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ABSTRACT

Climate change is generating demonstrable harm around the world. Political and legal efforts have sought to associate climate impacts with specific emissions, including in recent international policy discussion of Loss and Damage (L&D). However, no quantitative definition of L&D exists, nor does there exist a framework for linking specific emissions to specific damages. Here we develop such a framework, linking it explicitly to recent efforts to calculate the social cost of carbon dioxide (SC-CO2), and demonstrate its use in a variety of applications. We calculate that future damages from past emissions, one component of L&D, are at least an order of magnitude larger than historical damages from the same emissions, a more commonly discussed component of L&D: 1 ton of CO2 emitted in 1990 causes $4 in global cumulative discounted damages by 2020 and an additional $327 in discounted damages through 2100 (2% discount rate). These estimates of past and future damages from marginal emissions can be used to calculate L&D for a range of specific emitting activities: for instance, an individual taking one long-haul flight every year for the past decade will generate ~$5500 in damages through 2100, the emissions associated with multiple oil majors between 1988-2015 have already caused $50-200B of cumulative global economic damage by 2020, and CO2 emissions in the US since 1990 have caused ~$2T in global damage through 2020, with India ($293B) and Brazil ($167B) being harmed the most. Carbon removal offers an alternative to transfer payments for settling L&D, but we show that it becomes increasingly ineffective in limiting damages as the delay between emission and recapture increases.

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1 Introduction

Decades of scientific advances make clear that human activities are substantially changing the climate, these changes are negatively impacting a range of human outcomes, and that those experiencing the most harm are responsible for a small fraction of historical emissions[1,2]. These intersecting insights have prompted calls for compensation from emitting entities for ”loss and damage”, or the damages from climate change that harmed parties were neither able to adapt to nor mitigate. Similar claims have been made in ongoing litigation around the world, in which claimants in a given location assert damages as a result of emissions from specific (and often distant) emitters.

However, unlike the large body of empirical work which explores how global climate change will affect global and local economic outcomes, the question of whether and how emissions by specific entities (e.g. countries, companies, or individuals) can be linked to specific damages has received less formal and empirical attention. A central empirical challenge in making progress has been that emissions come from many sources and are well mixed in the atmosphere. As a result, damages from these emissions must be inferred relative to a counterfactual (a world with fewer emissions) that is unobserved.

Drawing from multiple fields, we show how existing approaches used to quantify future aggregate climate damages can be re-purposed to also quantify bilateral, attributable loss and damage from historical emissions. The calculation is developed in a basic accounting framework that mirrors how damages are calculated in other legal contexts where one individual or group is liable for damages (or benefits) to another group.

Specifically, we develop an approach to compute compensation owed by an emitter for emissions that caused harm external to the emitter and which will continue to generate future harm. The basic idea is to consider emission of a unit of GHG (we focus on CO_2) to be the creation of an “asset” that produces a subsequent stream of value. Unlike typical assets, however, this asset generates a flow of future value that might be negative, and this flow accrues to individuals that did not create the asset. These features are not unique to GHG-assets, and assets with these features are commonly traded in markets. For example, household garbage generates a flow of costs for whoever takes ownership of it. For this reason, households must compensate – and expect that they will be obligated to compensate – another entity (e.g. a waste disposal firm) to take it and store it on their premises. Here, we compute an analog to the value of unpaid garbage collection bills that would be owed, i.e. debt, for past GHG emissions if individuals were compensated for the costs imposed by this waste. The total sum of these costs are the residual loss and damages suffered by populations due to climate change. We emphasize that our use of "debt" and "compensation" is in an accounting sense, and does not address the challenging ethical question of actual legal obligation, which has not yet been determined.

2 Aligning Loss and Damage with the Social Cost of Greenhouse Gases

Our approach to computing L&D is designed to integrate seamlessly with calculations for the "Social Cost of Carbon Dioxide" (SC-CO_2), which is the net-present value of total additional net harm (or benefit) that accrues to society as a result of one additional unit of CO_2 emissions (equivalent concepts exist for other greenhouse gases; our focus here will be on CO_2). Such an integration is attractive, as SC-CO_2 is now a well-defined concept with consensus guidelines on its computation[3]. Since the language of L&D was agreed to in the establishment of the Warsaw International Mechanism in 2013[4], there have been multiple interpretations of what this language means in practice[5], including that L&D is indistinguishable from adaptation efforts and costs, that L&D is a focus on the deployment of tools (e.g. insurance) to reduce risk, or that L&D is the residual harm net of any adaptation effort. No formal definition of L&D has yet to be adopted[6], contributing to both conceptual and practical disagreements about how damages from climate change should be addressed.

Building on IPCC documents[7,8] and a growing academic literature[9,10], we propose that L&D be computed as *the net present value of economic and non-economic impacts attributable to the emissions of greenhouse gases through their impact on the climate*, net of any adaptation that was undertaken. Equivalently, L&D is the compensation schedule that would be required to make all individuals "whole" for the damages (or benefits) that they have experienced or will experience from climate change, paid for by the individuals that caused these impacts via emissions. We show how L&D from CO_2 emissions can then be computed from three components: the historical damages that have already occurred due to a past marginal CO_2 emission (which we denote HD-CO_2), the future damages expected to occur from this same past emission (FD-CO_2), and the future damages expected to occur from a present or future marginal emission (the SC-CO_2). Total L&D is then the discounted sum of each of these components multiplied by corresponding total past and future CO_2 emissions. It can be written in its simplest form as:

$$\text{Loss and damage} = \underset{\text{from historical emissions}}{\text{historical damages}} + \underset{\text{from historical emissions}}{\text{future damages}} + \underset{\text{from future emissions}}{\text{future damages}} \tag{1}$$

This approach enables decomposition of L&D into past and future damages, and aligns the financial accounting framework of L&D with the existing framework for SC-CO_2. Achieving alignment between L&D and SC-CO_2 has at least three important practical benefits. First, alignment in how these measures are defined and computed can harmonize their legal interpretation. Worldwide, many courts are grappling with the question of whether and how individuals should be compensated for past and/or future loss from climate change and the related question of whether emitters should be held liable or otherwise accountable for those payments[11]. Given the conceptual challenges of clarifying and establishing the legal frameworks for climate-induced damages, harmonizing both L&D and SC-CO_2 applications may expedite legal progress.

Second, alignment between L&D and SC-CO_2 is essential to ensure alignment of financial incentives, in any situation where charges and/or compensation for past and future damages is realized. Failure to align L&D and SC-CO_2 financially may result in market distortions (even if emissions markets are not explicitly implemented) or may incentivize agents to undermine one system in favor of the other. For example, if agents believe it will be cheaper to pay for past damages (via HD-CO_2) compared to future damages (via SC-CO_2) then they may be incentivized to delay financial settlement as long as possible, in order to maximize the quantity of emissions that are categorized as historical. Harmonization of these concepts is necessary, albeit not sufficient, to develop systems that achieve fair compensation but do not create such distortions.

Lastly, alignment between these two concepts enables the direct application of much of the scientific machinery used to compute the SC-CO_2, which was developed over the last several decades[3,12], to the calculation of L&D. The remainder of this paper explains how this calculation can be implemented and then implements it in a variety of applications.

2.1 Loss and Damage as Unpaid Fair Compensation

Our approach to computing L&D treats CO_2 emissions as an "asset" that generates a flow of revenue for population i, which may be negative, after it is created (Figure 1a). We then compute the net present value of that revenue flow that would be capitalized into the price of the asset, if the asset were traded in markets that fully and fairly valued this revenue flow. We consider this price "fair" if, in the hypothetical world where i had the ability to refuse the flow of value from the CO_2 asset, this price is what i would need to be compensated in order for i to be indifferent between accepting this flow and rejecting it. Of course, historically, no population had the ability to refuse this flow of value.

2.1.1 Discounting historical damages

Time plays a key role in the calculation of L&D. Of particular importance are four time-points: the time "responsibility" for past emissions begins, which we denote t_0, the time each unit of emissions occurs t_e, the year(s) in which damage occurs t, and the time "settlement" occurs for damages from these emissions t_s. We define t_s as the time when a transfer occurs such that i is made whole for the cumulative damages (past or future) resulting from the emission at t_e.

We propose that damages which occurred in the past, prior to settlement, are "discounted" similar to how damages in the future are discounted[13,14]. In essentially all financial or decision-making systems, future damages (or benefits) are discounted when they are weighed against damages occurring in the present using a per-period "discount rate" r that behaves similarly to an interest rate. As damages occur further in the future, they are valued relatively less in comparison to current damages when they are transformed into net present value terms. The selection of an appropriate discount rate for climate change policy has generated substantial controversy[15], although it is widely understood and agreed that a nonzero discount rate is crucial to the stability and consistency of inter-temporal decision-making[13,14,16]. We consider multiple potential discounting approaches.

