Title: Country-level social cost of carbon

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Abstract/First Paragraph:

The social cost of carbon (SCC) is a commonly employed metric of the expected economic damages expected from carbon dioxide (CO_2) emissions. While useful in an optimal policy context, a world-level approach obscures the heterogeneous geography of climate damages and vast differences in country-level contributions to global SCC, as well as climate and socio-economic uncertainties, which are larger at the regional level. Here we estimate country-level contributions to SCC using recent climate model projections, empirical climate-driven economic damage estimations, and socioeconomic projections. Central specifications show high global SCC values (median: 417 \$/tCO2, 66% confidence intervals: 177 – 805 \$/tCO2) and country-level SCC which are unequally distributed. However, the relative ranking of countries is robust to different specifications: countries incurring large fractions of the global cost consistently include India, China, Saudi Arabia and the United States.

The social cost of carbon (SCC) represents the economic cost associated with climate damage (or benefit) resulting from the emission of an additional ton of CO_2. One way to compute it is by taking the net present value of the difference between climate change damages along with a baseline climate change pathway and the same pathway with an additional incremental pulse release of carbon dioxide. The SCC provides an economic valuation of the marginal impacts of climate change. It has been estimated hundreds of times in the past three decades[10] using a range of assumptions about uncertain parameters (such as social discount rate, economic growth, and climate sensitivity). Recent estimates[1–6] of SCC range from approximately $10/tonne of CO2 to as much as $1000/tCO2. A recent report issued by the US National Academies highlighted the many challenges and opportunities associated with improving estimates of SCC.[11]

Among the state-of-the-art contemporary estimates of SCC are those calculated by the US Environmental Protection Agency (EPA). The latest figures equal to $12, $42 and $62 per metric tonne of CO2 emitted in 2020 for 5, 3 and 2.5 percent discount rates respectively[1]. These estimates are used, among other purposes, to inform US environmental rulemakings. Various alternative approaches to estimating SCC have been employed over the years, including more sophisticated treatments of time, risk and equity preferences[12–17], as well as those that incorporate more recent representations of climate damages and feedbacks[18–21]. A recent expert elicitation of climate scientists and economists[2] found a mean SCC of approximately $150–200 per tonne of CO2.

The global SCC captures the externality of CO2 emissions, and is thus the right value to use from a global welfare perspective. Nonetheless, country level contributions to the SCC are important for various reasons. Mapping domestic impacts can allow quantifying non-cooperative behavior, and thus better understand the determinants of international cooperation. The governance of climate agreements[22,23] is a key issue for climate change. The nationally determined architecture of the Paris climate agreement – and its vulnerability to changing national interests- is one important example. Country level estimates can also allow better understand regional impacts, which are important for adaptation and compensation measure. Finally, higher spatial resolution estimation of climate damage and benefits can impact estimates of net global climate damage[24,25], and its sensitivity to climate and socio-economic drivers.

Existing studies agree on the significant gap between domestic and global values of the SCC, but provide limited agreement on the distribution of the SCC by region[26]. Due to limitations on the availability of country-level climate and economic inputs, no previous analysis has partitioned global SCC into country-level contributions from each individual nation (CSCC). In this paper, we draw upon recent developments in physical and economic climate science to estimate country-level and aggregate SCC and quantify associated uncertainties. The CSCC captures the amount of marginal damage (or, if negative, the benefit) expected to occur in an individual country as a consequence of an additional CO_2 emission. While marginal impacts do not capture all information relevant to climate decision making, the distribution of the CSCC provides useful insights into distributional impacts of climate change and national strategic incentives.

Methodological Approach

Following the recommendations of the recent report by the US National Academies of Science, we execute our calculations of social cost of carbon through a process with four distinct components[11]: a socioeconomic module wherein the future evolution of the economy, including projected emissions of carbon dioxide, is characterized absent the impact of climate change; a climate module wherein the earth system responds to emissions of carbon dioxide and other anthropogenic forcings; a damages module, wherein the economy's response to changes in the Earth system are quantified; and a discounting module, wherein a time series of future damages is compressed into a single present value. In our analysis, we explore uncertainties associated with each module at the global and country level. We focus only on climate impacts, and do not carry out a full-fledged cost benefit analysis which would require modeling mitigation costs.

