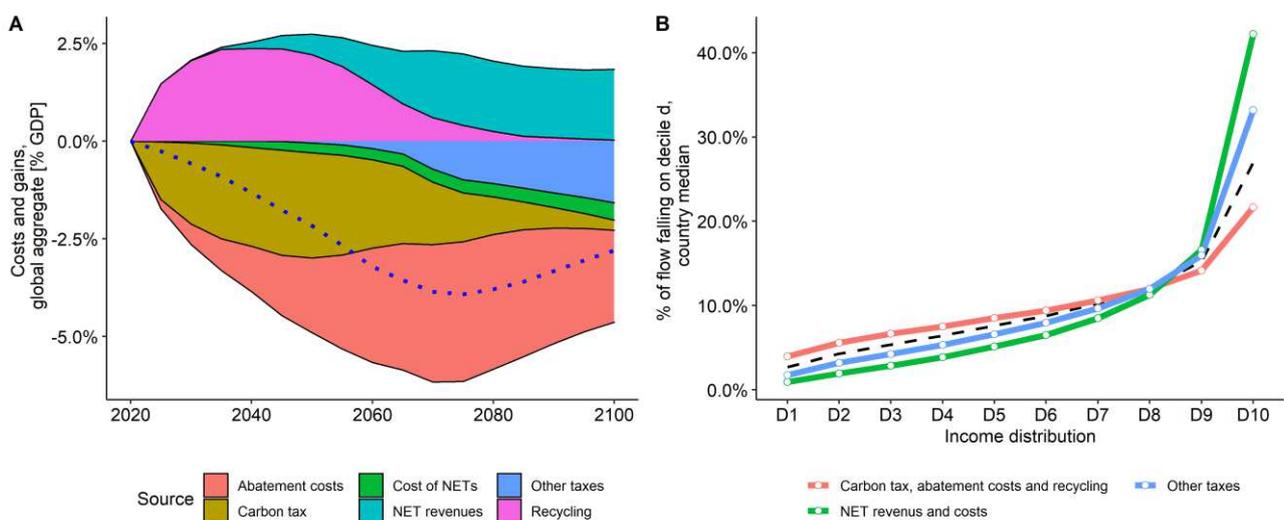


Figure 1: (a) Global financial flows and climate costs in % GDP aggregated for all countries and deciles, in a 1.5°C scenario with budget overshoot. The blue dotted line represents global net costs, i.e. the sum of abatement costs (red area) and NET costs (green area). The other fluxes sum to zero at each point in time. Other taxes (blue area) can only be raised to finance negative emissions after budget overshoot. Carbon tax revenues (brown area) are either used to pay for NET revenues (light blue area), and the excess is recycled in the economy (purple area). (b) share of resources (median across countries) accruing to each income decile per type of flow according to the calibration of carbon tax, equity ownership and other taxes regressivity, in year 2075. Black dotted lines represent the median across countries of income distribution across deciles. If the flow is a cost from the perspective of the households (carbon taxes, abatement costs, other taxes), it is regressive if it falls above the quantile line for low deciles and below for high deciles. If the flow is a gain from the perspective of the households (recycling, NET revenues), it is regressive if it falls above the quantile line for high decile and below for low deciles. The net regressivity of a flow (e.g. financing NET revenues with carbon taxes or other taxes) can be visualized as proportional to the distance between the two lines (red and green or blue and green, respectively).

The scenarios

To quantify the inequality implications of NETs ownership, we run a scenario consistent with the Paris temperature target of 1.5°C with 50% likelihood. Specifically, we impose a carbon budget of 700 GtCO₂ from 2019 to 2100², assuming a continuation of historical trends for economic growth, population growth, and the evolution of the income distribution (SSP2²³). The budget is reached with a global uniform carbon price until regional net zero. After that, prices decline because of technological learning and can differ across regions (Methods for details): the price necessary to completely abate emissions varies from hundreds to thousands of dollars per ton of CO₂. The climate constrained scenario is compared to a reference one based on extrapolated policies as pledged in the Nationally Determined Contributions (NDCs)^{24,25}.

While negative emission technologies are deemed as a key component of the portfolio of options to reach stringent mitigation targets, scenarios that limit or don't allow net negative emissions have been recently developed^{9,26}. To assess the implications of scenario design, we compare a case with and without overshoot of carbon budget.

Figure 2 summarizes the characteristic of these scenarios. Achieving climate stabilization requires emissions to decline rapidly and achieve net zero in a few decades, and net negative afterwards (Figure 2a). In the scenario without carbon budget overshoot, emissions remain at net zero in exchange for faster short-term reductions. This leads to a higher carbon price and higher policy costs before net-zero, and lower thereafter, confirming recent evidence from model comparisons^{9,26} (Figure 2c). The net zero scenario leads to a smaller temperature overshoot, which has been shown to reduce climate risks⁹. These benefits are not considered in this set up, but they are relevant because climate impacts also have distributional consequences. However, we don't explicitly consider them because of the lack of reliable data on their assessed regressivity.

The choice of budget overshoot effects not only the amount of carbon removed, but also its distribution: in the overshoot scenario, the geographical distribution on cumulative emissions (Figure 2b) is mainly driven by our assumption of geological storage potential of CO₂ as proxy for regional carbon removal capacity. Because this potential is linked to oil and gas reserves, big producers such as North America, Russia and the Middle East perform most of the removal. In the no overshoot scenario, the geological constraint is not binding and negative emissions are concentrated in regions with higher residual emissions to offset.

Given the large uncertainty surrounding the underlying socio-economic drivers as well as technological and storage potential for negative emissions, we test these assumptions by running all five shared socio-economic pathways (SSPs) with coherent narratives about negative emissions potential, technological assumptions as well as inequality, population, and economic growth (see Methods and ANNEX C).

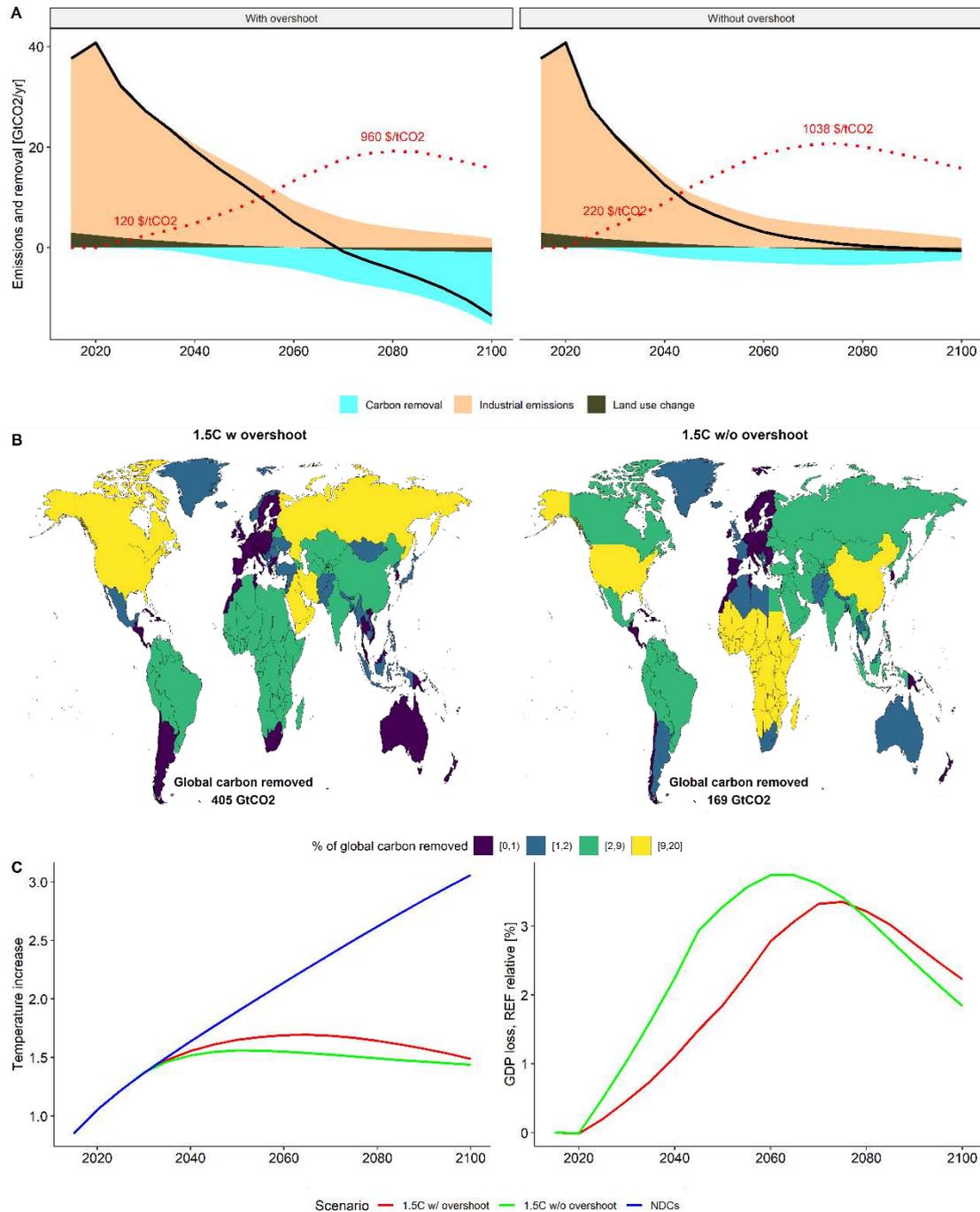


Figure 2: (A) emissions and carbon prices under a 1.5°C with and without overshoot. Black line represents net emissions and dotted red line the average of carbon prices, weighted by GDP. Carbon price in 2030 and at the maximum are highlighted. (B) Percentage distribution of regional cumulative emissions in the 1.5°C scenario. Global removal highlighted in text. (C) Temperature change and global GDP loss in the reference scenario and in the 1.5°C with and without budget overshoot, SSP2.

Negative emissions increase within-country inequality

We identify a clear connection between negative emission and inequality. In particular, we find that regions that carry out a larger share of their mitigation effort with negative emissions experience a higher inequality increase (Figure 3a). For regions that mitigate a large fraction of total emissions with NETs, the size of the negative emissions economy is significant and the profits of NETs owners can account for several points of GDP. Therefore, the *ownership effect* is larger in such regions.

The inequality impacts are concentrated in the second part of the century (Figure 3b), when negative emissions are deployed at scale. For most regions, the inequality increase peaks around net-zero, despite negative emission deployment increasing until 2100. This is the most expensive period to finance negative emission revenues because carbon prices peak and the entirety of NETs revenues are financed with the carbon tax from residual emissions.

To disentangle the effect of abatement costs (red area in Figure 3c), the *ownership effect* (blue area), and the *revenues drying effect* (green area), we perform a Shapley decomposition of the total inequality variation. The inequality effect of NETs is particularly pronounced in regions on the upper-right part of the bubble plot (Figure 3a), but non-negligible also for the rest of the world, accounting for 40% and 25% of total inequality increase at the net-zero year and in 2100 respectively (median values). In all cases, the *ownership effect* is predominant with respect to the *revenue drying effect*.

Despite the clear connection between NET and inequality, we identify a significant variability in this relation. To exemplify it, we highlight a series of regions that display a significant inequality increase (Figure 3). These include large deployers of negative emissions (US, Canada, Russia, Gulf States), small countries with high negative emission share of total mitigation (Sweden, Norway), and countries that suffer high inequality increase despite modest negative emissions (Egypt).

We identify three main sources of the variability, that coincide with the factors of the Shapley decomposition. A first factor of regional variation comes from the difference in abatement costs between countries (see Methods for details about regional cost curves). Second, the *ownership effect* depends on the size of the economies that carry out the removal and on the unitary profit margin for NETs firms. For example, while removing roughly the same amount of carbon, inequality increases more in Canada than in the US, given its smaller economy. However, the US is more impacted by abatement costs so that the total inequality increase is comparable between the two countries. In Norway, the higher inequality increase with respect to Canada is mainly due to the higher carbon price that increases unitary profits for NETs firms (see ANNEX C). Finally, the

regressivity of financing NETs revenues is country specific and depends on the calibration of equity concentration and of the regressivity of the carbon tax: in particular, the regressivity of removal is positively correlated with GDP per capita and negatively correlated with Gini (see Methods and ANNEX B). Therefore, countries such as Egypt with low baseline inequality are more impacted by inequality increase with respect to the Gulf Region or the US despite the lower share of carbon removed over total mitigation effort.

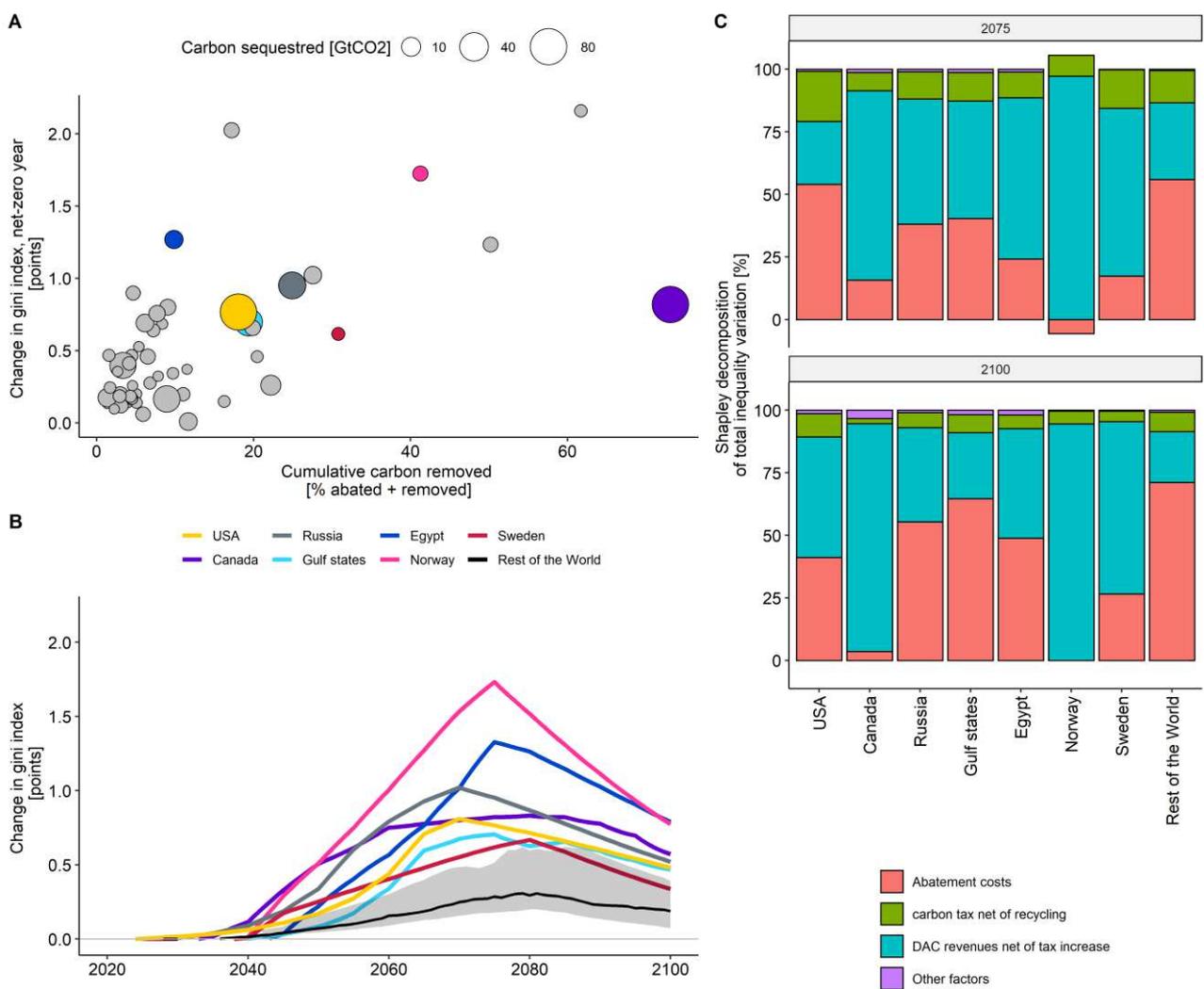


Figure 3: (a) inequality increase against cumulative negative emissions as share of total mitigation effort (carbon removed + abated) at the time of net zero for different regions. Bubble size represents cumulative CO₂ captured by each region through the century (Gt CO₂). (b) inequality increase over time in selected regions. Black line and grey range represent median and variance (25 to 75 percentile) of the inequality increase in all other regions but the selected ones. (c) Shapley decomposition of total inequality variation for selected regions and years, divided into conventional abatement costs, carbon tax revenues net of recycling (revenues drying effect) and DAC profits net of other taxes increase (ownership effect).