Discounting damages that have occurred in the past means that their value is *larger* at the time of settlement than at the time when they occurred (Figure 1b). Analogous to the effect of an interest rate on unpaid debt, the inter-temporal discount rate causes the value of past damages to grow exponentially until settlement occurs. This interpretation is conceptually and mathematically identical to how discounting future damage is understood (Figure 1c), the only difference is whether settlement occurs before or after damages are experienced (Figure 1d). The application of discounting to historical damages is consistent with standard practice in financial or legal systems, where unpaid costs accrue interest until they are settled.

Discounting of past harm is important for two practical reasons. First, the costs imposed on the harmed party i have an impact that grows with time, since the resources allocated to cope with the harm, or directly lost as a result of the harm, could have otherwise been applied productively (e.g. invested). Second, if discounting is not applied, then an emitting party j is always incentivised to delay settlement, since the resources that would be transferred in settlement can be productively utilized until settlement. Therefore, achieving fair compensation for i and alignment of intertemporal incentives for j require discounting of past damages.

2.1.2 Computing Losses

Here, we consider damages in the form of foregone income due to climate change caused by CO_2 emissions. This approach can be extended to other forms of non-market damage, but we restrict our attention in this analysis to the effects of annual average temperatures on income, which thus implicitly embeds the net costs and benefits of all adaptations[17]. Our focus on average temperature helps overcome concerns regarding the use of extreme event attribution in L&D assessments[18]; unlike many extreme events, average temperatures are well measured throughout the world (including in developing countries experiencing substantial harm), the science relating changes in average temperature to anthropogenic forcing is well established, and multiple existing analyses relate changes in average warming to economic losses.

Damage from marginal emissions Let Y_{it} represent income for population i in year t which depends on the climate realization C_{it} in that year, which in turn depends the entire history of anthropogenic CO_2 emissions $\mathbf{E}$. We wish to compute the change of income ΔY_{it} that would result (at an arbitrary "damage year" t) from perturbing this history of emissions to some alternate trajectory $\mathbf{E}'$. Here, the "damage year" t could be any year including and subsequent to the emissions year t_e; a unit of emitted carbon dioxide – and the associated heat added to the climate system – can remain in the atmosphere for centuries[19,20], causing warming and subsequent damage in many future years.

We initially consider a marginal (one year) perturbation at a specific time $t_e \leq t$ in the past, which we denote ΔE_{t_e}. For this marginal emissions case, $\mathbf{E}'$ and $\mathbf{E}$ only differ in year t_e; in other settings of interest, for instance eliminating an entire country's recent history of emissions, trajectories will differ in multiple years.

Because CO_2s are well-mixed in the atmosphere, impacts of this marginal unit of emission do not depend on who emitted it. Damage at a specific moment in time (a flow) from the marginal emissions perturbation ΔE_{t_e} is then the difference between the income expected under the perturbed emissions relative to counterfactual emissions history:

$$\Delta Y_{it}(\Delta E_{t_e}) = Y_{it}(C_{it}(\mathbf{E}')) - Y_{it}(C_{it}(\mathbf{E})) \tag{2}$$

This change could be either positive or negative depending on the time scale and population exposed. However, as we will show, $\Delta Y_{it}(\Delta E_{t_e})$ is typically positive – that is, in the exposed population, income is higher in the counterfactual setting with lower emissions – and so we use ”damage” as shorthand for the change in income.

Cumulative damage from marginal emissions We introduce two more time-points, t_1 and t_2, which represent the beginning and end years over which damages are cumulated. The cumulative damage to population i from a unit of emission in year t_e is the sum of damages experienced in that country between t_1 and t_2, discounted to their value at an arbitrary time of settlement t_s.

$$D_{i,t_e,t_s,t_1,t_2}(\Delta E_{t_e}) = \sum_{t=t_1}^{t_2}(1+r)^{-(t-t_s)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \tag{3}$$

Discounting is done as a function of the difference between the year of damage t and the settlement year. Equation 3 can be used to decompose damages from historical and future emissions into three additively separable components of damage, which is helpful both for mapping different popular conceptualizations of ”loss and damage” into an aggregate measure of total L&D, and for distinguishing loss and damage that has already occurred from that which is likely to occur in the future, as approaches to liability and compensation could differ across these damage types.

First is the historical damage that has already occurred due to a past marginal emission cumulated through the present day, which we term $HD\text{-}CO_2$. In this setting, the settlement time t_s equal to the present day (denoted t_p), damages begin cumulating in the emissions year ($t_1 = t_e$) and end in present day ($t_2 = t_p$), emissions are in the past ($t_e < t_p$), and damages are aggregated over populations globally:

$$HD\text{-}CO_{2,t_e} = \sum_i D_i(\Delta E_{t_e}) \tag{4}$$

This is the quantity depicted in Fig 1e, aggregated over populations. Because the damage year is prior to the year of settlement, the exponent on the discount rate is positive in Eq 3, which means a higher discount rate will amplify the value of past damages and raise estimates of HD-CO_2, as described above.

A past emission will continue to cause damage in future years. This occurs for two reasons. First, carbon dioxide emissions remain in the atmosphere for decades or centuries and will continue to cause warming, and thus damage, unless removed. Second, and somewhat more subtly, past damages drive a wedge between the observed size of the economy and how large the economy would have been without the warming; damage from future warming further expands the size of this existing wedge. Together, these effects create a stream of expected future damages from a past unit of emission, which we term $FD\text{-}CO_2$, or the future damage from historical emissions. This is the quantity depicted in Fig 1f, aggregated over populations. Calculation is as for HD-CO_2, but impacts of a historical emission are cumulated beginning present day ($t_1 = t_p$) and continued until some distant future year, which in practice is typically 2100 or 2300. See Appendix for mathematical representation. Here discounting works in the typical way, with higher discount rates reducing the value of cumulative damages and lowering FD-CO_2. Empirically, as we show, FD-CO_2 damages are very large relative to HD-CO_2, given the long timescales over which greenhouse gases and associated heat remain in the climate system. The implication is that even if a large historical emitter were to rapidly achieve net-zero, its past emissions would continue to cause substantial uncompensated damage.

The final component is the cumulative future damages expected expected to occur for a marginal emission in the present year or in future years, discounted to present day. Emissions are now or in the future ($t_e \geq t_p$), damages start cumulating in the year of emission ($t_1 = t_e$) and end in some distant future year as above, and settlement is the present day ($t_s = t_p$). Because this matches how the SC-CO_2 is typically computed, for simplicity we denote this component the SC-CO_2. This is the quantity depicted in Fig 1g, aggregated over populations.

Total L&D Total L&D from CO_2, or the compensation required to make all parties whole for cumulative damages from all past and future CO_2 emissions, is then the sum of these three components multiplied by total current past and future CO_2 emissions. Summation of damages begins in starting year t_0, or time at which parties begin to be held accountable for their emissions. Emissions may have occurred before t_0, but it is not necessary to track the resulting damage if parties agree not to hold the emitters responsible for those impacts. Existing agreements have not yet defined t_0, so in our analysis below, we present multiple calculations that vary t_0. We note that in many legal contexts, analogs to t_0 are set to the earliest time when it can be shown that a polluting party became aware that their actions could cause damage to other parties.

The above components correspond to damages from the marginal emission of one ton of carbon dioxide at different points in time. Given total global CO_2 emissions E_{t_e} in each past and future year, then total L&D can be written as:

$$L_{t_0} = \sum_{t_e=t_0}^{\infty} E_{t_e} \cdot (HD\text{-}CO2_{t_e} + FD\text{-}CO2_{t_e} + SC\text{-}CO2_{t_e}) \tag{5}$$

which represents the cumulative present value of all past and future damages from past (since t_0) and future emissions, net of adaptation, discounted to the present day. Here the summation is over damages from each year of emissions, where HD- and FD-CO_2 are non-zero for past emissions and $SC\text{-}CO_2$ is non-zero for future emissions. Again in practice, summation typically stops in some chosen future year (e.g 2100 or 2300).

This definition makes clear the direct link between our definition and computation of L&D and the widely understood concept of the $SC\text{-}CO_2$[3,12]. Most proposals that incorporate the $SC\text{-}CO_2$ charge the emitter the sum total of future damages at the time of emission, equivalent to our definition of $SC\text{-}CO_2$. Full compensation for total L&D would additionally require compensation for past and future damages from emissions that occurred in the past, calculated analogously.