We develop a method for calculating social cost of carbon that is oriented towards partitioning and quantifying uncertainties. While it follows the same module structure as the integrated assessment models that have been conventionally used to calculate SCC, rather than building reduced-form models of the climate or economy, we use country-level climate projections taken directly from gridded, ensemble climate model simulation data as well as country-level economic damage relationships taken directly from empirical macroeconomic analyses. Because climate and economic quantities are empirical in this analysis, these uncertainties are probabilistic in our output. Socioeconomic and discounting uncertainties are assessed parametrically using five socioeconomic scenarios and twelve discounting schemes.

Socioeconomic module: For the socio-economic projections, we use the shared socioeconomic pathway scenarios (SSPs)[9]. The SSPs provide five different storylines of the future (Supplementary Table S1). We use the GDP and population assumptions of the SSPs as well as subsequent work to estimate the emissions associated with each SSP absent climate mitigation policies[27].

Climate module: We match emissions profiles of the SSPs to those of the Representative Concentration Pathways (RCPs[28]) modeled in the fifth Coupled Model Intercomparison Project (CMIP5)[7] to estimate baseline warming (see Methods).To estimate the response of the climate system to a pulse release of carbon dioxide, we combine results from CMIP5 and a carbon cycle model intercomparison project[29] (Supplementary Tables S2 and S3). Carbon cycle uncertainty is represented by using the global-scale decay of atmospheric carbon dioxide after a pulse release of CO_2 into the present-day atmosphere. Climate system response uncertainty is calculated at the population-weighted country level using gridded output from the CMIP5 *abrupt4xco2* experiment in which atmospheric CO_2 is instantaneously quadrupled from preindustrial. By convoluting the results from these experiments (as in[30], but at the population-weighted country-mean level) we derive a range of country-specific transient warming responses to an incremental emission of CO_2. To test the sensitivity of our results to the uncertain feedbacks between economic growth and emissions, we perform the calculations for RCPs 4.5, 6.0 and 8.5 for all SSPs.

Damages module: We convert country-level temperature and precipitation changes into country-level damages using empirical macroeconomic relationships derived by Burke et al[8] and Dell et al[31]. Their econometric approaches exploit interannual climate variability in historical observations to estimate the impact of climate on economic growth. Estimating the economic damages associated with a given level of warming is a notoriously challenging problem for which there is no perfect state-of-the-art solution[11,32]. Gross domestic product (GDP) is an informative, but highly imperfect measure of welfare[33]. Among its advantages, an empirical macroeconomic approach: captures interactions and feedbacks among sectors of the economy; captures effects of climate on the economy that have been neglected or are difficult to partition and quantify; has higher geographical resolution (country-level) than existing alternatives; is empirically validated and has confidence intervals which allow to do uncertainty analysis; and is completely transparent and replicable. Because results are sensitive to the econometric specifications, e.g. whether lags are included to capture long run effects, and countries are distinguished between rich and poor to account for different capability to adapt [8], we compare all the existing empirical specifications. (See Methods and Supplementary Information)

Discounting module: We apply these damage functions to our country-level temperature pulse response, SSP and RCP projections, including associated climate and damage function uncertainty bounds (see Methods and Supplementary Figure S1) and then compress the time series of output into country-level SCC values using discounting. Discounting assumptions have consistently been one of the biggest determinants of differences between estimations of the social cost of carbon[13,35]. While intuitive, the use of a fixed discounting rate is not appropriate, particularly when applied universally to countries with highly disparate growth rates and with significant economic losses due to climate change. We thus use growth adjusted discounting determined by the Ramsey endogenous rule[36] with a range of values for the elasticity of marginal utility and the pure rate of time preference, but also report fixed discounting results in order to demonstrate the sensitivity of SCC calculations to discounting methods.

Global results

Global SCC (GSCC) is the sum of country-level SCCs. We calculate CSCC for each set of scenario, parameter and model specification assumptions, establishing an uncertainty range based on a bootstrap resampling method (see Methods and Supplementary Methods) and then aggregate to the global level. The median estimates of the global SCC (Figure 1) are significantly higher than the IAWG estimates, primarily due to the higher damages associated with the empirical macroeconomic production function[8], though similar SCC have been estimated in the past using other methodologies[14,21]. Under the ‘middle of the road’ socioeconomic scenario (SSP2) and its closest corresponding climate scenario (RCP6.0), and the central specification of BHM damage function (short run, no income differentiation) we estimate a median global SCC of $417/tCO2 (rate of time preference=2%, elasticity of marginal utility=1.5).