The implications of overshoot for inequality

We found that large-scale negative emissions contribute significantly to within-country inequality increase. Does this result depend on the fact that we allow the carbon budget to be overshoot, if temporarily? We test this hypothesis by comparing scenarios with and without overshoot. In the no overshoot scenario, each region is forced to remove at most its residual emissions, so that net emissions cannot be negative. This results in a global amount of cumulative carbon removed of 169 GtCO₂, less than half of the amount sequestered in the scenario with overshoot. On the other hand, the no-overshoot scenario has higher emission reductions in the first part of the century.

We find that the no-overshoot scenario has higher inequality before 2050, because of more and more costly regressive mitigation in the first decades (Figure 4). This increase is more accentuated for the selected regions and it is partly due to NETs (Figure 4b), because more negative emissions are deployed in the 2030s and 2040s²⁶ and are financed with a higher carbon price (see Figure 2). In the second half of the century, however, negative emissions are significantly lower if the budget is not overshoot. Consequently, the inequality implications of negative emissions are also reduced, especially for highly impacted countries Figure 4.

Thus, we find that allowing net-negative emissions by overshooting budget and temperature leads to an intertemporal inequality trade-off between regressive mitigation in the short term and regressive NET ownership in the long term. For the countries that are more impacted by the inequality repercussions of negative emissions, Figure 4 indicates that a smaller overshoot is preferable.

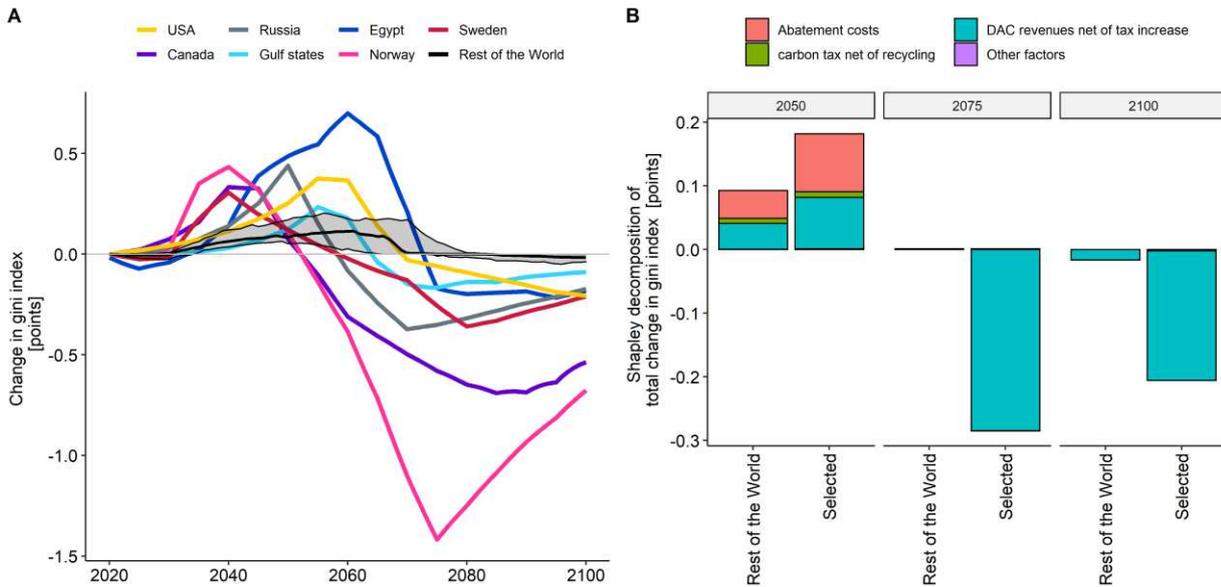


Figure 4: (a) inequality difference (variation in the Gini index) in the scenario without budget overshoot relative to a scenario with budget overshoot, for selected regions. The black line and range represent median and variance of the inequality increase in all other regions but the selected ones. (b) Shapley decomposition of the inequality variation between a no overshoot and an overshoot scenario, medians of the selected countries and all others ('Rest of the World').

Global inequality increases across technology assumptions, physical potential, and socio-economic projections

Global inequality is affected by negative emissions not only through the within-country effect which we have analyzed so far, but also through between-country inequality, since the geographical distribution of negative emissions varies across regions. If rich countries take up most of the carbon removal effort and bear the associated costs, negative emissions could be globally progressive because they would shift away part of the mitigation burden from poorer regions^{12,14}. Indeed, as discussed before, in our set up which uses direct air capture as a representative negative emission technology most of the NETs are carried out in the Global North¹ and China (65% of total removal in SSP2).

The net effect of these potentially opposing dynamics on the global income distribution depends on socioeconomic projections as well as technological assumptions. Both are uncertain. We consider different socio-economic scenarios using the five narratives of the shared-socio-economic pathways (SSPs); we further expand the SSP framework with different inequality projections, direct air capture potential and costs, and hard-to-abate emissions (see Methods for details).

¹ Europe, North America, Turkey, Russia, Australia, Japan, and Korea

Across all SSPs, we find that global inequality increases by 0.2 to 0.4 Gini points at the peak, which occurs around the time of net-zero (Figure 6). The variation in maximum inequality increase attributable to NETs varies from around 30% in SSP1, for which we assume cheap NETs and low overshoot, to almost 70% in SSP3, which assumes costly but widely utilized negative emissions.

The global inequality dynamics is characterized by a hump shape in all SSPs, with inequality increase declining after net zero. The overall trend is in line with that of within-country inequality (Figure 5, but declines more rapidly in the second part of the century as negative emissions and their associated costs are borne more by the rich countries (in relative terms). In the Global North and China, NETs cost 5 times more on a per capita basis than in the rest of the world in SSP2 (net present value). This contributes to reduce between-country inequality and thus counteracts the within-country inequality increase: in an SSP2, the global inequality increase is null at the end of century although the within-country is not (see Figure 3). Despite this, global inequality rises for the entire century.

In other pathways, the overall effect is a slight (SSP4) to significant (SSP3) global progressivity of negative emissions in the last decade of the century, while for SSP1 and SSP5 the impact remains globally regressive. Other than on the geographical distribution, this variability depends on technology cost and on the assumptions about convergence of growth across countries. In SSP3, costly but abundant NETs are deployed in a world of economic divergence, where the global North and China pay 3.5 times more per capita on CDR than the rest of the world. This causes a convergence in the global income distribution that overweighs the increase of inequality within-countries, that is by itself lower than in the other SSPs because of the low GDP per capita (see *ANNEX B*). In SSP5, cheap negative emissions are deployed in a world of rapid economic convergence where the North and China pay only 2 times more than the South for NETs deployment, and the within-country regressivity of negative emissions is high (see *ANNEX A and ANNEX B*). This results in a sustained increase in global inequality until the end of the century.

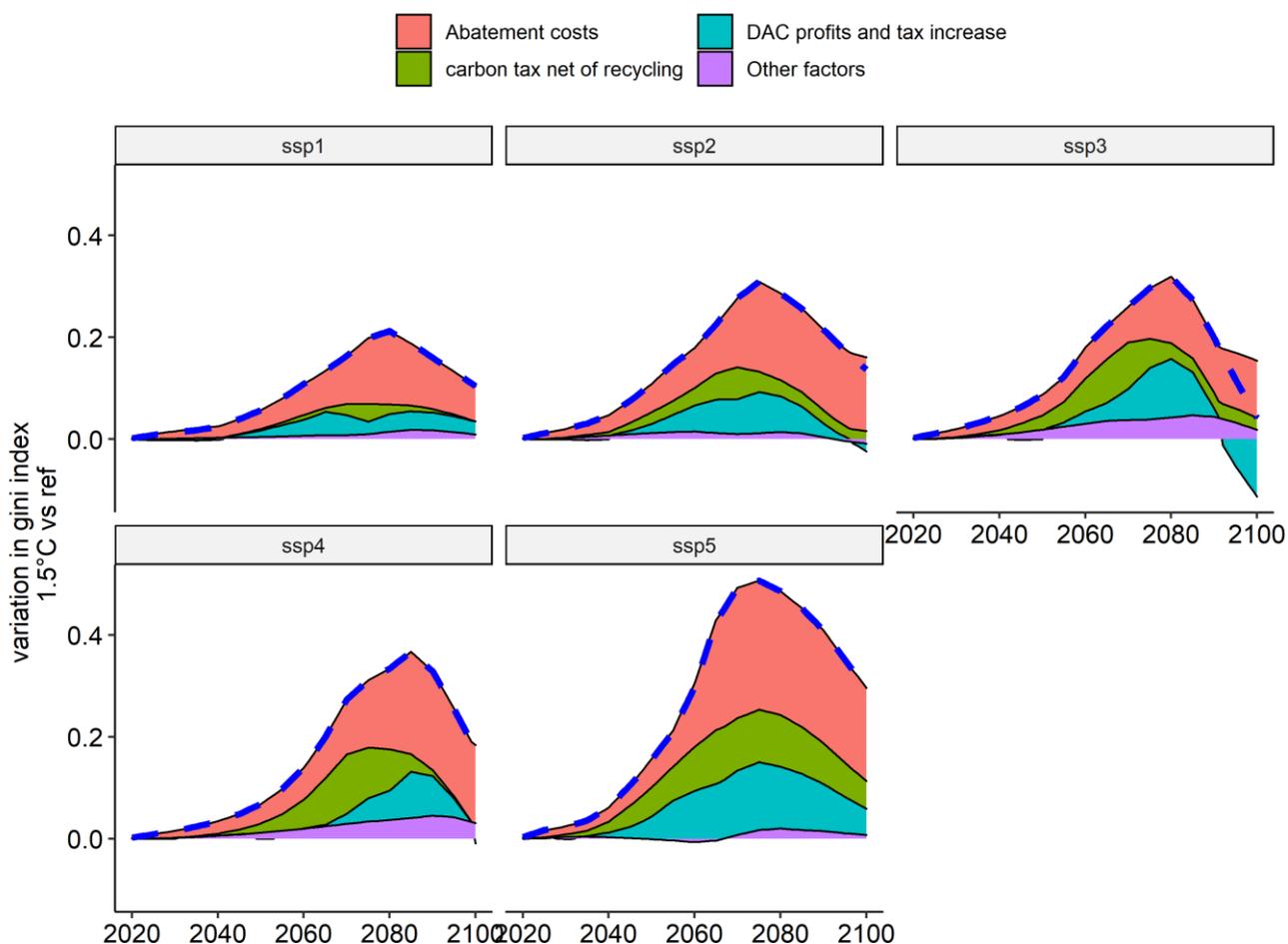


Figure 5: Global variation of Gini index in a 1.5°C scenario with overshoot relative to a NDCs scenario, for each SSP. Blue dotted line represents net variation, while areas highlight a Shapley decomposition of the total variation.

Conclusions

The framework presented in this paper shows that financing privately owned negative emissions technologies through a global carbon tax can cause a significant increase in income inequality. In countries that mitigate a large part of their emissions with carbon removal inequality increases by several Gini points, an amount similar but opposite to the assessed progressive potential of carbon tax recycling¹⁵. Globally, negative emissions contribute to around half of total inequality increase due to climate policy at the time of net-zero, and the finding is robust to a wide range of technological and socio-economic assumptions. A progressive distribution of the carbon removal effort can partly counteract the within-country regressivity at the end of the century, and this feature should be accounted for in policy design.

While government budget concerns arises only if the carbon budget is allowed to overshoot¹¹, these distributional concerns are present also in a no-overshoot scenario: reducing negative emissions after net-zero must be compensated with more conventional abatement and NETs in the first part of the century and leads to an intertemporal trade-off. For the regions that suffer most from late-century inequality increase, however, the gains of not overshooting the budget outweigh the short-term penalty.

To tackle the inequality increase due to negative emissions, a first possible intervention is to design the tax increase after net-zero to target the same area of the income distribution that owns NETs firms. While we assume an average progressivity of taxation systems, specific taxes can be very progressive (for instance, capital taxes) or very regressive (e.g., consumption taxes). However, we find that most of the inequality increase is concentrated around the time of net-zero when NETs revenues are still financed with the carbon tax. Therefore, the only way to structurally reduce or eliminate the regressive potential of negative emissions lies at the very structure of the carbon market and the ownership of the companies. Two possible solutions exist. First, public or participated ownership of NETs firms, possibly bound to a zero-profit condition like regulated natural monopolies. Second, a separate carbon market for negative emissions: a differentiated price would reflect the marginal abatement cost curve for negative emissions provision at the quantity required by the market, as in a “reverse” cap-and-trade system. The resulting carbon price would be significantly lower than the one necessary to completely abate positive emissions, therefore reducing the profit margin for NETs owners and the *ownership* effect.

The modeling framework presented here shows that it is possible to enhance planning tools to study a broader range of economic and technological dynamics. Achieving a socially just climate transition requires careful policy design and regulation of the very technologies which are needed to decarbonize our economies, such as negative emissions. These factors should and can be included in scenario-based policy assessments such as those reviewed by the IPCC.