Unit-specific L&D, and bilateral attribution to a single emitter The above approach also enables calculation of total damages experienced by a specific population i, as well as attribution of these damages to a specific emitting party j (e.g. a person, or a firm, or a country). As in total L&D, L&D for population i is the sum of three bilateral components (cumulative past damage in i from a marginal past emission, cumulative future damage in i from that marginal emission, and future damage in i from a future marginal emission), multiplied by past and future global emissions in each year. The component of these damages attributable to emitter j instead multiplies damages from past and future marginal emissions by yearly emissions from j (see Appendix for derivation).

There are multiple considerations in the calculation bilateral attributable L&D. First, both j and i are likely emitters, and emissions from i can cause damage in j just as emissions from j can damage i. The net compensation from j to i should then plausibly reflect the net damage flows. For country emitters, we report gross flows (impact of emissions from j on i, impact of emissions from i on j) from which net flows can readily be calculated.

A second consideration is if emissions from j caused estimated benefits in i, either in gross or net terms. While there is no theoretical reason why external damages should be compensated but external benefits not compensated, existing policy discussions regarding loss and damage appear to have only focused on damages – likely because aggregate damages are thought to be substantially larger than benefits, and countries experiencing damage tend to be substantially poorer than either emitting countries or high-latitude countries that might benefit from warming[21]. Nevertheless, we again report gross damage flows between j and i, and we do not constrain damages to be positive.

2.2 Ethical and legal considerations

Our proposed approach to computing L&D inherits three key challenges that embody ethical and legal principles that we cannot resolve here.

Selecting a discount rate The discount rate r embodies trade-offs in economic valuation between different time periods, and it plays an important role in our proposed calculation of L&D. Different approaches to selecting a discount rate have been widely debated in the context of computing the $SCCO_2$[13,14]. To summarize that discussion, at one end of the spectrum, some argue[22] for a low discount rate (e.g. 0.1-2% per year) on ethical grounds because it treats sequential generations more fairly; at the other end, some argue[23] for a higher discount rate (e.g. 4-6% per year) because it more closely reflects how inter-temporal tradeoffs are made in financial markets. We do not present a favored discount rate for calculation of L&D here, but instead present results across the range of values expressed in the literature. These include both fixed discount rates as well as so-called ”Ramsey” discounting, which links discount rates to future economic growth (Appendix). However, importantly, we again note that altering the discount rate changes how past and future climate damages are valued (in the present) in *opposite ways* (Figure 1D): A lower discount rate increases the present value of future damages, but decreases the present value of historical damages; conversely, a higher discount rate decreases the present value of future damages, but increases the present value of historical damages.

When is t_0? It remains widely debated when to begin counting emissions that parties should be held accountable for. GHG emissions rose rapidly beginning in the mid-20th century, and these emissions were usually the result of activities that benefited the emitters and their descendants. However, many legal systems do not hold parties accountable for generating damages if the party did not know their actions caused harm. Following this logic, previous analyses have worked to establish when some major emitters first understood that GHGs would cause harm. For example, scientists at Exxon warned company executives about potentially damaging global warming beginning in at least 1977, and multiple utilities and car companies were also aware of anthropogenic warming by the 1970s[24]; widely-publicized hearings on the science of anthropogenic climate change were held in US Congress by the mid-1980s. Here, we do not resolve what the correct value of t_0 is, but instead present results for a range of values. For country-level L&D estimates, we set our baseline estimate of the ”year of knowledge” as 1990, or a year after the establishment of the IPCC. Using text-based analysis of United Nations documents, other analyses set the date a decade earlier[25], and we thus compute estimates using 1980 as an alternate start year.

Consumption or production-based emissions Should emitting parties be held responsible for the emissions associated with production decisions made by the party, or should they be held accountable for the emissions associated with the goods and services consumed by the entity? This question is relevant for assigning emissions to countries, whose ability to trade means that production- and consumption-based emissions can differ[26]. It is also relevant for assigning emissions to companies, who emit during the production process but who also produce products whose consumption is associated with emissions[27,28]. Views differ on to whom emissions responsibility, and thus damages, should be assigned. Our approach, where possible, is to simply report both production- and consumption-based emissions and their associated damages.

3 Empirical implementation

To implement our proposed framework, we build on previous work[25,29] and combine emissions inventories, reduced- and full-complexity climate models, empirical damage functions, and observed and projected changes in socioeconomic conditions to estimate past and future economic damages from many observed or projected emissions perturbations (see Appendix for additional details). Figure A1 demonstrates the empirical approach to estimating historical L&D between a population i experiencing damage and an emitting entity j, using damages imposed on the Brazilian economy by US emissions from 1980 through 2020 as an example. We use the reduced complexity model FaIR to first calculate the estimated change in global mean surface temperature (GMST) from the removal of US emissions from global emissions totals between 1980 and 2020 (Fig A1a-b). We then use the CMIP6 ensemble of global climate models[30] to "pattern scale" GMST changes to country-level changes, subtracting country-specific estimated annual temperature changes from the observed time series of annual temperature in each country (Fig A1c-d). Next, using an updated statistical model trained on 60 years of global data that relates country-level economic growth rates to variation in average temperature[31], we estimate what GDP would have been in each country had US emissions not caused warming in each year (Fig A1e). The temperature-GDP damage function is robust across statistical models; has not changed appreciably in last 60 years (Fig A2) indicating limited adaptation to date; and provides strong evidence that temperature is affecting the growth rate of GDP, not just the level (Fig A3; Appendix). We show that an existing critique of these estimated temperature-growth relationships[32] uses an approach to model selection that can yield highly biased estimates of the relationship of temperature to economic output (see Appendix). Finally, we cumulate discounted damages between initial emissions year (here, 1990) and settlement year (here, 2020) (Fig A1f), using a range of discounting approaches including fixed discount rates and Ramsey discounting (see Appendix for additional description).

The approach is generalizable to the calculation of cumulative damages, for individual populations or globally, through 2020 and after 2020 for any marginal emission or sequence of emissions prior to (or including) 2020. Our focus is on CO_2 but could easily be extended to any other

GHG for which their existed the analogous computational components (i.e. emissions inventories and methods to estimate global and local warming from marginal emissions). We show how uncertainty can be propagated from each step in the process, including ”climate sensitivity uncertainty” regarding the translation of marginal emissions to changes in GMST, ”climate pattern uncertainty” in the translation of GMST to local warming, and ”regression uncertainty” in the translation of local warming to damages. We distinguish these sources of uncertainty from other analytic choices (e.g. the discount rate or the last future year in which impacts occur) over which there is also not certainty but where probability distributions are poorly defined.

4 Results

4.1 Marginal damages

Figure 2 shows estimates of HD-CO_2, FD-CO_2, and SC-CO_2, under different discount rates and different emission years from 1990-2020 (numeric values are given in Figure A4). In general, earlier emissions pulses tend to generate larger estimated cumulative damages. This pattern occurs for two reasons. First, earlier emission means warming is acting on an economy for more years, and thus will generate larger cumulative damages under most damage functions. Second, our damage function links GDP growth to annual temperature, and growth effects cumulate: the marginal effect of warming in one year on total GDP is a function of past cumulative impacts. The use of other damage functions (e.g. for mortality) will have this first feature but not the second.

However, damages are not monotonically decreasing as a function of the year of the emissions pulse, at least for past damages. Cumulative discounted damages through 2020 are highest for emissions pulses in the mid-1990s, as early-90s emissions pulses generate initial marginal benefits because the majority of global GDP is still below the estimated temperature optimum (Fig A5). For future cumulative damages between 2021-2100 from these historical emissions, earlier emission years generate uniformly higher cumulative damages, as by 2020 the majority of global GDP is beyond the historical optimum temperature.

Importantly, we estimate that FD-CO_2, the present value of future damages from a marginal past emission is at least an order of magnitude larger than the present value of past damage from the same emission (HD-CO_2), at least for emissions since 1990. The differences are larger the lower the discount rate. For instance, under a 2% discount rate, 1Gt CO_2 emitted in 1990 causes \$4 per ton in cumulative discounted global damages by 2020 and \$327 per ton in cumulative damages between 2021 and 2100, a 80-fold difference; at a 3% discount rate the difference is 54-fold, and at 5% it is 28-fold. The implication is that under most discount rates, L&D settlements equivalent to estimated past damages will only account for a very small subset of the anticipated total damages that a historical emission will cause. Settling debts for past damages will not settle debts for past emissions.

Aggregate past and future damages from historical emissions are a mix of modest benefits in high-latitude countries, where we find warming increases GDP growth, and widespread damage in mid-latitude and tropical countries, where warming harms growth (Fig 2b-c). This geographic pattern is consistent with previous studies that have used an earlier version of the damage function to quantify the country-level impacts of historical[21] and future[31,33] warming. It is also broadly consistent with the spatial pattern of estimated climate damages from other damage functions, including heat-related mortality[34] and crop productivity[35].