The choice of both socioeconomic and climate scenario has an impact on estimated GSCC (Figure 1 and Supplementary Figure S2). For a given RCP, scenarios with strong economic growth and reduced cross-country inequalities (SSP1 and SSP5) have smaller GSCC than worlds with low productivity and persistent or even increasing global inequality (SSP3 and SSP4). For a given SSP, higher emission scenarios lead to higher global SCC. When using fixed time discounting (Supplementary Figure S2), results are significantly different. In particular, global SCCs are lower across scenarios, and the ranking to SSPs and RCPs is often reversed. This highlights the importance of using the appropriate endogenous discounting rules to capture the feedback of climate on the economy.

Figure 1 also shows the sensitivity to the impact function specification. Under most socioeconomic scenarios, global SCC is significantly higher and more uncertain when calculated with a long-run (lagged) damage model specification (BHM-LR). This somewhat counterintuitive result indicates that whether climate’s primary impact on the economy is through growth or level effects, the negative cumulative effect of climate change on long-term growth is substantial and robust. The GSCC is always lower using the rich/poor specifications of the damages model with confidence intervals that, in most cases, extend into the negative SCC range. The DJO specification of the economic impact function[31] yields significantly higher GSCC value.

Confidence intervals (66%) illustrated in Figure 1 emphasize the large degree of empirical uncertainty surrounding SCC estimates, even if scenario and structural uncertainties are disregarded. These stem from both the uncertainties of the climate system response to CO_2 (climate sensitivity) and uncertainties in economic harm expected from climate change (damage function). The latter are especially significant for the long-run specifications, which by construction have larger confidence intervals.

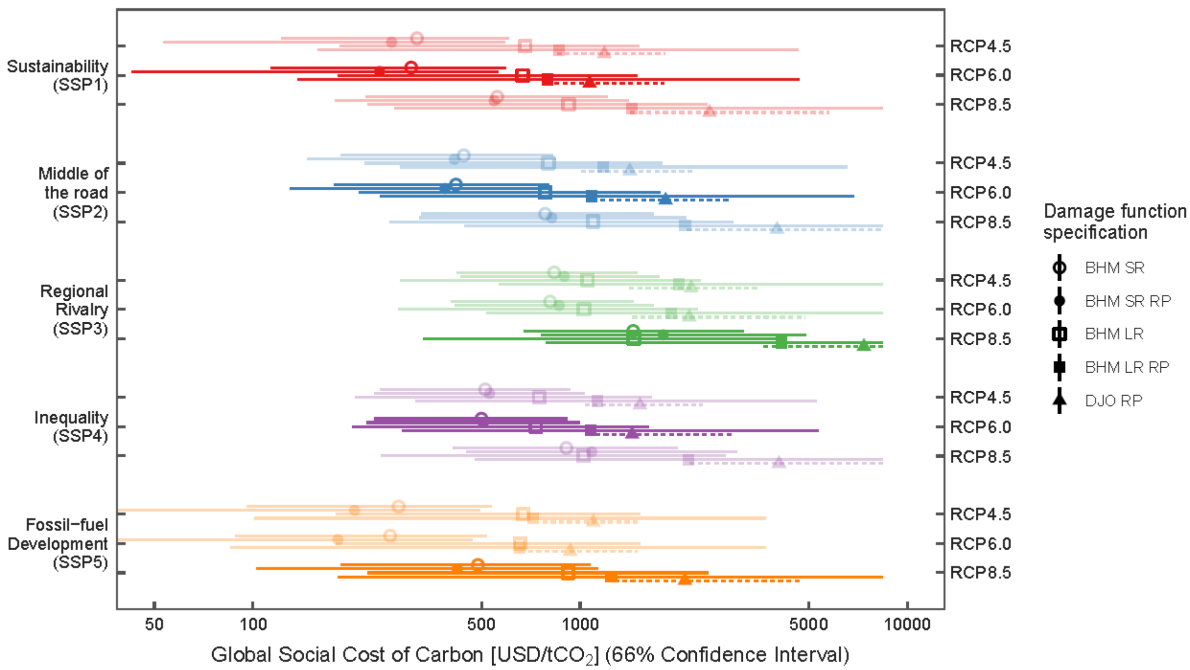

Figure 1 | Global Social Cost of Carbon in 2020 under various assumptions and scenarios. *Median estimates and 16.7% to 83.3% quantile bounds for global SCC under SSPs 1-5, and RCPs 4.5, 6.0 and 8.5. For each SSP, darker colors indicate the SSP-RCP pairing with superior consistency (see Methods and Supplementary Table S4). Five specifications of damage function: BHM (Short Run, SR, and Long Run, LR; pooled and with Rich and Poor, RP, distinction) and DJO. Values displayed assume growth-adjusted discounting with a pure rate of time preference of 2% per year and an inter-temporal elasticity of substitution of 1.5. Supplementary Figure S2 shows results with fixed discounting.*

Country-level results

These global estimates conceal substantial heterogeneity in country-level contributions to SCC (CSCCs). Figure 2a shows the spatial distribution of CSCCs under a reference scenario (SSP2-RCP6, standard BHM specification). All fixed discounting, alternative scenario, parameterization and specification results are available as a part of the database included in the Supplementary Information.