Methods

Model

RICE50+ is an open-source highly regionalized Integrated assessment model¹⁸, based on Nordhaus' DICE. It represents 57 different countries and regions, each characterized by a marginal abatement cost curve function calibrated from the ENERDATA database and by projections about socio-economic drivers and baseline emission intensity of GDP. The curves are heterogeneous by region, such that fully abating emissions can cost hundreds to thousands of dollars per ton of CO₂, and they assume exogenous technological learning. The model allows solutions with multiple possible set of coalitions, including the singleton coalitions (Nash solution) and the grand coalition (cooperative). Each planner solves an intertemporal maximization problem of discounted consumption, and the utility function explicitly includes inequality aversion other than intertemporal²⁷. Different baseline projections of socio-economic determinants are represented with the Shared Socioeconomic Pathways (SSP) as well as different impact functions from recent econometric literature such as Burke et al.²² and Kalkuhl et al.²⁹. The model is open source and available at <https://github.com/witch-team/RICE50xmodel>, and a description and presentation of the model is available at <https://doi.org/10.18174/sesmo.18038>³⁰.

Scenarios and budget implementation

We implement the global constraint on cumulative CO₂ emissions via a global uniform carbon tax, that increases exponentially at a growth rate of 5%/yr. In the first periods, the trajectory of the tax is smoothed out from the exponential path to avoid abrupt changes in the pricing profile. To mimic the existence of hard-to-abate sectors and emissions, the maximum rate of abatement via conventional mitigation can be lower than 100% and depends on the SSP (see *Methods: socio-economic projections*). Non-CO₂ gasses are not considered in the model, not priced, and don't contribute to the global budget.

To decrease the computational complexity of the problem and to avoid implicit transfers across regions via mitigation effort shifting, we run the scenario in Nash-mode, i.e. each region solves as an independent optimization, and convergence is granted by solving iteratively all regions until the free variables in the optimization stabilize.

Abatement is fixed at each iteration by the carbon tax trajectory, and saving rates are fixed to the long-term convergence value of 5%. Therefore, the only free variable in the model is investment in negative emissions. At each iteration, the starting level of the carbon tax is shifted via a bisection algorithm until the budget is reached, and all free variables are stable across iterations.

Within the optimization problem at each iteration the carbon tax is fixed and constraints the emission control rate at the equivalent point in the marginal abatement cost curve, such that:

$$MAC(MIU, t, n) = CPRICE(t, n) \quad (1)$$

With $CPRICE$ defined as:

$$CPRICE(t, n) = \min(ctax(t), MAC(MIU_{max}, t, n)) \quad (1)$$

$CPRICE_{max}(t, n)$ corresponds to the marginal abatement cost curve for the maximum abatement control allowed by the residual emission assumption in the SSP scenarios. This maximum price is both country specific because the marginal abatement cost curves differ across regions, and time varying because the MACCs flatten over time because of exogenous technological learning (see ANNEX C). The carbon price so defined also regulates the amount of CDR in the system thanks to a subtractive term in the income equation

$$- CPRICE(t, n) * (E(t, n) - E(iter - 1, t, n)) \quad (2)$$

Since $E = E_{base} * (1 - MIU) - E_{neg}$ but MIU is fixed by (1) at each iteration, the only decision variable linked to equation (2) is the investment in the representative CDR technology that regulates the amount of gross negative emissions.

The term described in equation (2) therefore grants that, given the carbon price at each iteration, negative emissions will be deployed if the marginal cost of deployment (including storage) is lower than the carbon price and no other constraint is reached. At convergence, $E(t, n) - E(iter - 1, t, n) < tolerance$ and the solution stabilizes, while the term in equation (2) goes to zero in the income equation. For details about the implications of the carbon budget implementation on the scenarios, see ANNEX D.

Implementation of the income distribution

In order to model the distributional effects of Negative Emission Technologies we introduce a decile-based representation of household heterogeneity, conceptually following the NICE model¹⁹.

As in the standard DICE, final income is calculated by subtracting to the gross income that emerges from a Cobb-Douglas production function (calibrated to match exogenous GDP projections) the cost of abatement and the damages of climate change. To assign these costs to each decile, we implement weights w^i that are driven by an elasticity v :

$$w^v(t, n, dist) = \frac{quantiles_ref(t, n, dist)^v}{\sum_{dist} quantiles_ref(t, n, dist)^v}$$

Such that if $i = 0$ the costs are distributed equally per capita and therefore will benefit the richest deciles, and if $i = 1$ the cost is assigned distribution neutrally across the deciles. Therefore, the higher the elasticity, the more progressive the distribution of the cost. If the flow is positive (i.e. describes gains, such as carbon tax recycling) the opposite holds, and a lower elasticity indicates more progressive flows.

The final income for each decile is described by:

$$\begin{aligned} Y_{DIST}(t, n, dist) = & Y_{GROSS}(t, n) * quantiles_ref(t, n, dist) & (1) \\ & - (ABATECOST(t, n) + CTX(t, n)) * w^\omega(t, n, dist) \\ & + (REVENUES_{NET}(t, n) - COST_{NET}(t, n)) * w^\varepsilon(t, n, dist) \\ & + TRANSFER(t, n, dist) - GENTAX(t, n, dist) \end{aligned}$$

With each term defined as follows: $CPRICE$ is the carbon price in the region, E_{IND} emissions from the industry and energy sector, E_{NET} the carbon removed with NETs (nature-based solutions are not paid for since AFOLU is exogenous in the model):

$$CTX(t, n) = CPRICE(t, n) * E_{IND}(t, n)$$

$$REVENUES_{NET}(t, n) = CPRICE(t, n) * E_{NET}(t, n)$$

$$GENTAX(t, n, dist) = \max(0, NETREV(t, n) - CTX(t, n)) * w^{tax}(t, n, dist)$$

$$TRANSFER(t, n, dist) = \max(0, CTX(t, n) - NETREV(t, n)) * w^{redist}(t, n, dist)$$

Since we do not consider the marginal cost of raising public funds nor intertemporal and international transfers, the algebraic sum of carbon tax revenues, subsidies to NETs, other taxes and transfers must for each period and region equal zero. This is equivalent to modelling an implicit government tasked with balancing the difference in its budget due to climate policy. On the other hand, abatement costs and the cost of installing and operating NETs are not redistributed back in the economy and represent therefore a loss of income.

Calibration of elasticities

ELASTICITY	MEDIAN AND RANGE	CALIBRATION
DAC revenues and costs	1.5 [2;1.2]	Convex function of income gini, calibrated on wealth to income distribution elasticity from a panel data of 163 country in 102 years. Assumes financial capital is equally concentrated as wealth, and that deciles in terms of income coincide with deciles in the wealth dimension in terms of underlying households. Perfect coincidence between wealth and income deciles.
Abatement costs and carbon tax	0.8 [0.7;1.2]	Decreasing linear function of GDP per capita (Source: Budolfson et al. 2021). Greater than 1 (progressive) for low-income countries, and lower than 1 (regressive) for high income countries.
Transfers	0.8 [0.7;1.2]	Design choice, set equal to the carbon tax elasticity above to compensate losses from carbon pricing.
Other taxes	1.2 [1;1.5]	Decreasing linear function of income gini, calibrated on pre-tax and post-tax income of a data panel of 43 countries for up to 44 years.

Table 1: Calibration of the income elasticity of the different factors

To correctly characterize the distributional effects of each flow, the elasticities are calibrated as summarized in *Table 1*: abatement cost and carbon tax costs are calibrated as in (Budolfson, 2021)¹⁵,

in which they perform a meta-study on the distributional effect of carbon taxation and regress the result against GDP, finding a weak negative correlation.

To complete our model, two more calibrated parameters are needed: the income-to-capital-ownership elasticity, and the income-to-taxation elasticity.

To estimate the first one, since data on capital ownership are available for only a small subset of countries and year, we use the wealth income distribution as a proxy of capital ownership. Since wealth includes real estate other than equity, and since real estate tends to be less concentrated on the top of the distribution with respect to equity, the equivalence produces a conservative assumption about equity concentration.

We use a panel of data of 163 countries and 106 years divided into percentiles from publicly available WID database (<https://wid.world/>). We consider post-tax income and wealth distributions and clean the data by zeroing negative values that can occur at the bottom of the distribution. We then estimate the elasticity by fitting the following model for each country and year with non-linear least square methods (*nls()* function in stats package R), where $q_{j,i}$ represent the quantiles on wealth and income respectively:

$$q_{wealth,i} = \frac{q_{income,i}^\eta}{\sum_i q_{income,i}^\eta} \quad i \{0:100\}$$

The model assumes perfect coincidence between the quantiles, i.e., an household in the n th percentile for the income distribution will belong to the same percentile of the wealth distribution.

The wealth-to-income relationship is plotted in Figure 6 (a), that shows the Gini index calculated over the income distribution against the Gini index calculated over the wealth distribution, for all countries (colors) and years. In general, as expected, the Gini on wealth is significantly higher than the Gini on income, because wealth is more concentrated than income. Qualitatively, two regions in the map plot can be identified and are highlighted with corresponding regression lines (in blue): for low Gini on income (<0.6), the relationship with the concentration of wealth is relatively flat, indicating that, even in countries with low inequality, wealth tends to remain concentrated at the top of the distribution. For high income inequality, however, a strong positive relation with wealth inequality is visible.

This results in a U shape for the estimated elasticities plotted in Figure 6 (b). Ultimately, the regressed parabola shown in grey in Figure 6 (b) is extrapolated using ordinary least squares and

implemented in the model as a function of the exogenous projections of income Gini from (Rao et al, 2019)³¹.

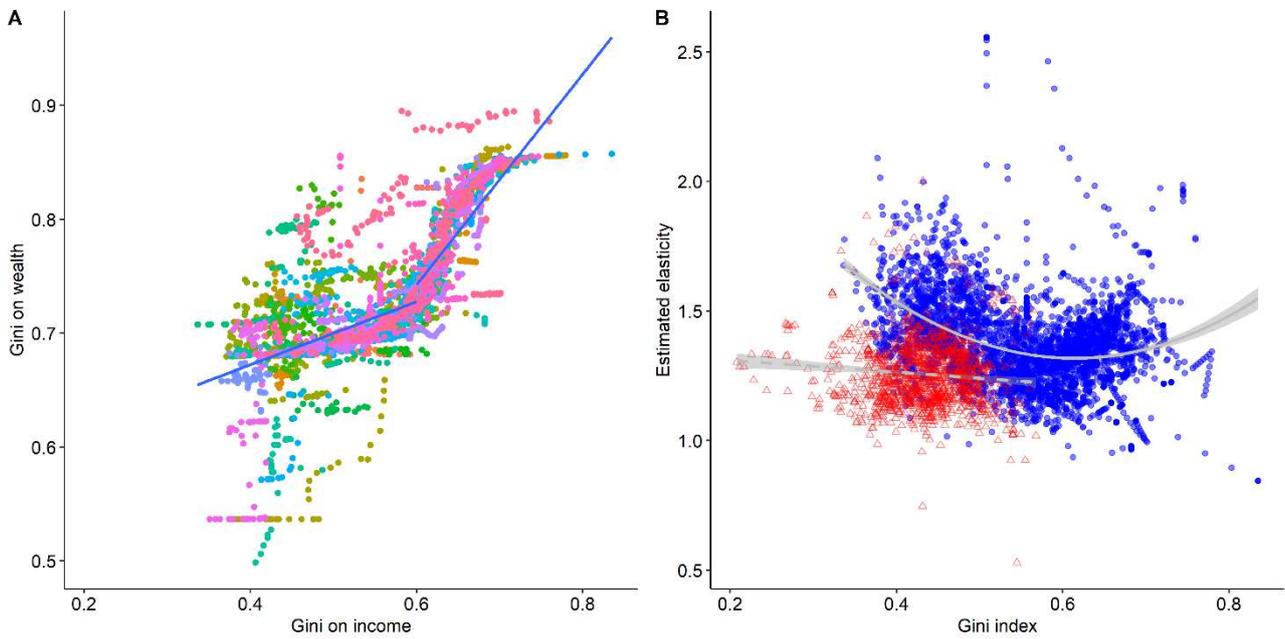


Figure 6: (a) gini on income against gini on wealth, for all available countries and years. (b) estimated elasticity of income to wealth elasticities (blue dots) and tax revenues collection elasticities (red dots) against gini on income, for all available country and years.

The elasticity of the taxation system is extrapolated in a similar manner. First, we build the percentage of total government revenues from taxes per percentile, calculated as:

$$t_i = \frac{income_{pre,i} - income_{post,i}}{\sum_i income_{pre,i} - income_{post,i}} \quad i \{0: 100\}$$

This quantity is not a common metric of taxation progressivity, but represents, for a dollar of taxes, how much on average is taken from each percentile of the income distribution. Since pre-taxation income data are available only for a subset of country, the sample for the estimation is smaller than the previous (panel of 43 countries for 44 years). We then relate this quantity as before estimating the following model for each country and year:

$$t_i = \frac{q_{income,i}^{\eta_{tax}}}{\sum_i q_{income,i}^{\eta_{tax}}} \quad i \{0: 100\}$$

The resulting estimated η_{tax} are shown in Figure 6 (b) as red triangles, plotted against the Gini index for income. The variance is high, but a linear regression shows a weak indirect correlation with the Gini index of income, that supports the intuitive consideration that more unequal societies tend to put in place more regressive taxation schemes. We implement this regression in the model.

Therefore, progressivity of abatement cost and the carbon tax are linearly decreasing with income per capita, the progressivity of the taxation system decreases linearly with the exogenous projection of the Gini index, while the financial-capital-to-income elasticity depends quadratically on Gini index as well, with a minimum around 0.6. The resulting picture for each elasticity that governs how cost and benefit of climate policy are distributed within deciles is shown in Figure 7 for all SSPs, with each line representing a country and dotted line the median across countries. The higher the spread among the three lines, the higher the regressive potential of CDR will be for a specific country and year.