As depicted in Fig 1, higher discount rates reduce future damages from historical emissions but tend to amplify historical damages from these emissions. The effect is larger on the former than the latter, given the longer time period over which future damages are aggregated. For instance, a 1Gt emission in the year 2000 generates $4.2 in cumulative global damages per ton by 2020 under a 2% discount rate versus $5.3 in cumulative global damages per ton by 2020 under a 7% discount rate. By contrast, the same emission generates $294 in damages per ton after 2020 (through 2100) under a 2% discount rate versus $48/ton under a 7% discount rate. The effect of discounting on historical damages is less consistent for emission years early in our sample (pre-1995), as many large economies initially benefit from warming and those benefits get large weight under a high discount rate, reducing damages (see Fig A5; after 1995, higher discount rates generate larger historical damages.

Social cost of carbon dioxide Given its policy salience, we report SC-CO_2 values under a broad range of analytic choices, including different discounting schemes, assumed counterfactual future growth rates (the rate at which economies would grow absent warming), whether growth effects or damages occur past 2100, and which statistical model is used for a damage function. See Figure A6 for a schematic depiction of how damages are computed under alternate time horizons.

Under relatively conservative assumptions (2% discount rate, slow counterfactual growth, no temperature impacts on growth past 2100) we estimate a SC-CO_2 of $471/ton, substantially larger than recent "bottom up" estimates proposed by the US EPA[36] (Fig 2e), but comparable to past estimates using a similar approach[33]. However, cumulating impacts through 2300, assuming lower fixed discount rates or using Ramsey discounting, and/or assuming higher counterfactual growth rates – all choices consistent with recent guidance – yield substantially higher estimates (Fig A8). See Appendix for additional details on these choices.

For a set of analytic choices regarding discounting, time horizon of impacts, counterfactual growth rates, and the statistical model used for the damage function, we can calculate uncertainty in the estimated SC-CO_2 resulting from quantifiable uncertainties in our empirical pipeline. We find that the two largest sources of uncertainty are uncertainty in the historical relationship between temperature and growth (as estimated by our regression analysis), and uncertainty in the sensitivity of GMST to a marginal emission (as estimated by FaIR; Fig A9). Less important is uncertainty across the climate model ensemble in the mapping of GMST to local warming. We do not consider uncertainty in emissions inventories.

4.2 L&D attributable to specific emitters

We show how these estimates of HDCO_2, FDCO_2, and SCCO_2 can be used to calculate components of L&D from three types of emitters: individuals, companies, and countries. Building on multiple recent efforts to calculate average emissions reductions that would result from changes in individual behavior[37,38], we estimate the reduction in global damage that would occur if multiple of these behaviors had been sustained by an individual over the last decade (2010-2020). We find that taking one additional long-haul airline flight (8000km, or roughly round trip from San Francisco to New York) per year for the last decade would have generated $20 in discounted global damages through 2020 and would be expected to generate $5500 in discounted damages between 2021 and 2100 (2% discount rate; Fig 3a and Fig A10a). Switching to a vegetarian diet from a representative non-vegetarian diet, installing and using a heat pump, or reducing driving by 10% would have each resulted in $1-2k of global economic benefits (reduced damages) through 2100 if undertaken for the past decade, and recycling or eating 1 fewer serving of beef per month over the same period would generate ~$100 in global discounted future benefits. As with marginal emissions, the cumulative past damages from these past emissions are about two orders of magnitude smaller than the future damage from these past emissions, indicating the lasting impact of even relatively small changes in individual behavior.

Given the high estimated costs of airline travel in particular, we extend our analysis to settings in which individuals utilize private rather than commercial travel, a topic that has been debated widely in public forums[39]. Using public data on private jet flights and associated emissions by numerous American celebrities for a single year (see Appendix for details on the data), we calculate the future discounted damage of flights these celebrities (or their aircraft) took in 2022. We calculate that emissions from private flights taken by Bill Gates, Jeff Bezos, Floyd Mayweather, Elon Musk, Jay-Z, and Taylor Swift in 2022 will each generate more than $200k in discounted aggregate damages by 2100, or between 0.05% (Mayweather) and 0.00002% (Gates, Musk) of each individual's net worth (Fig 3b). These estimates highlight the substantial, and perhaps unrecognized, social cost of particular individual consumption choices.

Building on recent efforts to estimate firm-level emissions over time[40], we estimate the cumulative historical and future damage associated with emissions from the production and use of fossil fuels (i.e. combined "Scope 1" and "Scope 3" emissions) produced by global "carbon majors", or large state-owned, publicly-owned or private companies that are substantial producers of oil, gas, or coal. We estimate that emissions between 1988-2015 from the largest single company emitter, Saudi Aramco, resulted in $240B in cumulative global economic damages by 2020 (Figure 3c, Fig A10c). This damage estimate is equivalent to roughly 0.6years of revenue from the company, using revenue data from 2021. We estimate future damages from these past emissions to be >50x larger, totaling $13T in cumulative discounted damages through 2100. Cumulative damages from the largest non-state-owned emitter, ExxonMobil, equalled $120B over the same period, cumulated through 2020, or roughly equivalent to 36% of annual revenue in 2021. We estimate that future damages through 2100 from ExxonMobil's past emissions equal $5.9T. Historical damages from other carbon majors are equivalent to between 17% of current annual revenue (China National Petroleum Corp) to 143% of annual revenue (Gazprom). Excluding "Scope 3" emissions from this calculation (emissions associated with the use of sold products) and restricting attributed damages to "Scope 1" emissions from carbon majors (the emissions resulting directly from the production of the products sold) yields damage estimates an order of magnitude smaller (Figure A11).

Finally, we calculate country-level bilateral estimates of historical damages from past emissions, i.e. the country-level cumulative damages to date from historical emissions from other countries, for emissions between 1990-2020 (Fig 4). The existence and magnitude of such damages are common focal point of recent policy discussions on L&D, and have been estimated in a small body of recent work[25,29]. US CO_2 emissions over the period were the largest source of damages, resulting in $1.97T cumulative damages by 2020 (2% discount rate). ~15% (or $293B) of these damages occurred in India and an additional ~8% ($167B) in Brazil from US emissions, the two countries that we calculate have suffered the largest total damages to GDP. Emissions from China were the second largest source of damages over the period ($1.7T), followed by emissions from the EU countries ($1.24T). Estimates are roughly twice as large for emissions starting in 1980 rather than 1990 (Fig A12), highlighting the importance of clarifying t_0 in historical L&D calculations. Estimates without land-use emissions are roughly similar (if slightly smaller) for most emitters, and differ most substantially for countries for whom land use emissions are a large fraction of historical emissions (e.g. Brazil, Fig A14). Computing loss and damage estimates from consumption-based rather than production-based emissions (neither accounting for land use products) results in a roughly similar ranking of countries responsible for the largest damages, although estimates for China and Russia are roughly 14-37% smaller and estimates for other large importers (e.g. Japan) are 16% higher (Fig A13).

While compensation for economic benefits experienced as a result of warming is not currently a focus of L&D policy discussions, we estimate that a smaller set of high-latitude countries experienced substantial negative damages – i.e. benefits – from historical global emissions. We calculate that EU countries' economies were in aggregate \$3.62T larger due to warming from other (and own) countries emissions since 1990, and that Canadian and Russian economies were both \$1.33T and \$1.24T larger (bottom panel, Fig 4). In principle, these countries could compensate the emitting countries that generated the warming, which include all the top emitters that also generated the damages already described. We calculate that US emissions since 1990 caused \$1.97T in aggregate damages to one set of countries but \$1.46T in aggregate benefits to another.

4.3 Paying down damages

Direct monetary compensation offers one approach for an emitting entity to address damages caused by its emissions, and is perhaps the only reasonable approach to address damages that have already occurred (HD-CO_2). However, for the future damages from past or current emissions (FD-CO_2, SC-CO_2), emitting entities could instead consider greenhouse gas removal (or specifically carbon dioxide removal, CDR) as a way to limit future damages, particularly if the per-ton cost of permanent and verifiable CDR fell below HD-CO_2 or SC-CO_2.