India's CSCC is highest (86 [49–157] $/tCO2; 21% [20–30%] of global SCC), followed by the USA (48 $/tCO2 [1–118]; 11% [0–15%] of global SCC) and Saudi Arabia (47 [27–86] $/tCO2; 11% [11–16%] of global SCC). Three countries follow at above 20$/tCO2: Brazil

(24 [14–41] $/tCO2), China (24 [4–50] $/tCO2) and United Arab Emirates (24 [14–48] $/tCO2). Northern Europe, Canada, and the Former Soviet Union have negative CSCC values since their current temperatures are below the economic optimum. These results are among the most sensitive in the analysis, as under the BHM long-run and DJO damage model specifications all countries have positive CSCC. Under the reference case and other short-run model specifications, about 90% of the world population have a positive CSCC. While the magnitude of CSCC varies considerably depending on scenario and discount rate, the relative distribution is generally robust to these uncertainties. Damage function uncertainty is a larger contributor to overall uncertainty, but at the country level, either climate or damages uncertainty may be larger. The alternative economic damage functions confirms the broad heterogeneity of CSCCs and relative country ranking (see Figure 2b and Supplementary Figure S5).

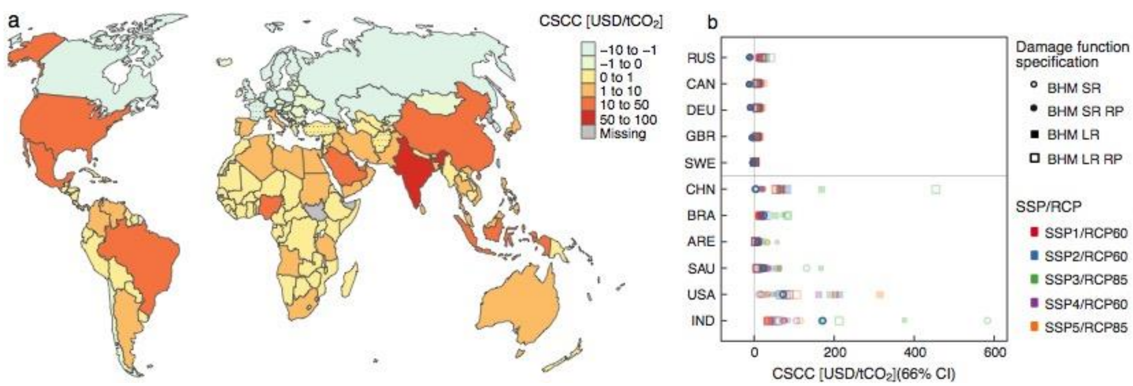

Figure 2 | Country-level social costs of carbon (CSCCs). (a) *Spatial distribution of median estimates of the CSCC computed for the reference case of scenario SSP2/RCP60, short-run pooled specification of BHM impact function (BHM-SR), and a growth adjusted discount rate with 2% pure rate of time preference and IES of 1.5. Stippling indicates countries where BHM damage function is not statistically robust*[8] ***(b)*** *CSCCs for alternative scenarios and damage function specification combinations for the five smallest and six largest CSCCs in the reference case (blue open circles).*

Consistent with past work on the geography of climate damages[4,8,37], we find that the international distribution of SCC is inequitable (Lorenz curves in Figure 3). The magnitude of the inequality is sensitive to the model specification of the economic impact function. As discussed above, there is an unsettled debate as to whether empirical evidence points towards the influence of climate on the economy operating primarily via growth or level effects, something that has been analyzed without definitive conclusion in BHM and follow-up work[38]. Our results indicate that this uncertainty is consequential from a strategic perspective (i.e., in determining relative gains and losses to particular countries). In particular, with long-run (LR) and DJO specifications all countries have positive CSCCs. This results in higher (almost twice as much) global values of the SCC (as already observed in Figure 1) and lower inequality with respect to the short terms specification. The distinction between income groups in the impact function (rich and poor countries) has smaller impacts, reducing global SCC and either leaving inequality unchanged (for the short-term specification) or lowering it (for the long-term one).