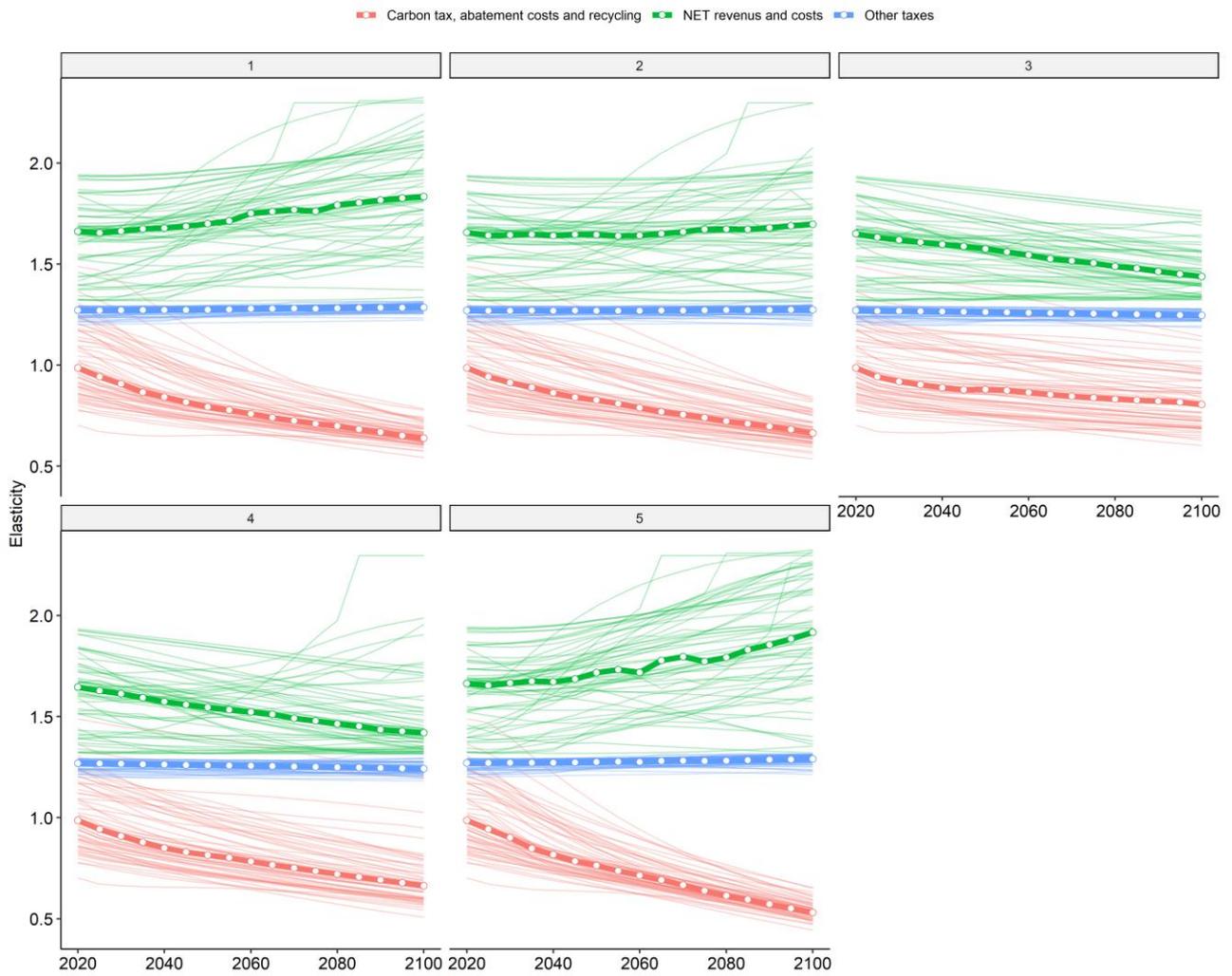


Figure 7: recomputed elasticities. Each line represents a country, dotted line is country median.

DAC as a representative technology for NETs

In the standard release of RICE50+ negative emissions are allowed, as in the original DICE model, because the decision variable $MIU(t, n)$ that controls the percentage of baseline emissions abated can reach higher values than 100% (specifically 120%, meaning that each region can remove at most 20% of its baseline emissions in each given year). Since $CPRICE = MACC_n(MIU(t, n))$, this removal happens at the top of the marginal abatement cost curve, for carbon prices that exceeds 1000 \$/tonCO₂. However, most proposed negative emission technologies⁴ are projected to be competitive at much lower costs, ranging from 100 \$/tonCO₂ of bioenergy with carbon capture and storage to 200 \$/tonCO₂ of direct air capture. While there is large uncertainty surrounding these costs, this means that such technologies would become competitive at lower levels of the marginal abatement costs curve, de facto modifying its shape. Moreover, embedding negative emissions into a single MACC doesn't allow the explicit representation of offsetting, that is necessary in our set-up to model the distributional implications of financing NETs even before net-zero.

Therefore, we explicitly model Direct Air Capture as a representative, investable technology in the model, such that each region can choose to reduce emissions with either standard abatement or via carbon removal with DACs. Since we explicitly model a carbon dioxide removal technology, $MIU(t, n)$ is capped to 100%, meaning DAC is the only mean to reach net negative emissions.

DAC are modelled as in Realmonte et al.²⁰ as an investable technology with depreciating capital, and emission captured must be stored geologically. The storage cost depends on the storage type (aquifer, exhausted oil & gas field, etc.) and each storage type has a regional cumulative capacity limit. No leakage is considered from the geological sites.

$$E_{DAC}(t + 1, n) = E_{DAC}(t, n) * (1 - \partial) + \frac{I_{DAC}(t, n)}{invcost(t, n)}$$

$$COST_{DAC} = I_{DAC} + E_{DAC}(t, n) * o\&m_{DAC} + storcost * E_{DAC}(t, n)$$

$$E_{DAC}(t, n) = \sum_{stor} E_{STOR}(stor, t, n)$$

$$\sum_t E_{STOR}(stor, t, n) < CUMSTOR(stor, n)$$

Investment cost and operating cost are calibrated from an expert elicitation survey³² and decrease with learning-by-doing. Total cost of DAC is assumed, in the central projection, to start from

780\$/ton CO₂ removed, and the floor cost is set at 214 \$/ton CO₂. Total cost is assumed to be 60% due to investment costs, and 40% to O&M costs (including expenditures for energy).

Two additional constraints are considered. First, maximum global capacity of DAC is capped to 30 GtCO₂/yr of removal, and the constraint is distributed across regions according to the ratio of regional total storage capacity over the global value. Second, maximum capacity growth is capped at 6%/yr, to mimic historical ramp-up of similar technologies as in Realmonte et al.²⁰. Since our model doesn't explicitly consider the cost of energy and the increase in investments in clean energy technologies necessary to cover the demand of large-scale DACs, we add an additional constraint on the maximum capacity growth that depends on the carbon budget (i.e., the temperature target in 2100) with a logistic function, such that the total amount of carbon captured is consistent with projections from the WITCH model⁹, an energy-detailed integrated assessment model shown in Figure 8.

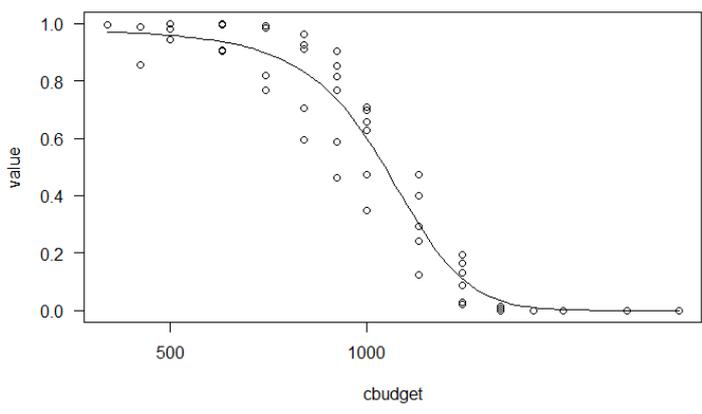


Figure 8: logistic relation between cumulative carbon removed with DACs (normalized to maximum value) and carbon budget. Each point is a scenario from the ENGAGE database of the WITCH integrated assessment model.

Socio-economic projections

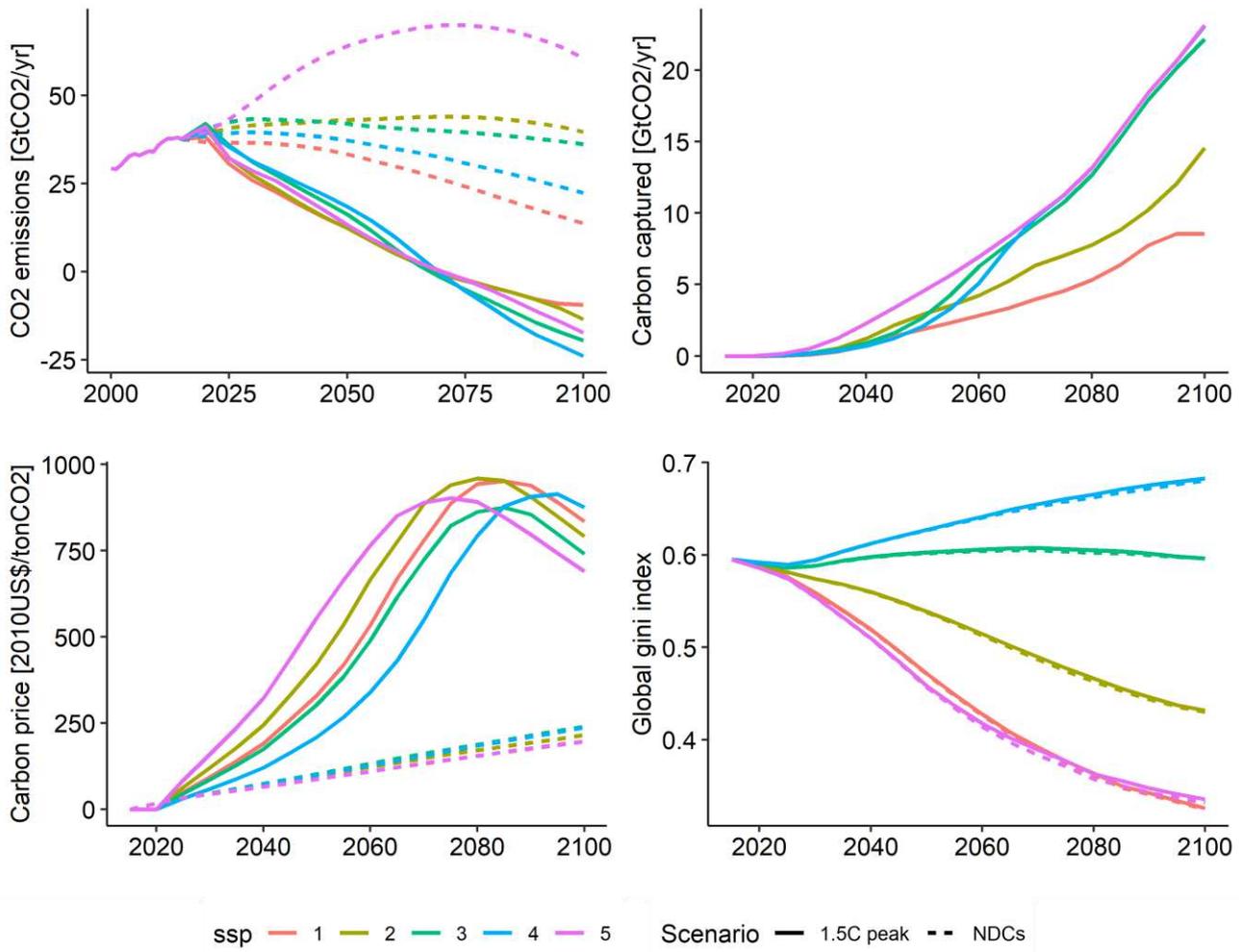


Figure 9: Scenario characterization for all SSPs.

We complement the SSPs projection already present in the model about population, GDP and baseline carbon intensity with narratively coherent projections of within country inequality, extrapolating decile-based information from (Rao et al., 2019)³¹ as in (Emmerling et al., 2022)³³, and with different assumption about negative emission technologies costs and availability, following (Fuhrman et al., 2021)³⁴. These assumptions are synthetized in Table 2. Costs and potential are divided into three ranges (HIGH, LOW, MEDIAN) and assigned to each ssp. Table 3 numerically specifies the assumptions in the different categories.

SSP1 is assumed to be a world in which negative emission technologies are cheap by highly constrained, because of social acceptability, fear of large-scale adverse feedback on humans and the climate system, and negative trade-offs with other sustainable development goals. The constraint about hard to abate emissions is assumed to decline to zero, because of high technological development. SSP2 contains median or best guess assumptions about technology and

potentials. In SSP3, NETs are assumed to be costly while storage potential and maximum capacity are assumed to be high, reflecting a high will to postpone mitigation with negative emissions and to risk potentially adverse effects. Moreover, the learning rate of the technology is low, following sluggish technological capacity, and we assume no cross-country spillover because of the low cooperation environment. SSP4 follows similar assumptions on deployment capacity, but technology cost is assumed to be best guess and hard-to-abate emissions are low. SSP5 has optimistic assumption about technology improvement, high maximum capacity of negative emissions as well as high hard to abate emission because of the high reliance on fossil fuels in the baseline. Socio-economic projections are summarized in Table 2 and follow the SSP narratives as in (Riahi, 2017)²³, and result in scenarios summarized in Figure 9 for the a 700 GtCO₂ budget.

Table 2: characterization of the SSPs.

	SSP1	SSP2	SSP3	SSP4	SSP5
Cost of DAC	LOW	MEDIUM	HIGH	MEDIUM	LOW
Cost of storage	LOW	MEDIUM	HIGH	MEDIUM	LOW
Storage capacity	LOW	MEDIUM	HIGH	HIGH	HIGH
Maximum capacity	LOW	MEDIUM	HIGH	HIGH	HIGH
Learning rate	LOW	MEDIUM	HIGH	MEDIUM	LOW
Cross-country spillover	YES	YES	NO	NO	YES
Underlying inequality (within country)	LOW	MEDIUM	HIGH	HIGH	MEDIUM
GDP per capita	HIGH	MEDIUM	LOW	LOW	HIGH
Hard to abate emissions	LOW	MEDIUM	HIGH	LOW	HIGH

Table 3: low, high and best guess estimates for DAC technological parameters and constraints. REF refers to the initial total cost for DAC costs, and to the equation that regulates the maximum capacity constraint as a function of the carbon budget. CB stands for carbon budget and cap_max for the global maximum capacity constraint.

	LOW	MEDIUM	HIGH	REF
Floor cost of DAC	124	214	453	780
Storage capacity	1335	3035	5696	-
Maximum capacity	9.4	21.3	40	$\frac{cap_max}{1 + e^{0.00631*(CB-1069)}}$
Learning rate	0.03	0.06	0.09	-

Bibliography

1. Stripe, Alphabet and Others to Spend Nearly \$1 Billion on Carbon Removal. *Bloomberg.com* (2022).
2. P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.). *IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. (Cambridge University Press).
3. Fuss, S. *et al.* Negative emissions-Part 2 : Costs, potentials and side effects. *Environmental Research Letters* **13**, 063002 (2018).
4. Smith, P. *et al.* Biophysical and economic limits to negative CO₂ emissions. *Nature Climate Change* **6**, 42–50 (2016).
5. McLaren, D. & Duncan McLaren. Quantifying the potential scale of mitigation deterrence from greenhouse gas removal techniques. *Climatic Change* **162**, 2411–2428 (2020).
6. Grant, N., Hawkes, A., Mittal, S., Shivika Mittal & Gambhir, A. Confronting mitigation deterrence in low-carbon scenarios. *Environmental Research Letters* **16**, 064099 (2021).
7. Markusson, N., McLaren, D. & Tyfield, D. Towards a cultural political economy of mitigation deterrence by negative emissions technologies (NETs). **1**, (2018).
8. IPCC. *Summary for Policymakers. In: Global Warming of 1.5C. IPCC SR1.5C*. (World Meteorological Organization, Geneva, Switzerland, 2018).
9. Drouet, L., Bosetti, V., Padoan, S., Aleluia Reis, L. & Bertram, C. Net zero emission pathways reduce the physical and economic risks of climate change. *Nature Climate Change* (2021) doi:doi:10.1038/s41558-021-01218-z.
10. Johannes Bednar *et al.* Operationalizing the net-negative carbon economy. *Nature* (2021) doi:10.1038/s41586-021-03723-9.
11. Johannes Bednar, Michael Obersteiner, & Fabian Wagner. On the financial viability of negative emissions. *Nature Communications* (2019) doi:10.1038/s41467-019-09782-x.