We abstract from the critically important and largely unresolved issues of feasibility, scale, and economics of CDR[41], and consider a simple scenario that assumes a CDR technology exists that can remove a desired quantity of CO_2 permanently from the atmosphere. We find that the effectiveness of using CDR for reducing future damages from past emissions declines with the time elapsed between emissions and capture (Fig A15). For a ton of CO_2 emitted in 2020, an immediate removal of an equivalent ton fully eliminates damages. Delaying removal for 10 years results in a roughly 80% reduction in damages relative to no removal, considering cumulative damages through 2100 only, and a 25 year delay results in a 50% reduction in damages through 2100. Damages increase with delay length both because (1) additional warming (and thus damage) that occurs during the years in which the extra ton of CO_2 is in the atmosphere and (2) because of the widening wedge between the emissions-perturbed economy versus the counterfactual economy during these years – a wedge that is sustained (but does not further grow) even as the perturbed economy returns to its counterfactual growth rate after the ton is removed (see Fig A15c for a schematic representation of this effect). As a consequence, damages do not stop when an emission is re-captured and the magnitude of these continuing damages increase with the delay between emission and capture. Thus, use of CDR as a tool to redress future damages from past or current emissions requires careful attention to the timing of removal.

5 Discussion

We propose a formal definition for quantifying L&D that is grounded in economic principles and in recent advances in the measurement of climate change damages. We also develop a framework for its estimation and an empirical implementation of that framework. Our resulting estimates of damages caused by emitting entities to receiving entities do not necessarily equal what is "owed" by the former to the latter, as that is a moral and legal question. However, our estimates do offer a set of quantitative benchmarks for the size of transfer needed to make the recipient party "whole".

Multiple avenues exist for addressing damages that have already occurred (HD-CO_2), including lump sum payments through the international system, or "debt-for-climate" swaps that have been proposed to fund mitigation or adaptation[42]. Challenges in these aggregated approaches include whether those who have been harmed, which includes individuals and households, would receive meaningful compensation. Well-developed opportunities for transfer payments also exist outside the international system, such as bilateral, low-cost transfer payments to the mobile phones of low-income households in developing countries, which have been shown to have substantial economic benefits for recipient households and communities[43,44]. Our results, however, do not speak to who within countries is deserving of, or entitled to, such transfers.

For the future flow of damages from these same historical emissions (FD-CO_2), a suite of options could in principle be used to limit or eliminate these damages beyond direct compensation, including CDR, solar radiation management, or investments in adaptation in the harmed country to reduce future damages. All face substantial challenges. CDR could have advantages relative to monetary compensation in the setting in which direct compensation is difficult, for instance if there is no feasible way to transfer resources to those who have been harmed (e.g households with no access to financial services) or a concern that aggregate transfers at the country level will not appropriately benefit parties within the country who were harmed. However, as we show, even if it were cost-effective and feasible at scale, using CDR to remove past emissions only eliminates a portion of ongoing damages, with that portion declining the greater the delay between emissions and capture. Regarding solar radiation management, the benefits and costs of possible approaches remain poorly understood, with important sectors in developing-country economies unlikely to benefit from some proposed approaches[45,46], and its deployment remains highly controversial. Finally, investments in adaptation are a critical approach for limiting future damages, but there exists scant quantitative evidence that identifies specific investments that are able to reduce risk and limit damages at scale[47], and limited evidence that adaptation has been happening in the aggregate in recent decades (Fig A2b). Credible use of these alternate strategies to compensate future harm from past or current emissions will likely require a stronger evidence base than currently exists. Providing this evidence base is a critical area for future research.

Our framework cannot resolve difficult legal, ethical, and empirical questions related to the extent to which an emitting entity ”owes” another entity for damages caused by emissions related to its activities. We do not take a stand on whether a party is responsible for the emissions associated with its production or consumption activities, or whether they are responsible for the emissions resulting from the use of products they produce. At the country level, using production-based or consumption-based emissions results in relatively minor differences in bilateral attributed L&D for historical damages. However, choices over whether to attribute emissions resulting from the use of a company's product (”Scope 3” emissions) rather than just the emissions from producing the product has large implications for attributable damages among fossil fuel companies. Our approach also focuses on the (typically negative) externality that emissions from an emitting entity creates for other entities, due to the warming and subsequent economic impact from these emissions. We do not consider the potential for related externalities, both positive and negative, that could occur as a result of the economic activity in the emitting entity that generated the emissions. These could include, for instance, the development of technologies or practices with benefits in the "receiving" entity (e.g. new vaccines), or conversely any economic advantage that is gained by the emitting entity that harms the receiving entity (e.g., the utilization of a inexpensive coal resource giving one region an advantage in low-cost manufacturing at the expense of another). We know of no empirical work that addresses the relevant bi-lateral magnitudes of these additional externalities.

Our quantitative estimates capture an important aggregate channel – GDP – through which climate damages have occurred, and likely subsume a large class of microeconomic channels through which warming can have negative economic impacts, including changes in agricultural productivity, labor supply and labor productivity, and energy use. Other channels that are poorly captured in GDP data (e.g. heat related mortality[34]) or that are not highly correlated with interannual variation in country level temperatures (e.g. sea level rise[48]) will not be reflected in our current estimates. To the extent that these channels are quantitatively important, our damage estimates will understate the total damages associated with historical emissions. Similarly, our approach does not account for the impact of pollutants that are co-emitted with CO_2; these pollutants (e.g. particulates) tend to be less well-mixed than GHGs and thus their damages depend on the location of emission[49]. However, our basic approach could be amended to include these other channels.

More broadly, our framework for computing loss and damage should be applicable in any setting where there exists the following ingredients: accurate baseline measurements of some outcome of interest (GDP, health, etc), a credible damage function linking that outcome to a measured climate variable, a modeling approach able to estimate local changes in that climate variable as a function of emissions perturbations, and accurate estimates of emissions from an emitting entity of interest. Given rapid scientific progress on damage estimation[50], climate attribution[51], and emissions measurement (e.g.[52]), opportunities for a substantially expanded quantitative understanding of loss and damage appear close at hand.

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Figure 1: **Framework for emissions damage accounting.** **a**. A unit of emissions in year t_e creates an emitted asset which generates a flow of damages in future year(s) t in population i. These damages can be compensated (i.e. paid for in transfer payment the emitter to i) in settlement year t_s. If settlement year is after damage year ($t_s > t$), then the damage accrues interest (**b**). If the settlement is in advance of anticipated future damage ($t_s < t$), then future damage is discounted back to the settlement year (**c**). **d**. A higher discount rate amplifies present value of past damages, and decreases present value of future damages, relative to a lower discount rate. **e** Payment owed for multiple periods of uncompensated past damage (HD-CO_2) is additive. **f** Past emission can continue to create future damage even if past damage is compensated (emissions remain in atmosphere), requiring additional compensation (FD-CO_2). **g** The social cost of carbon dioxide (SC-CO_2) is a special case where settlement for future damages occurs at the time of emission.