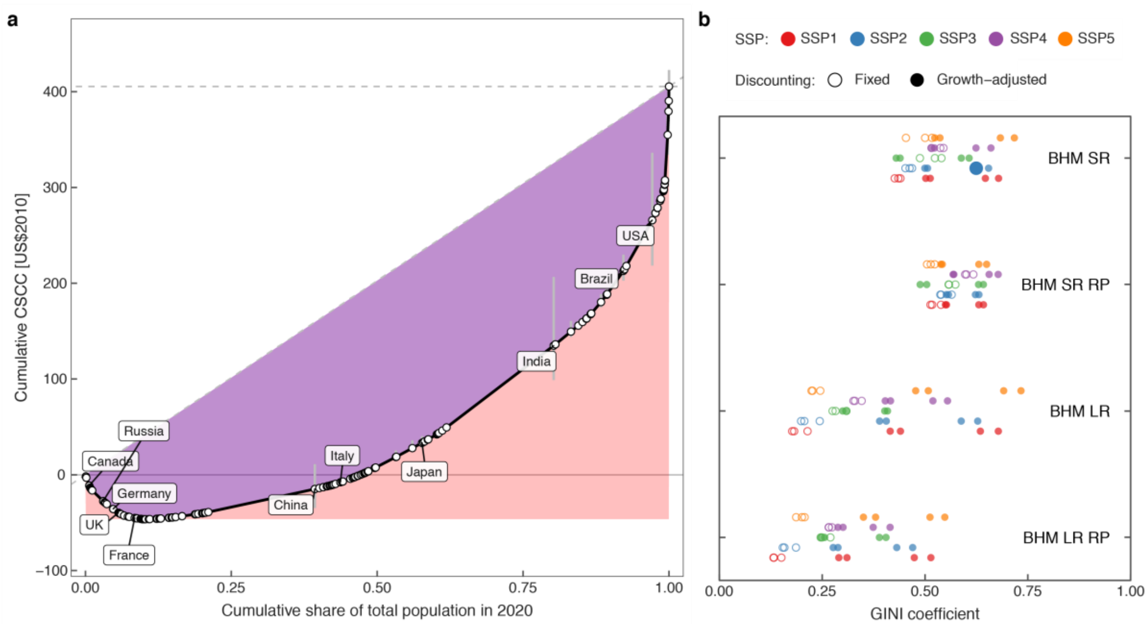

Figure 3 | Lorenz curve and Gini coefficients for the country-level contributions to the Global SCC in 2020. (a) *Cumulative global population plotted versus cumulative SCC, with countries ranked by CSCC per capita, produces a Lorenz curve for the reference case of scenario SSP2/RCP60, short-run pooled specification of BHM impact function (BHM-SR), and a growth adjusted discount rate with 2% pure rate of time preference and IES of 1.5. The red and purple shaded areas illustrate the quantities required to calculate the Gini coefficient, a synthetic metric of heterogeneity/inequality, which is equal to the purple area divided by the sum of the purple and red areas.* ***(b)*** *shows Gini coefficients for all four damage model specifications from top to bottom: the BHM short-run pooled model (SR), short run rich-poor specification (SR-RP), long-run pooled (LR) and the long-run rich-poor (LR-RP). Shared Socioeconomic Pathways*

(SSPs) are distinguished by color for both fixed (open) discounting with rates 2.5%, 3% and 5% and growth-adjusted (solid) discounting with prtp=(1%,2%) and ies=(0.7,1.5). The reference case (Gini coefficient=0.62) is illustrated with a large, solid blue point.

Figure 3(b) summarizes the inequality of CSCC across all scenarios through Gini coefficients[39,40] a synthetic measure of global heterogeneity. Under the BHM-SR specification, Gini values increase moderately with the RCP forcing. It is higher for SSP1 and SSP5, and significantly lower for SSP3, which is also the socio-economic scenario with the highest global SCC value. Socioeconomic uncertainty also becomes more important to future outcomes under a long-run economic impact models, whereas the rich-poor distinction plays a smaller role. The discounting method also plays an important role: fixed discounting leads to significantly lower Gini coefficients for CSCC for most specifications.