12. Carlos Pozo, Ángel Galán-Martín, David Reiner, Niall Mac Dowell, & Gonzalo Guillén-Gosálbez. Equity in allocating carbon dioxide removal quotas. *Nature Climate Change* (2020) doi:10.1038/s41558-020-0802-4.
13. Kaylin Soo Bin Lee, Claire Fyson, & Carl-Friedrich Schleussner. Fair distributions of carbon dioxide removal obligations and implications for effective national net-zero targets. *Environmental Research Letters* (2021) doi:10.1088/1748-9326/ac1970.
14. Claire L. Fyson, Susanne Baur, Matthew Gidden, & Carl-Friedrich Schleussner. Fair-share carbon dioxide removal increases major emitter responsibility. *Nature Climate Change* (2020) doi:10.1038/s41558-020-0857-2.
15. Budolfson, M. *et al.* Climate action with revenue recycling has benefits for poverty, inequality and well-being. *Nature Climate Change* **11**, 1111–1116 (2021).
16. Jan Christoph Steckel *et al.* Distributional impacts of carbon pricing in developing Asia. *Nature Sustainability* 1–10 (2021) doi:10.1038/s41893-021-00758-8.
17. Nils Ohlendorf, Michael Jakob, Jan Minx, Carsten Schröder, & Jan Christoph Steckel. Distributional Impacts of Carbon Pricing: A Meta-Analysis. *Environmental and Resource Economics* **78**, 1–42 (2020).
18. Paolo Gazzotti *et al.* Persistent inequality in economically optimal climate policies. *Nature Communications* (2021) doi:10.1038/s41467-021-23613-y.
19. Francis Dennig *et al.* Inequality, climate impacts on the future poor, and carbon prices. *Proceedings of the National Academy of Sciences of the United States of America* (2015) doi:10.1073/pnas.1513967112.
20. Realmonte, G. *et al.* An inter-model assessment of the role of direct air capture in deep mitigation pathways. *Nat. Commun.* **10**, 3277 (2019).
21. Emmerling, J. & Tavoni, M. Representing inequalities in integrated assessment modeling of climate change. *One Earth* **4**, 177–180 (2021).
22. Minx, J. *et al.* Negative emissions—Part 1: Research landscape and synthesis. *Environmental Research Letters* **13**, 063001 (2018).

23. Riahi, K. *et al.* The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change* **42**, 153–168 (2017).
24. Roelfsema, M. *et al.* Taking stock of national climate policies to evaluate implementation of the Paris Agreement. *Nature Communications* **11**, (2020).
25. Heleen L. van Soest *et al.* Global roll-out of comprehensive policy measures may aid in bridging emissions gap. , *Nature communications* (2021).
26. Cost and attainability of meeting stringent climate targets without overshoot | Nature Climate Change. <https://www.nature.com/articles/s41558-021-01215-2#Abs1>.
27. Berger, L. & Emmerling, J. Welfare as Equity Equivalents. *Journal of Economic Surveys* **34**, 727–752 (2020).
28. Burke, M., Hsiang, S. M. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527**, 235–239 (2015).
29. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management* **103**, 102360 (2020).
30. Gazzotti, P. RICE50+: DICE model at country and regional level. *Socio-Environmental Systems Modelling* **4**, 18038–18038 (2022).
31. Rao, N. D., Sauer, P., Gidden, M. & Riahi, K. Income inequality projections for the Shared Socioeconomic Pathways (SSPs). *Futures* **105**, 27–39 (2019).
32. Soheil Shayegh, Valentina Bosetti, & Massimo Tavoni. Future Prospects of Direct Air Capture Technologies: Insights From an Expert Elicitation Survey. (2021) doi:10.3389/fclim.2021.630893.
33. Emmerling, J., Andreoni, P. & Tavoni, M. The impact of climate change, policies, and redistribution on global within-country inequality. in *EAERE 2022 conference proceedings* (2022).
34. Fuhrman, J. *et al.* The role of direct air capture and negative emissions technologies in the Shared Socioeconomic Pathways towards +1.5°C and +2°C futures. *Environmental Research Letters* (2021) doi:10.1088/1748-9326/ac2db0.
35. Hof, A. F., van der Wijst, K.-I. & van Vuuren, D. P. The Impact of Socio-Economic Inertia and Restrictions on Net-Negative Emissions on Cost-Effective Carbon Price Pathways. *Frontiers in Climate* **3**, (2021).

Data availability

The model will be available open source at the publication of the manuscript. The scenarios and the scripts used to perform the data analysis and visualization will be available at request to the corresponding author for the review process, and publicly deposited at publication.

Contributions

All authors designed and conceptualized the research questions and scenarios. Pietro Andreoni and Johannes Emmerling performed the model advancements. Pietro Andreoni run the scenarios, analyzed the data, and produced the figures for preliminary analysis. Pietro Andreoni wrote the first draft. All authors extensively contributed to the final version of the manuscript and figures and reviewed it.

Acknowledgments

This research has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 821124 (NAVIGATE). The authors have no conflict of interest to declare.

Supplementary information

ANNEX A: within-country inequality in SSPs

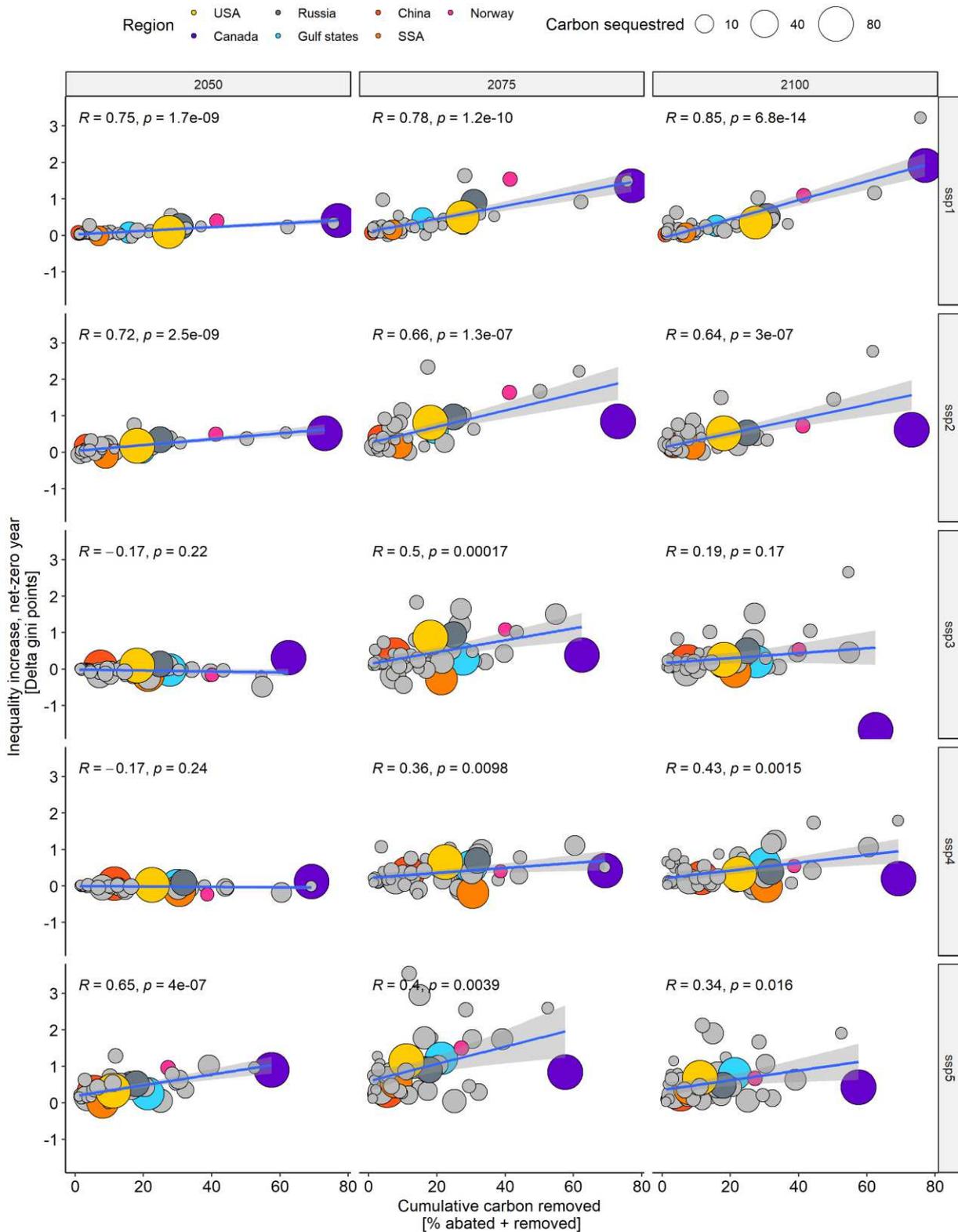


Figure 10: Regional total inequality variation with respect to the reference scenario per year and SSP against share of total mitigation effort performed with carbon removal. Bubble size represents total carbon sequestered by each region through the century. Tendency lines and coefficient of determination highlighted for each scatterplot.

ANNEX B: calibration of elasticities

The within-country regressivity of financing a dollar of negative emissions depends on the calibration of the elasticities that regulate how much of each economic flow accrues to each decile. Because revenues from carbon taxes and other taxes must balance at each time-step NETs revenues and carbon tax recycling, four type of net-flows, i.e. a cost potentially balanced by a revenue, can effectively take place in the model: recycling of the carbon tax, abatement costs, and financing of NETs revenues via carbon tax or via other taxes increase. Each net flow possesses a characteristic distributional effect, that depends on the calibration of the elasticities that regulate each component of the net flow: intuitively, the more regressive the cost (i.e. falling more on the bottom of the income distribution) and the more regressive the revenue (i.e. falling more on the top of the income distribution), the more regressive is going to be the net flow. Figure 11 summarizes the regressivity of each flow. More downward sloping lines imply higher regressivity. Given our assumptions and calibration, all possible flows are regressive except for the recycling of the carbon tax, that is distribution neutral by design. Financing NETs with other taxes has a similar distributional effect than standard abatement. Financing NETs with the carbon tax is significantly more regressive.

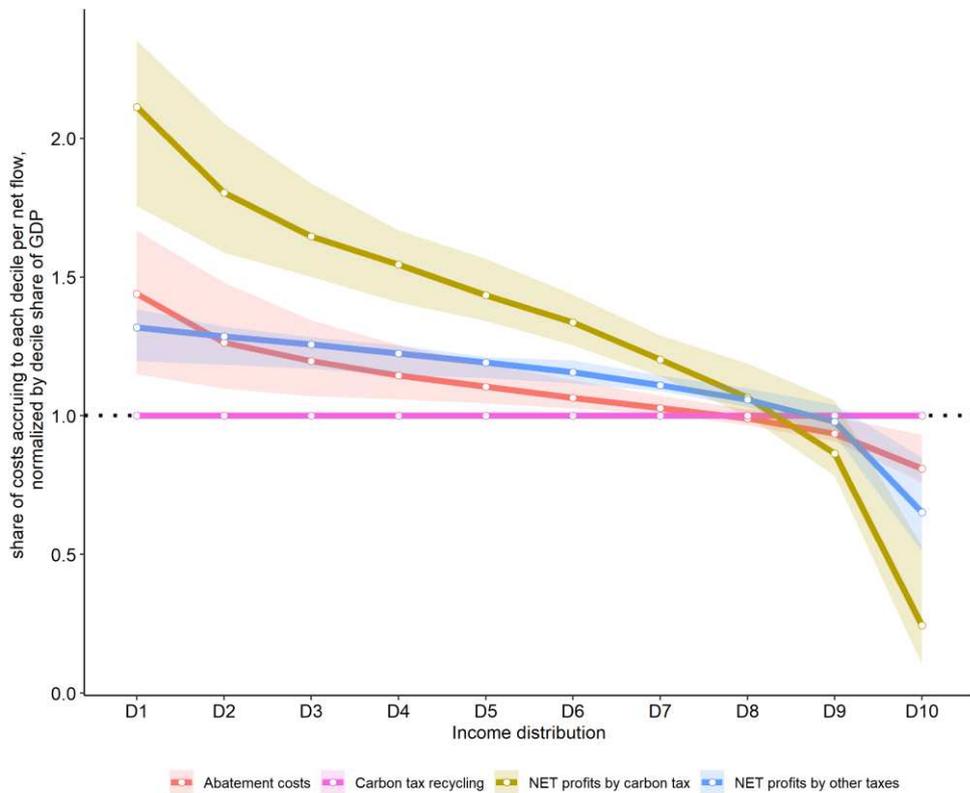


Figure 11: share of costs accruing to each decile per net-flow, normalized per decile share of GDP. A value of 1 represents a distribution neutral flow, and higher values imply that the flow penalizes more a certain decile, i.e. the more downward sloping the curve, the more regressive is the net-flow. Lines represent medians and areas represent range, from 10th to 90th percentile, for all regions and years in SSP2. Carbon tax recycling is distribution neutral by design, while abatement costs are regressive following the calibration on GDPc. Financing a dollar of NET revenues with other taxes is similarly regressive as spending on dollar on abatement, while financing NET revenues with carbon tax is significantly more regressive, because it means not only giving resources to the top of the income distribution, but also subtracts these resources from the relatively poor.

The net within-country distributional effect of financing a dollar of negative emissions revenues therefore is significantly different if the financial resources are financed with the carbon tax (before net-zero) or with other taxes (after net zero). Before net-zero, 100% of the revenues are financed with the carbon tax, therefore the net distributional effects of negative emissions coincide with the gold line in Figure 11. After net-zero, a part of the resources to finance negative emissions come from other taxes, but unless residual emissions are zero (in which case 100% of revenues comes from other taxes, and the distributional effect of negative emissions coincide with the blue line in Figure 11), a part will still come from the carbon tax revenues, and the net regressivity of the flow can be visualized as a curve in between the blue and the gold lines. Therefore, for each decile:

$$NETFLOW_{cdr,i} = w_{\varepsilon,i} - a * w_{\omega,i} - (1 - a) * w_{tax,i}$$

Where $w_{j,i}$ represents the percentage of flow j pertaining to each decile i and a represents the ratio between positive and negative emissions and is defined as:

$$a = \frac{E_{pos}}{E_{neg}} \quad \text{if } \frac{E_{pos}}{E_{neg}} < 1 \quad \text{and } 1 \text{ otherwise}$$

We can represent $NETFLOW_{cdr,i}$ as the product of a “net elasticity” η_{net} such that:

$$NETFLOW_{cdr,i} = \frac{q_{income,i}^{\eta_{net}}}{\sum_i q_{income,i}^{\eta_{net}}}$$

The elasticity can be estimated with a non linear model regression as in Methods, or approximately calculated as the difference between the elasticity of each type of flow as:

$$\eta_{net} = \eta_{\varepsilon} - a * \eta_{\omega} - (1 - a) * \eta_{tax}$$

This notation allows to visualize in a synthetic way the characteristic regressivity of financing a dollar of removal. Since it represents profit as positive, the regressivity of the flow will be higher for higher elasticities and is distributionally equivalent to subtracting a dollar from the quantiles equally per capita and redistributing it into the economy with the elasticity η_{net} . Figure 12 and Figure 13 show the estimated net elasticity regressed, per year and SSP, against baseline Gini and GDP per capita, the two main socio-economic indicators that drive the calibration of the elasticities that η_{net} is an aggregate of.