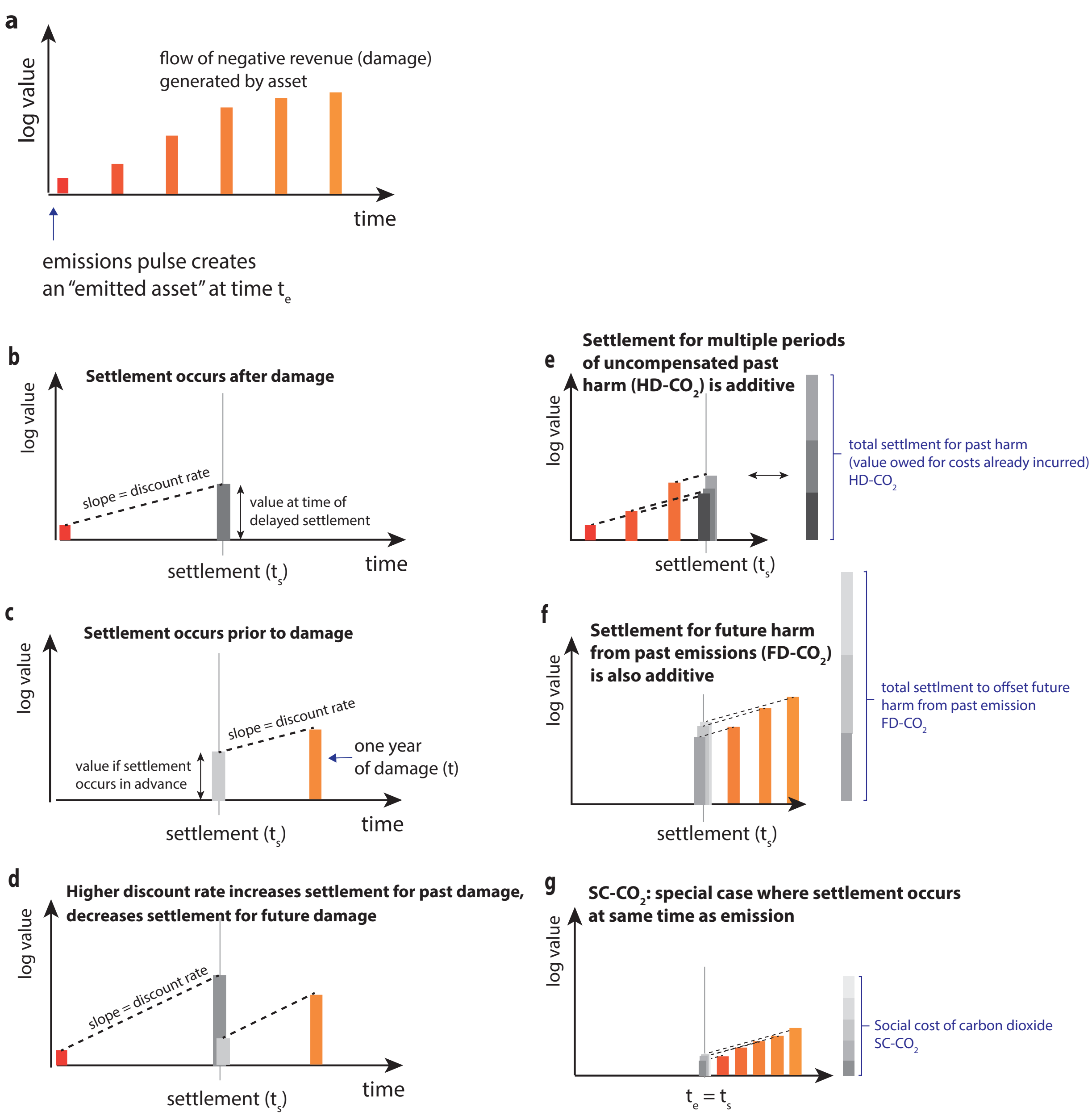


Figure 2: **Estimated damage from a marginal unit of past or future emissions**. **a.** Estimates of HD-CO_2, calculated as per tonne cumulative impacts through 2020 of a 1Gt pulse of CO_2 emitted in a given year, starting in 1990, under different fixed discount rates. **b.** Estimates of FD-CO_2, or the cumulative damages after 2020 of each of these pre-2020 emission pulses. Here we assume damages end in 2100. The post 2020 damage estimates for a pulse in 2020 are estimates of the SC-CO_2 in 2020. Numeric values are provided in Figure A4. **c-d.** Spatial distribution of HD-CO_2 and FD-CO_2 from 1990 1t CO_2 emission, under a 2% discount rate. Countries with blue colors have cumulative benefits, countries with red colors have cumulative damages, countries in grey have no data. **e.** Estimate of the SC-CO_2, here a 1t CO_2 pulse in 2020, under three sets of analytic choices: impacts end in 2100, comparable to estimates in (b); temperature has no effect on economic growth after 2100 but impacts cumulate through 2300 (see Fig A6 for schematic); and growth impacts continue through 2300. For each, SC-CO_2 is computed under two discounting schemes: a fixed 2% discount rate (red) and Ramsey discounting calibrated to a near-term rate of 2% (purple).

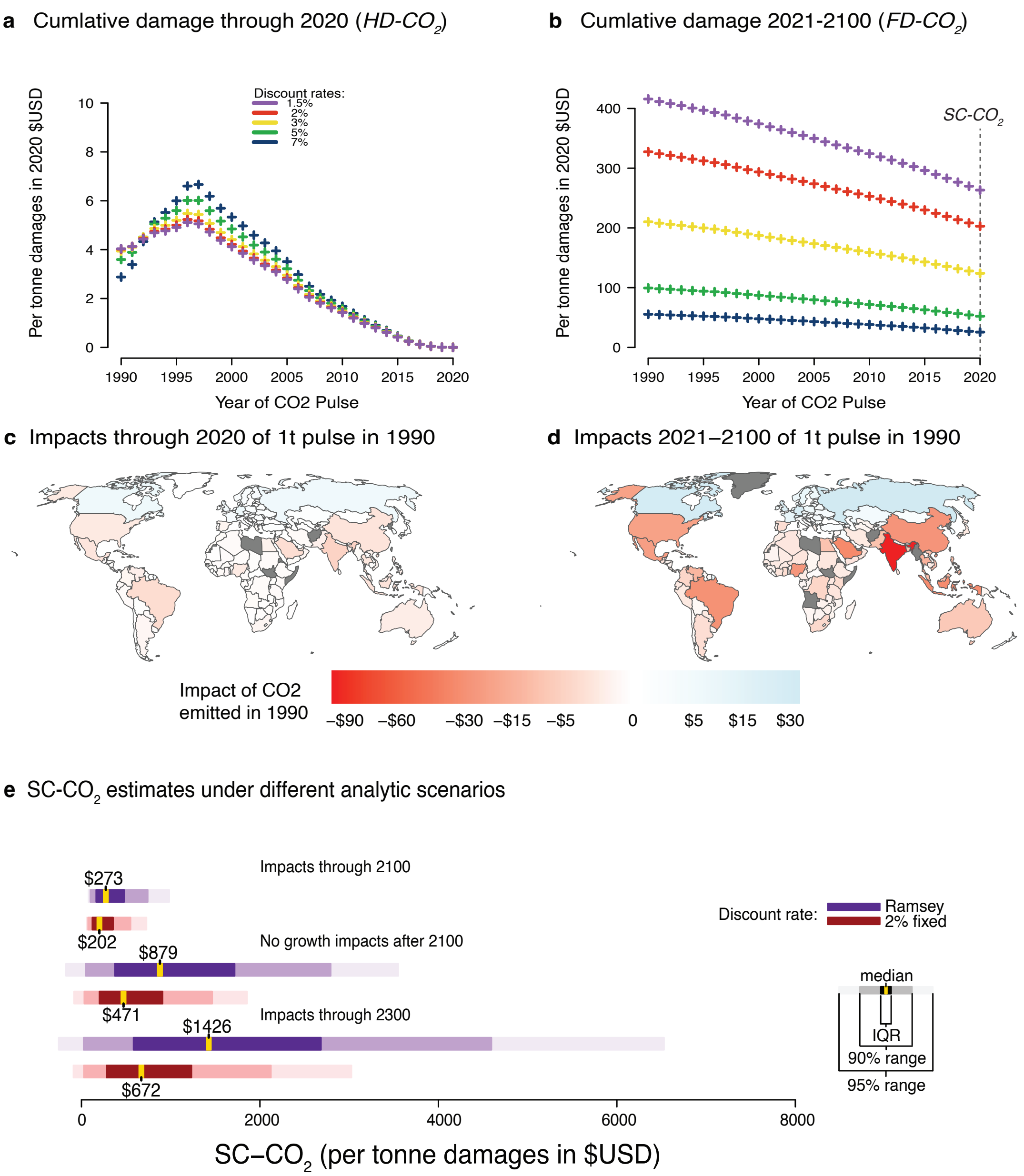


Figure 3: **Estimated damages from emissions related to individual behaviors or firm output over varying time periods**. Estimates show cumulative past (through 2020) and/or expected future damages (through 2100) from estimated emissions resulting from different choices by individuals or firms. Cumulative damages are discounted at 2%. **a.** Estimated past or future cumulative global damages from emissions associated with individual behaviors, under the assumption that each was carried out by one individual for the 2010-2020 decade (for instance, one fewer long-haul flight per year for a decade); future damages exceed past damages by two orders of magnitude (note log scale). **b.** Cumulative damages through 2100 from emissions flights taken in 2022 by celebrities' private jets. Damage as a percentage of net worth of each individual shown in parentheses. **c.** Cumulative damages through 2020 and from 2021 through 2100 from the emissions associated with the production and use (Scope 1 + 3) of products produced by different large oil and gas companies ("carbon majors") between 1988-2015. Numerical values are provided in Fig A10.