Figure 4 highlights a mapping of winners and losers from climate change among G20 nations. While the magnitude of CSCC is subject to considerable uncertainty, the shares of global SCC allocated among world powers remains relatively stable (Supplementary Figures S7-S9) in all short-run impact model specifications. Russia dominates all other nations in gains from emissions, while India is consistently dominated by all other large economies with large losses. Other developing economies, such as Indonesia and Brazil, will accrue a significantly greater share of global SCC than their current share of global emissions. The world's biggest emitters -China and the US- both stand to accrue a smaller share of global SCC than their share of emissions, but are consistently dominated by the EU, Canada, South Korea and -- in the case of the US -- Japan.

Relative ranking of SCC is highly consistent among most of the 276 scenario-impact-discounting uncertainty cases with the notable exception of the relative positions of major world powers occurs under the long-run impact model specifications (Supplementary Figures S7-S9). Countries like Russia, Canada, Germany and France that have negative CSCC under the reference case switch to having among the highest positive CSCCs (Supplementary Figure S9). After the short- and long-run differences, the largest shifts in country-order relative to our reference case occur under the high-emissions SSP5 scenario and in the transition between growth-adjusted and fixed discounting (Supplementary Figure S8).

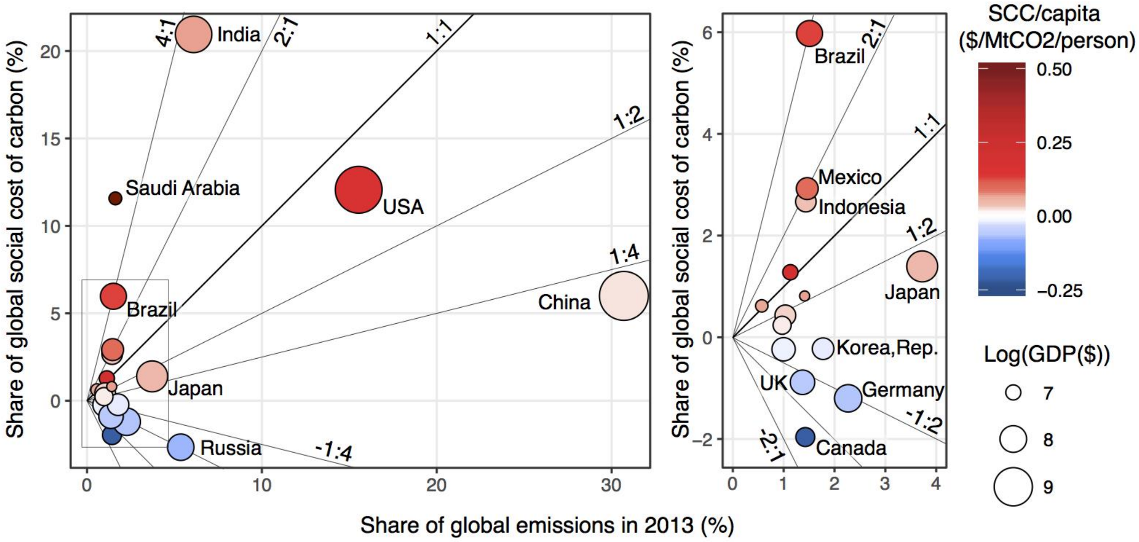

Figure 4 | 'Winners' and 'Losers' of climate change among G20 nations. *Country-level shares of global SSC (i.e., CSCC/GSCC) versus shares of 2013 CO2 emissions. CSCC is the median estimate with growth adjusted discounting for SSP2/RCP6.0, BHM-SR reference specification (short run, pooled countries). Bubble size corresponds to the country's GDP (log(USD)) and the color indicates per-capita CSCC ($/MtCO2/person). Diagonal lines show the ratio of global SCC share to emissions share. Ratios greater than 1:1 indicate that a country's share of global SSC exceeds it share of global emission. Grey box in left panel indicates the bounds of the detail shown in right panel.*

Discussion

The discord between country-level shares in CO_2 emissions and country-level shares in the social cost of carbon illustrates an important reason why significant challenges persist in reaching a common climate agreement. If countries were to price their own carbon emissions at their own CSCC, approximately only 5% of the global climate externality would be internalized. At the same time, our results consistently show that the three highest emitting countries (China, the U.S. and India) also have the among the highest country-level economic impacts from a CO2 emission. These high emitter CSCCs are on par with carbon prices foreseen by detailed process IAMs for climate stabilization scenarios (see Supplementary Figure S10). That is, internalizing the domestic SCC in some major emitters could result in emissions pathways for those countries which are consistent with 1.5 -2 °C temperature pathways. Fully internalizing the CO2 externality (ie., pricing carbon at global SCC) would allow meeting the Paris Agreement goal and beyond.