The net regressivity of removal tends to be positively correlated with GDP per capita, because so is the regressivity of carbon taxes. The correlation is stronger around 2050, because most countries are before net-zero. In 2100, a large part of NET revenues is collected via other taxes, therefore the correlation with GDP per capita is more sparse. On the contrary, the net regressivity of removal negatively correlates with Gini, and the correlation remains significant through the whole century.

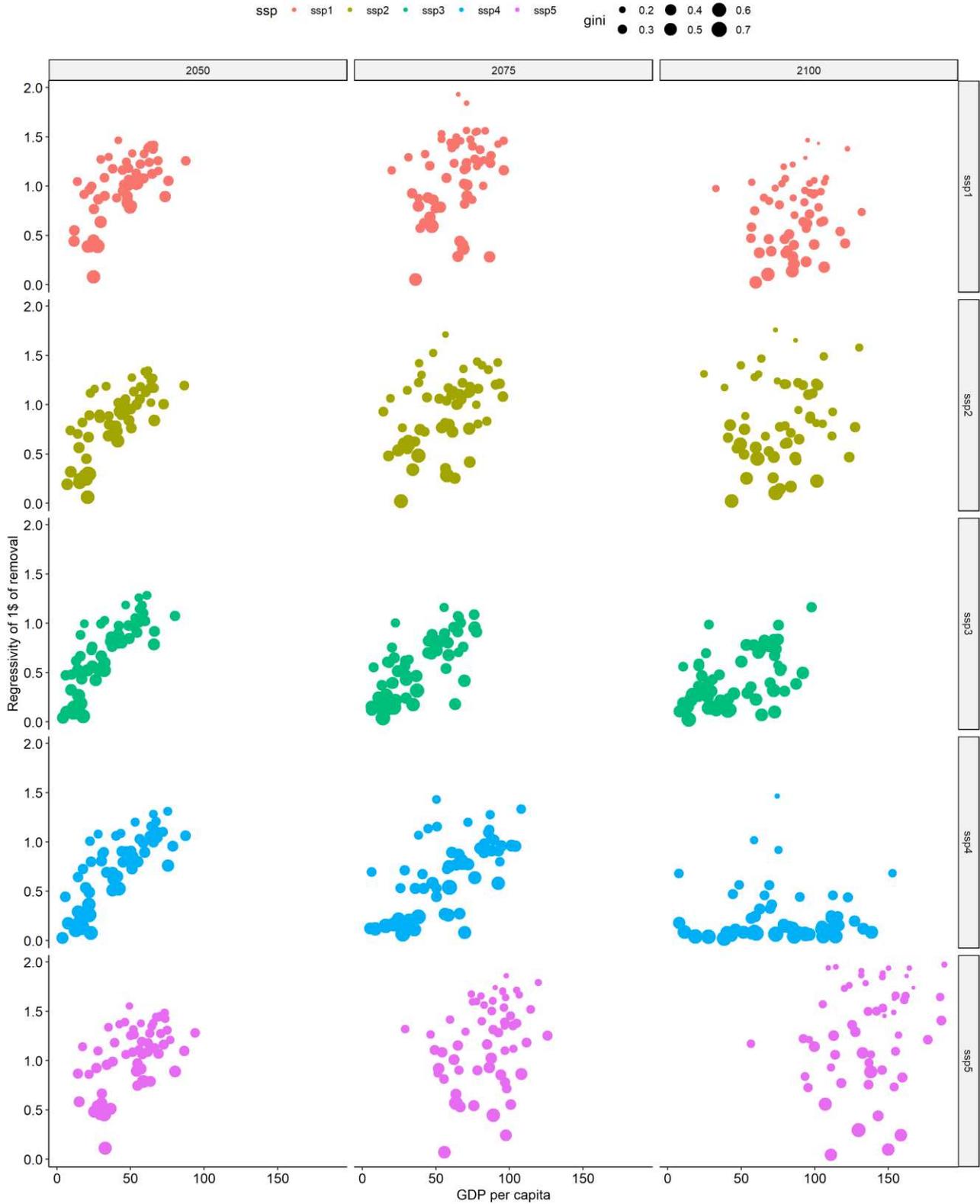


Figure 12: regressivity per dollar of removal vs GDP per capita. Higher values indicate more regressive net-transfer for financing a unit of carbon removal. Each country represent a dot, bubble size indicates exogenous gini projections for baseline inequality. Per SSP and year. A positive correlation exists between regressivity of removal and GDP per capita, mainly because for rich countries the carbon tax is more regressive. The correlation becomes weaker at the end of the century because a large part of NETs revenues are financed by increasing other taxes.

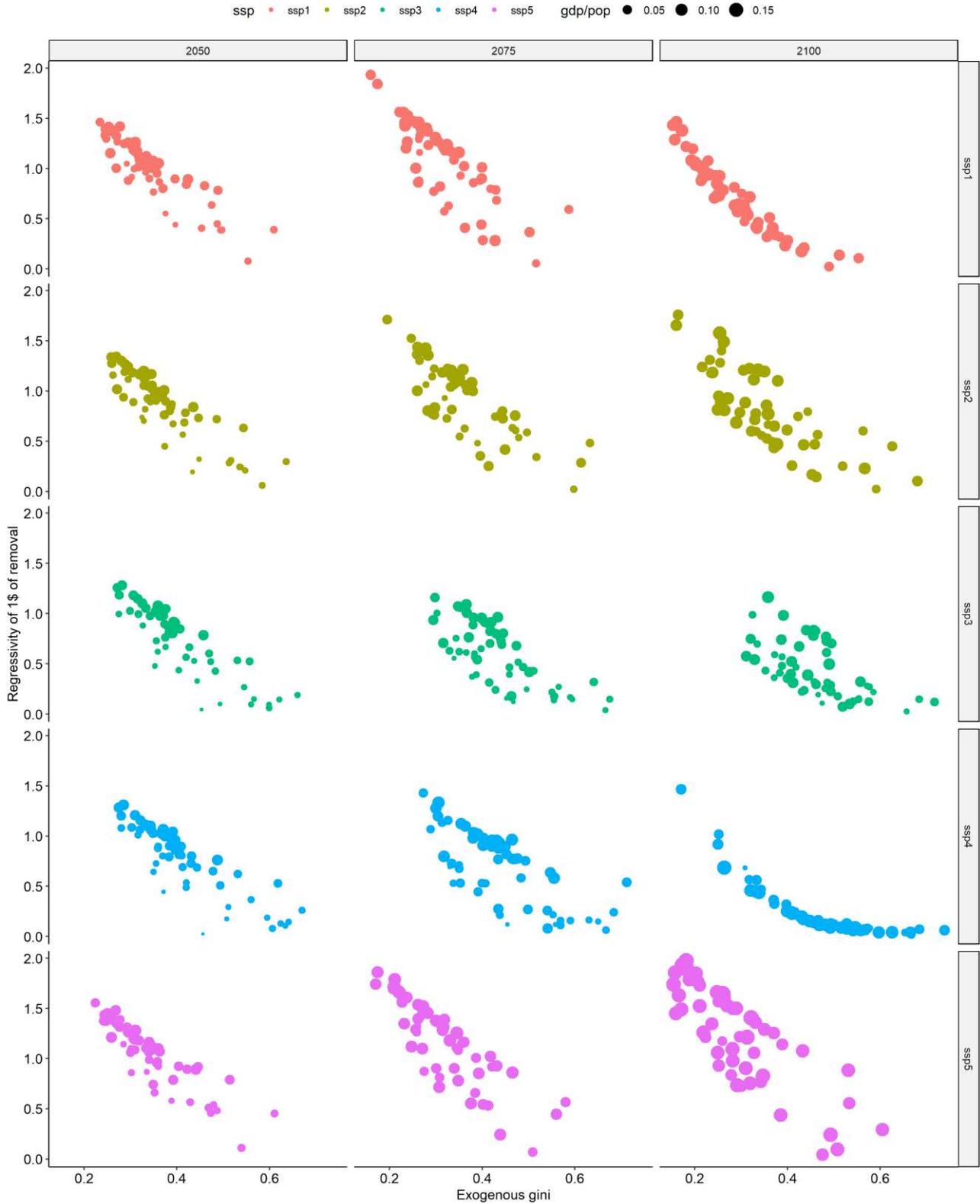


Figure 13: regressivity per dollar of removal vs baseline Gini projections. Higher values indicate more regressive net-transfer for financing a unit of carbon removal. Each country represents a dot, bubble size indicates GDP per capita. Per SSP and year. A clear negative correlation is visible between regressivity of removal and exogenous Gini. In SSP1 and SSP4, the correlation is almost perfectly quadratic in 2100 because no residual emissions are assumed for these SSPs. Therefore, the entirety of NETs revenues is financed with other taxes in 2100. The shape therefore reflects the calibration of equity ownership as a function of baseline Gini.

Figure 14 visualizes, per year and SSP, the regional value of η_{net} . Clearly, the regressivity of a unit of removal tends to decrease during the century (because other taxes are progressive while the carbon tax is regressive), and it tends to be higher in SSP with high growth and low inequality (SSP1, SSP5).

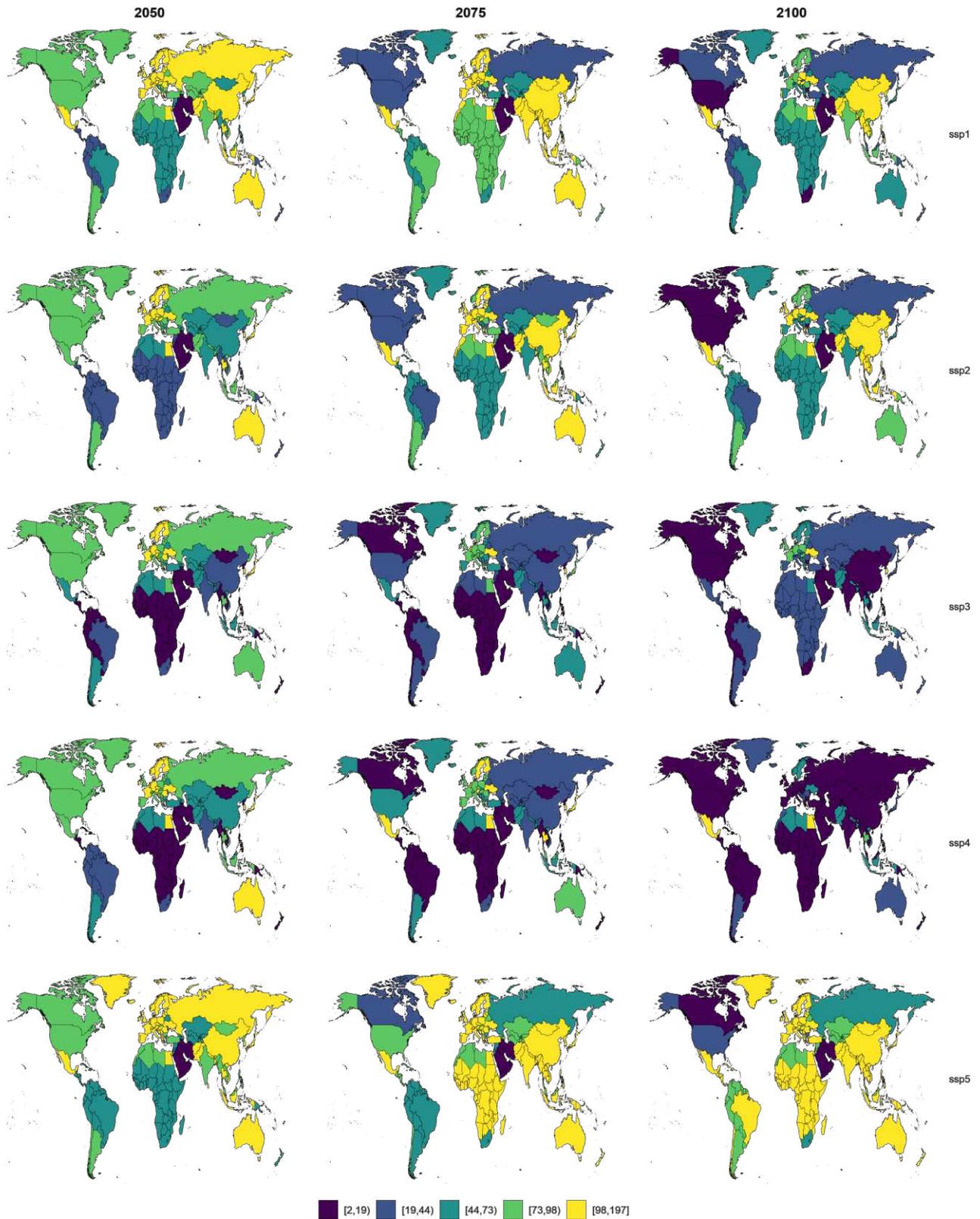


Figure 14: net regressivity of one dollar of removal per region, SSP, and year. Values represent the estimated net elasticity * 100. The higher the value, the more regressive the financing of NETs.