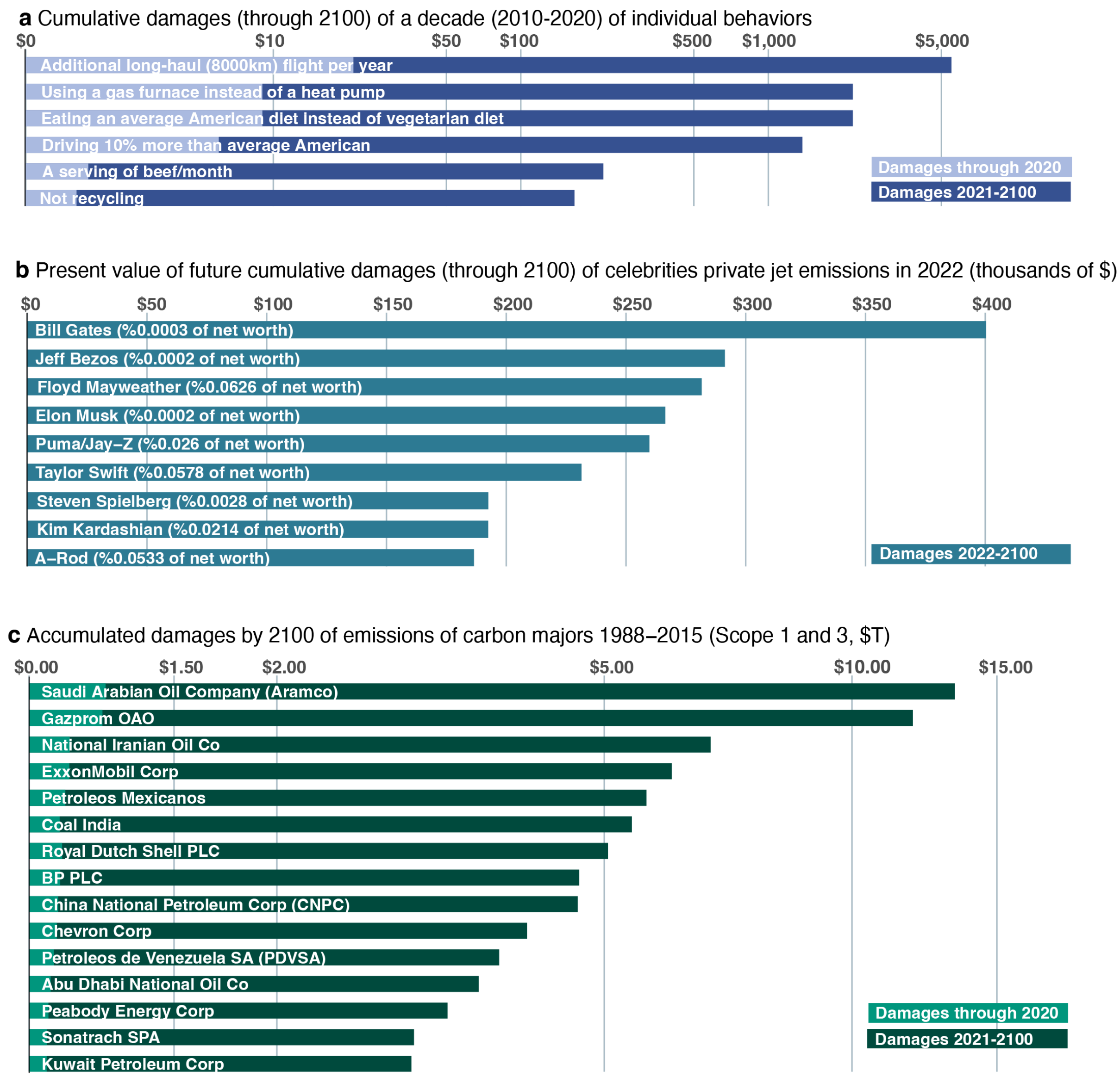
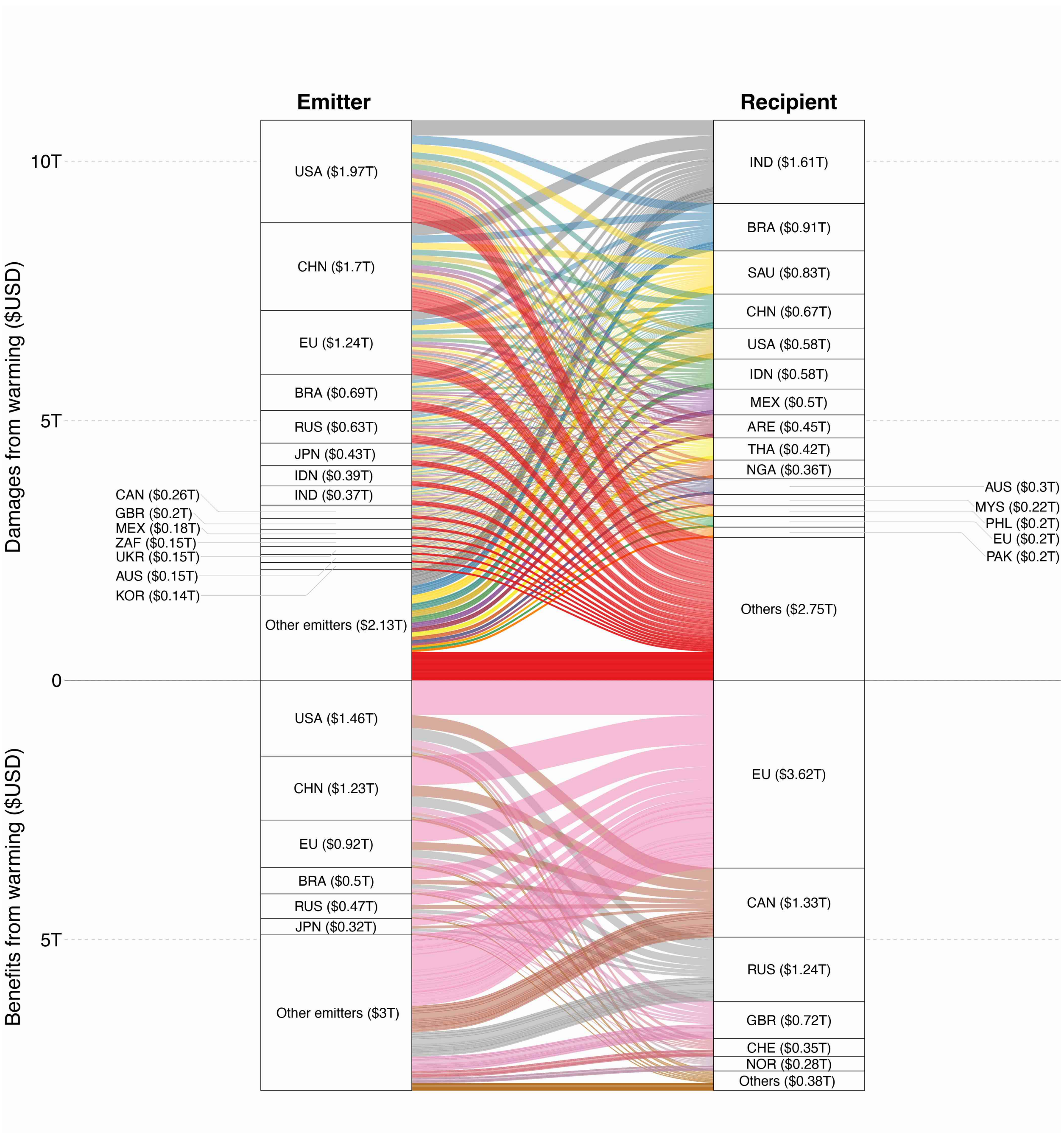


Figure 4: **Bilateral attribution of historical damages or benefits due to country-level emissions since 1990**. Emissions include both fossil fuel and land use emissions. Emitting countries shown in left column, "receiving" countries shown in right column. Bar widths are proportional to damages or benefits. Total cumulative damages attributable to each emitter, or experienced by each recipient, are in parentheses. Flows above the zero line are damages, flows below the zero line are benefits; for instance, US emissions since 1990 generated $2.07T in damages in one set of countries, and $1.46T in benefits in another set of countries. All estimates are under a fixed 2% discount rate.



A Appendix

A.1 Concept definitions

Here for completeness we write out the definitions for HD-CO_2, FD-CO_2, SC-CO_2, as well as for total and bilateral L&D. HD-CO_2, or the cumulative global historical damage from a marginal emission in past year t_e cumulated and discounted to present day t_p, is:

$$HD\text{-}CO2_{t_e} = \sum_i \sum_{t=t_e}^{t_p} (1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \tag{6}$$

where $\Delta Y_{it}(\Delta E_{t_e})$ is damage in year t for population i from this marginal emission as defined in Equation 2 above. In this calculation, $t_e < t_p$ and t_p is the present day (2020 in our calculations).