Empirical, macroeconomic damage functions have advantages and disadvantages compared to the approaches that have typically been used to estimate social cost of carbon in the past. Strengths include transparency, a strong empirical basis and capacity to account for interactions among all sectors of the economy, and for impacts difficult to isolate and quantify. However, there are a number of long-term effects of climate change that are not captured by this type of relationship. We present a number of these excluded contributors in Supplementary Table S5, along with an indication of the likely sign of impacts on CSCCs and global SCC. For example, adjustment costs associated with adaptation are not accounted for in this model. Such costs could be high or, given that climate change is not a surprise, could be modest compared to the type of effects that are represented (and which are demonstrably large). Already in our analysis, impacts from climate change are large enough in some countries to lead to negative discount rates (see Supplementary Figure S11). Most of these additional contributors would be expected to increase the global social cost of carbon.

Globalisation and the many avenues by which countries fortunes are linked mean that high CSCC in one place may result in costs as the global climate changes even in places where CSCC is nominally negative. For many countries, the effects of climate change may be felt more greatly through transboundary effects, such as trade disruptions[41], large-scale migration[42], or liability exposure[43] than through local climate damage. While CSCC in 2020 is negative for many rich, northern countries, if the non-linear climate damages hold over time, CSCC will become positive in most countries as the planet continues to warm. Furthermore, reducing greenhouse gas emissions can yield positive synergies on other environmental goals, such as improving air quality, which have large welfare impacts already now[44]. These considerations suggest that country-level interests may be more closely aligned to global interests than indicated by contemporary country level contributions to the social cost of carbon. What's more, climate decision making does not occur in a vacuum. Some countries, such as northern Europe and Canada, are leaders on climate policy despite potentially negative SCCs, while other countries with the highest

CSCCs, like USA and India, lag behind. Clearly, a host of other strategic and ethical considerations factor into the international relations of climate change mitigation.

The recent U.S. National Academy of Sciences report on social cost of carbon, the Working Group cites three essential characteristics for future social cost of carbon estimates: scientific basis, uncertainty characterization and transparency[11]. Our work includes improvements upon past estimates of SCC on all three counts. Past estimates of social cost of carbon were based on reduced form climate modules and damage function calibration with limited empirical support[45], while ours uses output from an ensemble of state-of-the-art coupled climate model simulations and two independently-generated empirical damage functions. Past estimates of SCC have included limited uncertainty analysis, focusing mostly on a limited set of parameters such as the social discount rate, while our estimates include quantified uncertainty bounds for carbon cycle, climate, economic and demographic uncertainties, while also providing disaggregation to the national level. In addition, past estimates of SCC were often generated using opaque models and/or proprietary software. We provide all of our source code and the full output of our analysis for complete transparency (see Supplementary Data).

The high values and profound inequalities highlighted by the country-level estimates of the social costs of carbon provide a further warning of the perils of unilateral or fragmented climate action. We make no claim here regarding the utility of country-level social cost of carbon in setting climate policies. Carbon dioxide emissions are a global externality. Despite “deep uncertainty”[46] about discounting, socioeconomic pathways and appropriate models of coupling between climate and economy, by all account the estimates of global SCC made by the Interagency Working Group on Social Cost of Greenhouse Gases, United States Government (ref. 1) appear much too low. More research is needed to estimate the geographical diversity of climate change impacts and to help devise policies which align domestic interests to the global good. However, large uncertainties in the precise magnitudes of social cost of carbon, both national and global, cannot overshadow the robust indication that some of the world’s largest emitters also have the most to lose from their effects.

Methods

We combine socio-economic, climate and impact data to estimate country-level social costs of carbon, that is the marginal damages from CO2 emissions, for each of the possible scenarios SSP-RCP, using exogenous and endogenous discounting. Lemoine and Kapnick (2016) uses a similar methodology to calculate growth rate impacts rather than CSCCs based on SSPs and damage estimates in Dell et al (2012).[37] The sequential process for calculating each CSCC is summarised in Supplementary Figure S1. Global SCC is calculated by summing all CSCCs.

Suppl. Table 1 summarises the underlying narratives, which cover different challenges to mitigation and adaptation. Several integrated assessment models have recently completed the implementation of the SSPs, computing for each of them future emissions as well as climate outcomes based on the medium complexity MAGICC6 model.[27] This allows us to map the SSPs onto four different carbon dioxide emission pathways known as representative concentration pathways (RCPs).