ANNEX C: baseline projections for socio-economic parameters

SSP1

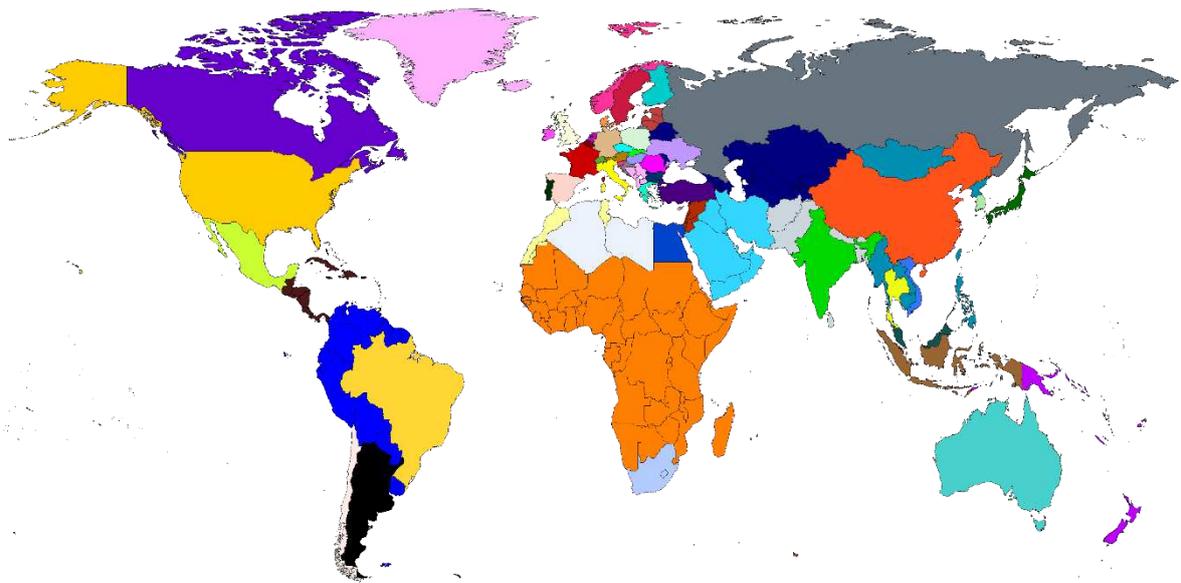
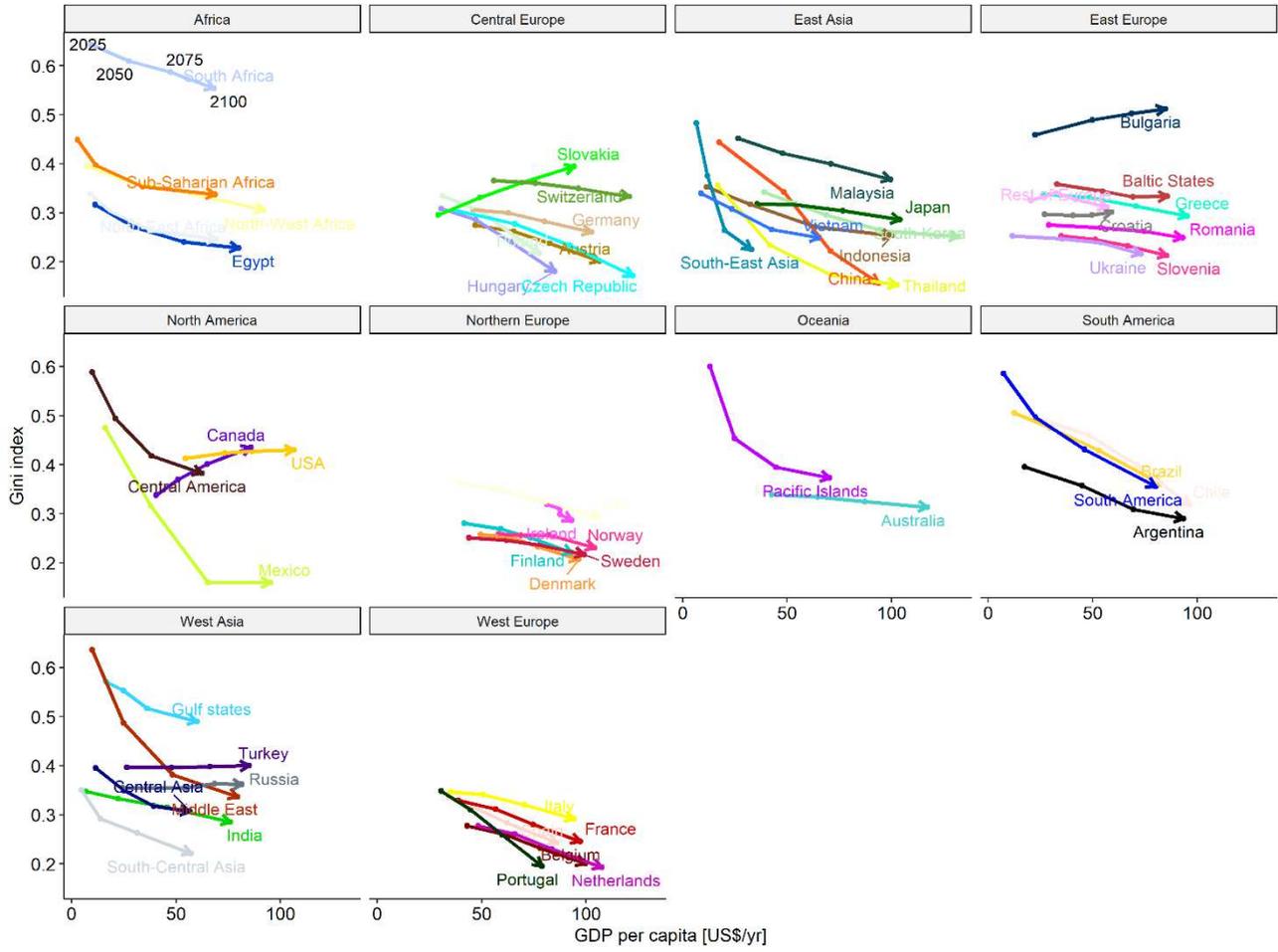
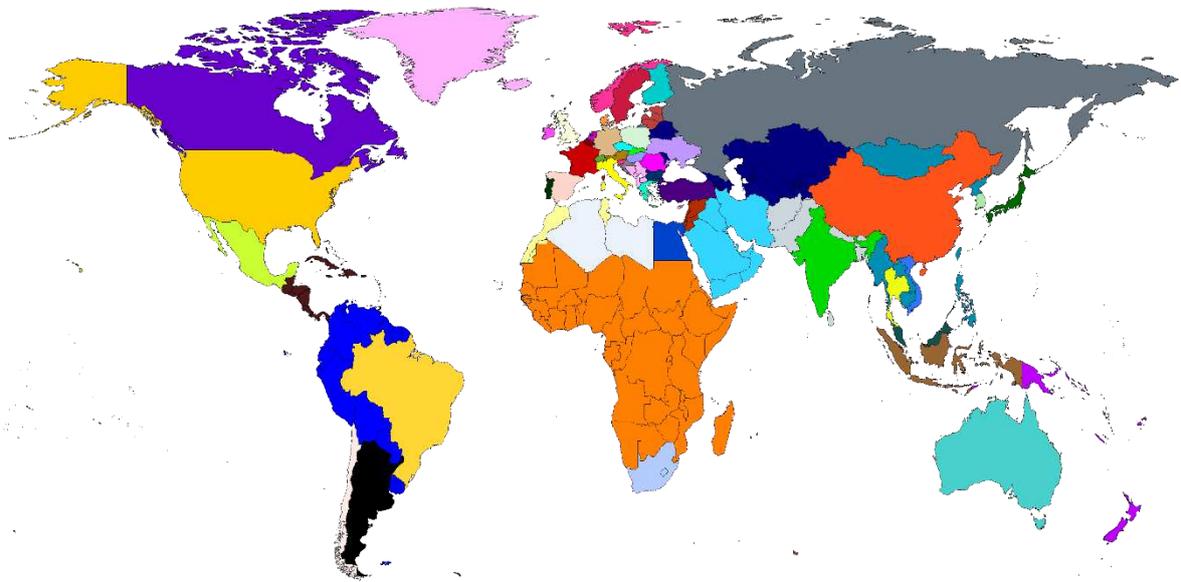
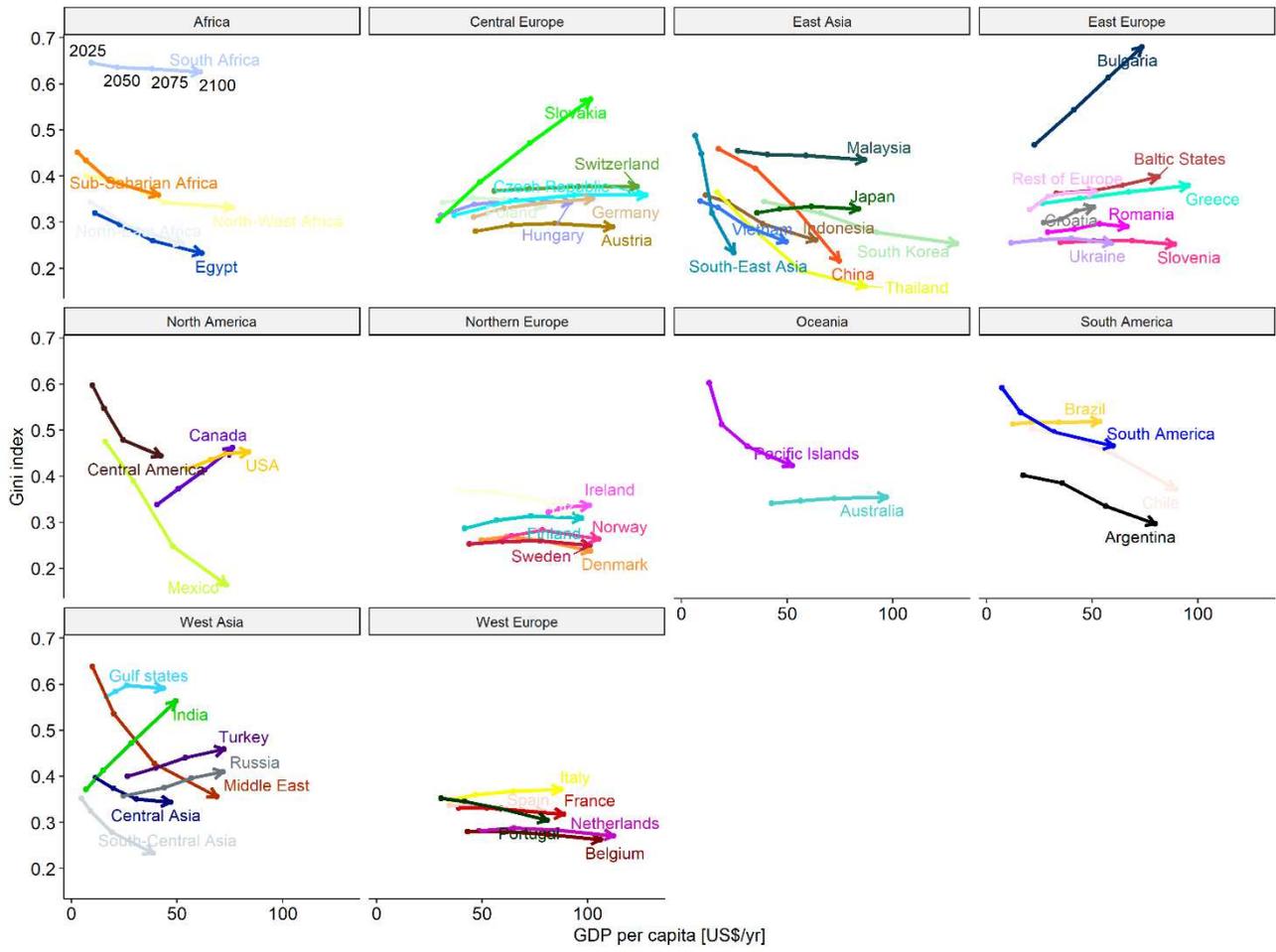
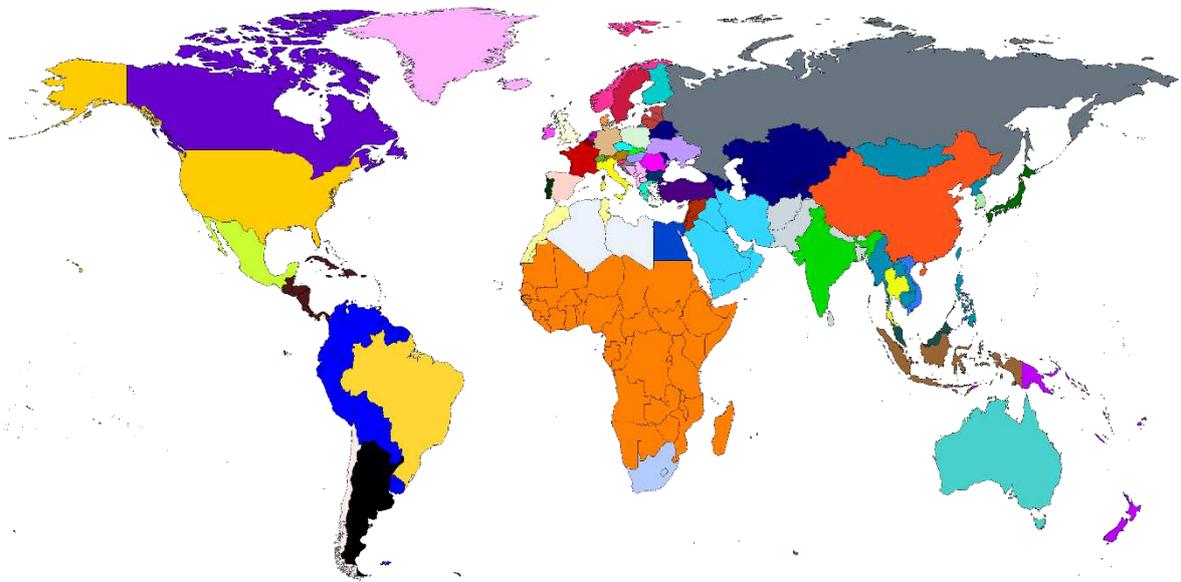
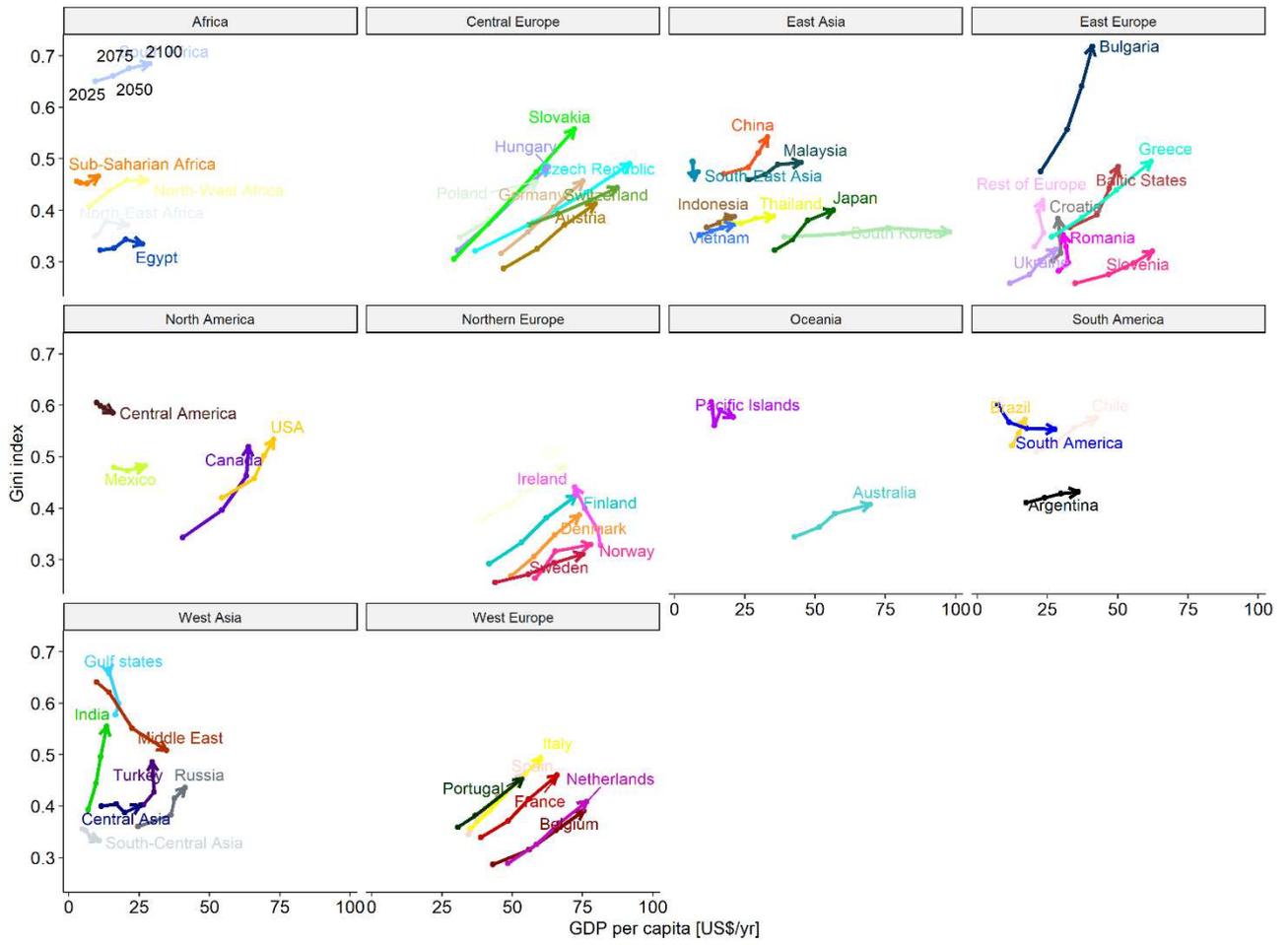