Data. The SSP database provides the socio-economic projections at country-level for the 5 SSP narratives (available at https://tntcat.iiasa.ac.at/SspDb[32]). The GDP projections were produced by the Organisation for Economic Co-operation and Development (OECD), and the population projections were generated by the International Institute for Applied Systems Analysis (IIASA). We compute annual GDP per capita growth rates for each country. The population-weighted average temperature increase at country-level is calculated for three Representative Concentration Pathways (RCP4.5, RCP6.0 and RCP8.5) using the gridded temperature projections provided by a total of 26 global climate models contributing to the fifth phase of the Coupled Model Intercomparison Project (CMIP5). See Suppl. Table 2. GDP per capita growth rates and temperature increases cover the period 2020-2100. The population-weighted average temperature response over time at country-level to the addition of 1 GtCO2 in the atmosphere is obtained by combining the results from the CMIP5 model's outcomes and a total of 15 carbon-cycle models from a carbon-cycle modelling project[30] (available at http://climatehomes.unibe.ch/~joos/IRF_Intercomparison/). Additionally, baseline temperature at the country-level is computed as the annual population-weighted average temperature increases from 1980 to 2010 from the Willmott and Matsuura gridded observational temperature data set[47].

Climate projections. Population-weighted country-level temperature time series are calculated for all RCP warming scenarios as well as the abrupt4xco2 experiment. Projections are bias corrected using a 1980-2010 observational baseline[47]. To remove the influence of interannual variability, for the purposes of the SCC calculations, RCP scenario time series represented as a quadratic polynomial fit and abrupt4xco2 time series were represented as a 3-exponential fit. Carbon cycle response to a CO2 pulse was also represented with a 3-exponential fit.

Impact projections. We follow the same procedure described in Ref 8 to project the economic impacts from the temperature increase. GDP per capita in country i at year t is $G_{i,t} = G_{i,t-1}\left(1 + \eta_{i,t} + \delta\left(T_{i,t}\right)\right)$, where $\eta_{\{i,j\}}$ is the growth rate coming from the data, in which no climate change occurs. $\delta(T_{i,t})$ is a response function of the temperature increase at year *t*. The projected warming effect is adjusted by the baseline temperature effect (see Ref 8). When applying a BHM rich-poor model, we specify the impact function recursively. Because a number of countries transition from poor to rich within the course of a given century-long simulation, for each year simulated, if a country is "rich" the rich-country impact function is applied and if it is "poor" the poor-country impact function is applied. For more details about the application of the alternative climate impact functions, see the Supplementary Information.

The Country-level Social Cost of Carbon. The difference in GDP per capita, including the temperature change impacts, between the scenario with and without pulse provide the yearly compound of the CSCC until 2100 (see Supplementary Figure S12). After 2100, the compound is kept constant to its value in 2100 until 2200 (or set to zero, see sensitivity analysis in Supp. Table S6). The CSCC is the net present value of the yearly compound multiplied by the population projection.

Discounting.
CSCCs were calculated using both exogenous and endogenous[12] discounting. For conventional exogenous discounting, two discount rates were used: 3 and 5%. Results under endogenous discounting were calculated using two rates of pure time preference (ρ=1, 2%) and two values of elasticity of marginal utility of consumption (η=0.7, 1.5) for four endogenous discounting parameterizations.

Reference scenarios

Recent work (Ref. 28) calculated the forcing paths associated with SSPs by 5 marker models. For each SSP, we consider the RCP forcing scenario with the minimum Euclidian distance between the SSP as a reference scenario (Supplementary Figure S13 and Supplementary Table S4).

Uncertainty.

The uncertainty analysis uses a full ensemble of carbon and climate model combinations to represent climate uncertainty (210-345 model combinations, varying according to the scenarios). Damage function uncertainty is analysed via bootstrapping (1,000 sets of parameter values). The combined uncertainty is obtained by convolution. At the end, a Bayesian bootstrap resampling analysis is conducted to provide the estimates of the median and the quantiles along with their confidence interval.

Lorenz curves and Gini coefficients

Lorenz curves are generated using the classical approach[39]. The Gini coefficients are generated using the method of Raffinetti et al (2015)[40] which developed a coherent approach to incorporating negative income into measurement of inequality, adhering to the principle that 0 designates perfect equality and 1 maximum inequality.

Code and data availability

All scripts used to calculate CSCCs and global SCC are available as a part of the Supplementary Materials. The database of country-level SCCs with uncertainty bounds under all scenarios, model specifications and discounting schemes is available as a part of the Supplementary Materials.

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Supplementary Information is available in the online version of the paper.

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