Figure 15: baseline Gini against baseline GDP per capita per region, all SSPs

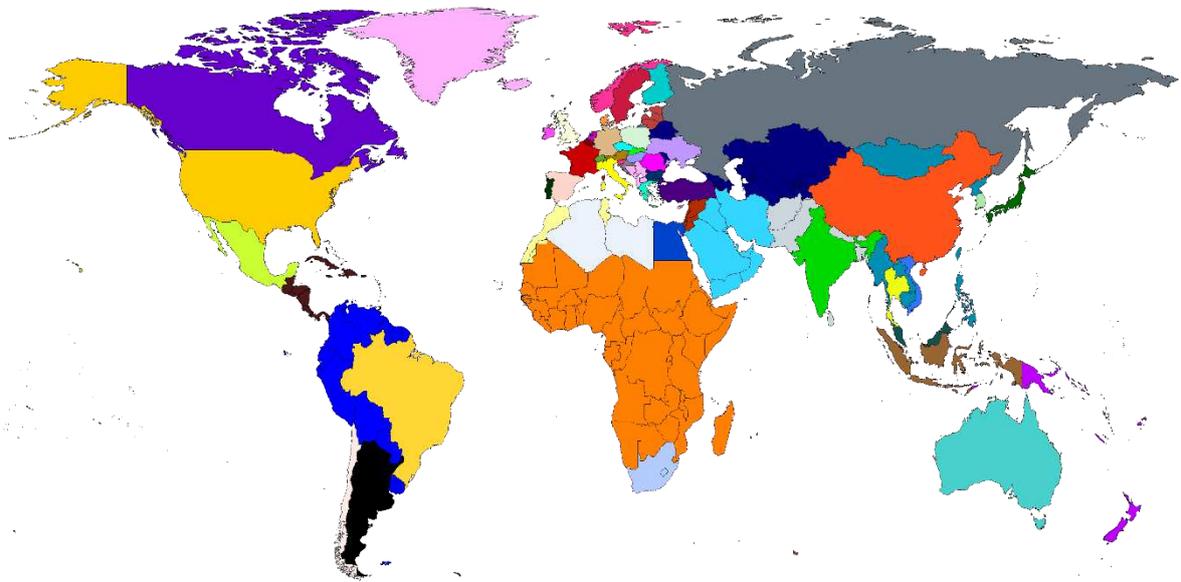
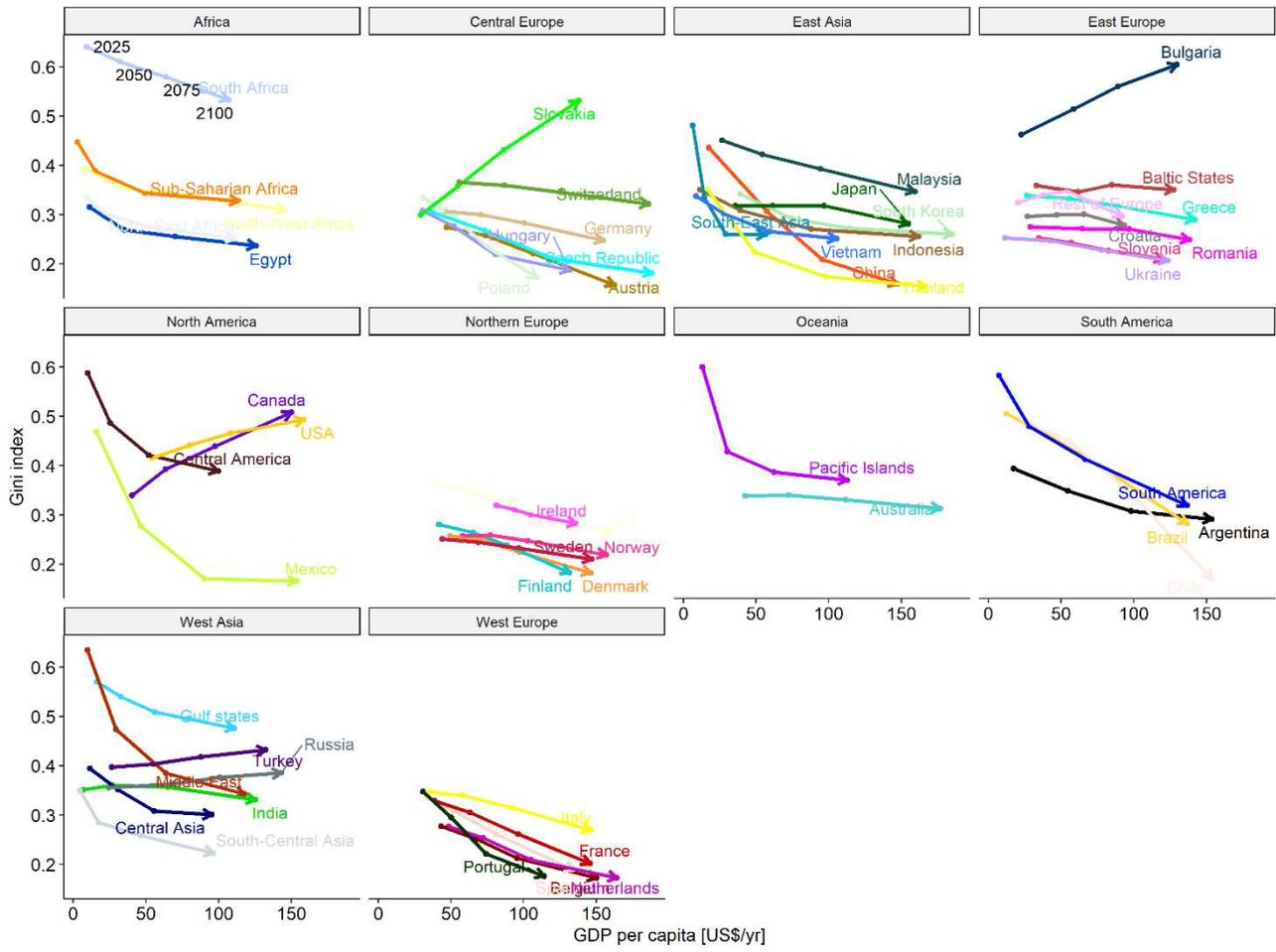
SSP2



SSP3



SSP5



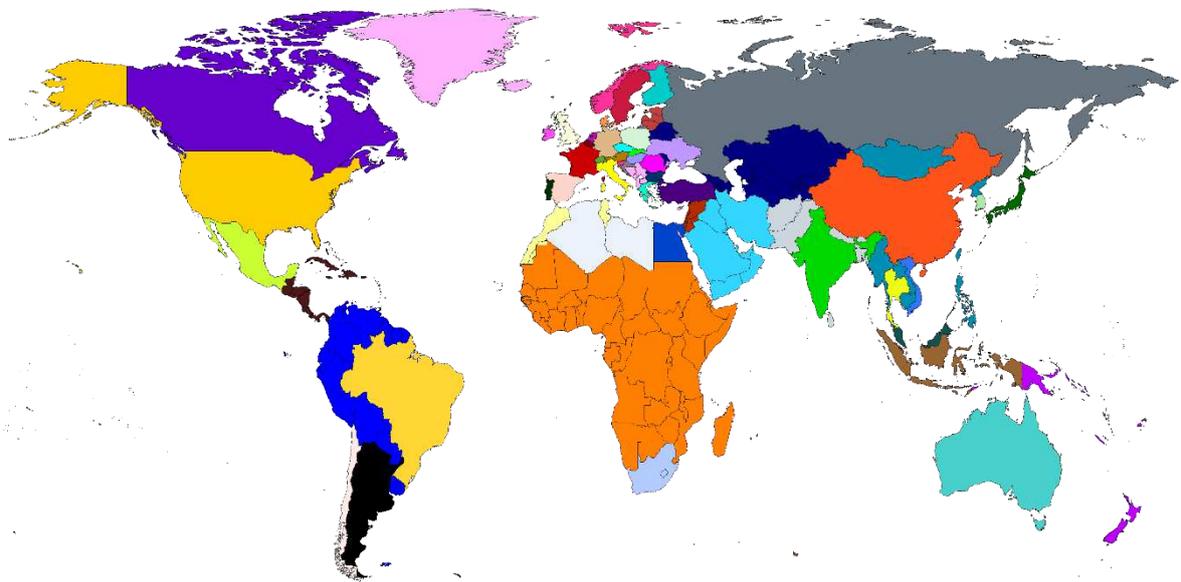
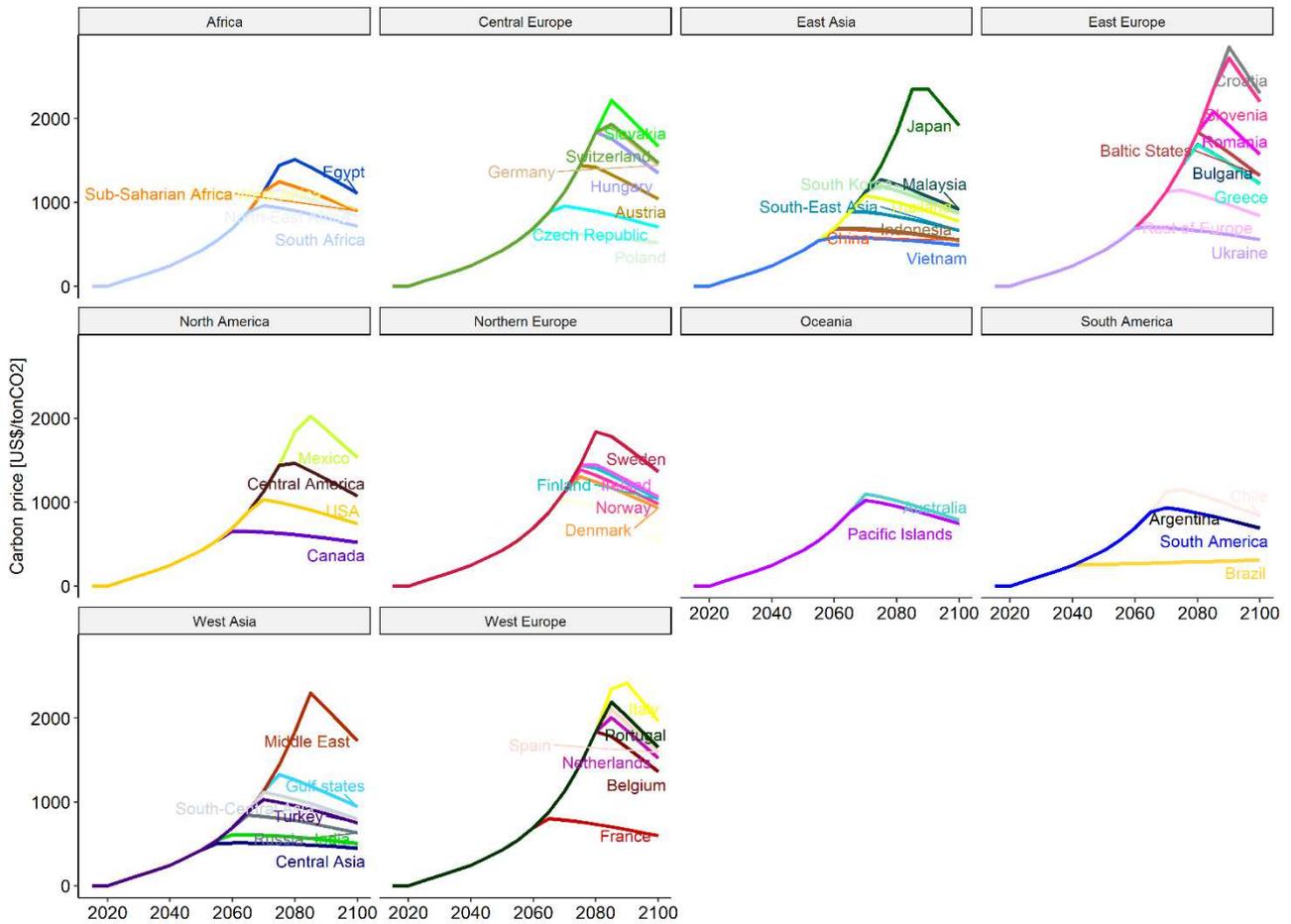


Figure 16: regional carbon prices in the SSP2, 700GtCO₂ carbon budget overshoot scenarios. Prices are fixed to the global carbon tax level until regional net-zero, but when they reach the constrained imposed by residual emission assumptions they decline because of the exogenous technological learning modelled into the calibrated marginal abatement cost curves.

ANNEX D: implications of the Hotelling rule for the scenarios

Since the carbon tax is prescribed following the Hotelling rule, we assume the optimal trajectory of the carbon price. The Hotelling rule is optimal even if negative emissions are available to recover from budget overshoot. It is not, however, in case of dynamics such as technological learning³⁵, that is included in our model both for standard abatement (exogenously) and CDR (iteratively, via learning by doing). Therefore, we have no guarantee that our scenarios are a first-best solution given the structure and boundaries of the problem. However, Hotelling prices are a standard assumption in many process-based IAMs that also include negative emissions and technological learning, which implies high profit margins for CDR company. Since the objective of the paper is not to produce first-best results in a cost-effective setting, but to identify and quantify the inequality implications of large-scale removal in IPCC-like scenarios, the use of widely utilized Hotelling paths for carbon prices is coherent and follows a well-established literature. One implication of this setting is that our representative negative emission technology does not behave as a backstop technology, in the sense that the market carbon price can be higher than the marginal cost of the negative emission technology. NETs behave as a perfect backstop technology, however, only under the assumptions of no constraints on the maximum rate of market growth or the maximum removal allowed by the NETs. Since that's not the case (see Methods: NET modelling), the presence of NETs as a separate and investable technologies effectively creates an implicit aggregate marginal abatement cost curve, composed by construction as the sum of the marginal abatement cost of positive and negative emissions. Therefore, even if we cannot guarantee the optimality of Hotelling rule, carbon prices significantly higher than the marginal cost of carbon removal are not theoretically inconsistent with the availability of the negative emission technology.