Damages from this past emission continue into the future. The discounted cumulative global total of damages from this past emission, i.e. FD-CO_2, beginning in present day and ending in some distant future year, is:

$$FD\text{-}CO2_{t_e} = \sum_i \sum_{t=t_p}^{\infty} (1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \tag{7}$$

Emissions are again in the past ($t_e < t_p$) but damage years t begin in the present year and go into the future. Discounted global damages from a marginal present or future emission, i.e. SC-CO_2, are written identically to FD-CO_2 but are only defined when $t_e \geq t_p$:

$$SC\text{-}CO2_{t_e} = \sum_i \sum_{t=t_p}^{\infty} (1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \tag{8}$$

Total L&D is then the cumulative sum of each of these components multiplied by total CO_2 emissions in each year starting in some year t_0, as shown in Equation 5. Bilateral attributable L&D for damages experienced by population i due to emissions from emitter j, which we write $L_{j\rightarrow i,t_0}$, is the analogous sum of population-specific historical and future damage components, multiplied by emissions from j and cumulated:

$$
\begin{aligned}
L_{j\to i,t_0} = \sum_{t_e=t_0}^{t_p} \Bigg(& \underbrace{\sum_{t=t_e}^{t_p}(1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \cdot E_{j,t_e}}_{HD\text{-}CO_{2,i,t_e}} + \underbrace{\sum_{t=t_p}^{\infty}(1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \cdot E_{j,t_e}}_{FD\text{-}CO_{2,i,t_e}} \Bigg) + \\
& \underbrace{\sum_{t_e=t_p}^{\infty} \sum_{t=t_p}^{\infty}(1+r)^{-(t-t_p)} \cdot \Delta Y_{it}(\Delta E_{t_e}) \cdot E_{j,t_e}}_{SC\text{-}CO_{2,i,t_e}}
\end{aligned}
\tag{9}
$$

In each term, the outer summation is over emission years, and the inner summation is over the subsequent years in which each emission year creates damages in i.

A.2 Calculating damages from an emissions perturbation

To estimate Equations 6-9, we seek to quantify how a given quantity of greenhouse gas emitted in an initial year t_0, or a sequence of GHG emissions in multiple years, affects local and global climate in subsequent years, and how these climate changes shape economic output relative to a counterfactual where emissions were unchanged.

To translate any emissions history into a change in local climate, we first use a reduced-complexity climate model to translate emissions into a change in global mean surface temperature (ΔGMST), and then use the CMIP6 ensemble of fully-coupled global climate models[30] to translate global temperature changes into local changes. Specifically, for the first step, we use v2 of the Finite Amplitude Impulse Response model (FaIR)[53], a reduced complexity climate model with a carbon cycle that is able to simulate equilibrium and impulse-response behavior of more complex global climate models. For any emission pulse in time E_{t_0}, FaIR returns estimates of ΔGMST in years $t > 0$, which we denote $\delta T_t = v(E_{t_0})$. In such a pulse experiment, we note that this estimate will represent the amount of warming in year t that occurred due to emissions starting in t_0, which will not be equal to the amount of warming since t_0, since the latter is substantially affected by any prior emissions. Similarly, we can use FaIR to compute the change in temperature in any year from a perturbed history of emissions, by differencing estimates run under perturbed versus counterfactual trajectories: $\delta T_t = v(\mathbf{E}^*) - v(\mathbf{E})$. Following previous work, we calculate uncertainty in estimates of δT_t by resampling key parameters in FaIR, including the transient climate response, the realized warming fraction used to calculate the equilibrium climate sensitivity, the short thermal adjustment time and the timescale of rapid carbon uptake by the ocean mixed layer, using parameter values from previous work[54].

To map this GMST change to local temperature changes for population i (typically a country, in our applications), we use a pattern scaling approach based on FAQ4.3 of the IPCC WGI AR6[55] to compute, using the CMIP6 ensemble of global climate models (GCMs), the ratio of location-specific warming to area-weighted GMST. Following the IPCC, we calculate the forced temperature response as the difference between temperature projected in the late 21st century of the SSP3-7.0 future climate forcing scenario and the early-industrial historical period, for each of the 30 GCMs for which we are able to match a historical and SSP3-7.0 realization in the CMIP6 archive. For each GCM, we calculate the forced temperature response separately for each model grid cell and for the latitude-weighted average across all grid cells globally. Then, for each grid point, we compute the ratio of the grid-specific warming to the global-average warming. These grid-specific ratios are then applied to the FaIR-estimated change in GMST, and aggregated to the spatial unit of interest (e.g. country).

Specifically, denoting each CMIP6 model as m and grid cell as g, we compute grid- and model-specific warming as the difference in temperature between projected temperature under SSP3-7.0 averaged over 2080-2100 ($\bar{T}^f_{gm}$) and model-estimated temperature in the early-industrial period averaged over 1850-1900 ($\bar{T}^h_{gm}$)

$$\delta\bar{T}_{gm} = \bar{T}^f_{gm} - \bar{T}^h_{gm} \tag{10}$$

$$\delta\bar{T}_m = \frac{1}{g}\sum_g \lambda_g \delta\bar{T}_{gm} \tag{11}$$

$$r_{gm} = \frac{\delta\bar{T}_{gm}}{\delta\bar{T}_m} \tag{12}$$

We then apply this ratio of grid-to-global average warming to the estimate of GMST from FaIR to arrive at grid-specific estimates of warming due to the emissions perturbation of interest, and then we calculate warming in spatial unit i as the population-weighted average of warming in each grid cell that falls into i:

$$\delta T^*_{gmt} = \delta T_t * r_{gm} \tag{13}$$

$$\delta T^*_{imt} = \frac{1}{g}\sum_{g\in i} \gamma_g \delta T^*_{gmt} \tag{14}$$

where γ_g are grid-cell populations[56]. This is computed separately for each year in which the emissions perturbation led to warming, with r_{gm} held fixed, and repeated for each spatial unit i and climate model m.

To translate changes in temperature into economic impacts, let $f()$ represent a damage function that maps changes in temperature to changes in an outcome of interest. Because many outcomes, including agricultural productivity, mortality, energy use, and aggregate economic output, exhibit a non-linear response to warming, we calculate impacts in a desired location i and year t as the difference in outcomes between a counterfactual temperature in that year T_{it} and perturbed temperature in that year $T_{it} + \delta T^*_{imt}$:

$$\delta y_{imt} = f(T_{it} + \delta T^*_{imt}) - f(T_{it}) \tag{15}$$

When damages are being assessed historically – i.e. where $t < 2020$ – counterfactual temperature T_{it} is simply the observed population-weighted annual average temperature in unit i, using data from ERA5[57]; the perturbed temperature then adjusts this temperature by the pattern-scaled δT^*_{imt} as computed above, to reflect the warming effect of the emissions perturbation of interest. When t is a future year, we construct counterfactual temperatures for a given location by again using the FaIR + pattern-scaling approach described above. Specifically, for each country i, future counterfactual temperature in years after 2020 is the average of observed temperature over the last ten years of the historical dataset (2010-2020) plus the projected change in temperature in each future year relative to 2020, based on historical emissions and projected future emissions following the SSP3-7.0 trajectories. As above, we use FaIR to calculate the change in GMST from these emissions and the GCMs to pattern-scale this global warming to local warming. In this setting, future warming is affected both by all past (observed) and all future (projected) global emissions. Perturbed future temperature in future years δT^*_{imt} is calculated similarly, but with the desired emissions perturbation added or subtracted from the ”baseline” SSP3-7.0 trajectory before recomputing GMST change and pattern-scaled local warming.

To estimate the damage function $f()$, we focus on an existing empirically-derived damage function that links temperature fluctuations to GDP growth rates, updating previous work[31] with data through 2019, as described below. Because growth is a cumulative process, the effect of a given year’s temperature fluctuation on economic output depends on the previous year’s temperature fluctuation and its effect on output. In this setting, damage in a given year is then a function of temperature in both current and past years. Relative to a counterfactual with no warming, hot temperatures can reduce output in a given year because growth in that year is slowed due to contemporaneous hot temperatures, but also because contemporaneous growth rates are acting on an economy that was already smaller due to previous hot temperatures.

To capture these dynamics, we amend equation 15 and compute the change in year- and location-specific growth rates resulting from the change in temperature, and then adjust the observed time series of growth in location i and re-calculate damages in each year as:

$$\delta g_{it,m} = f(T_{it} + \delta T^*_{imt}) - f(T_{it}) \tag{16}$$

$$D_{it,m,k} = Y_{ik} \prod_{t=k}^{t} (g_{it} + \delta g_{it,m}) - Y_{ik} \prod_{t=k}^{t} g_{it} \tag{17}$$

where Y_{ik} is GDP in initial year k and g_{it} is the growth rate in country i and year t. For historical years, we take growth rates from World Bank data[58]. For future years, we use SSP3 projected growth rates as our main estimates through 2100. For calculations that require growth rates past 2100, our main estimates fix post-2100 rates at SSP-predicted levels in 2100. We check sensitivity by prescribing either 1% or 2% growth rates for all future years; these values are roughly at the 17th percentile or median projected growth rates by 2100 in an independent recent analysis[59].

To calculate the present value of cumulative damages, we compute the discounted sum of damages in each year between the emissions year and a chosen end year. Both the emissions year and end year differ by application, as described below. For the discount rate r, we follow earlier work and either use constant discount rates between 1% and 5%, or use time-varying "Ramsey" discounting. In the latter approach, discount rates are calculated using the Ramsey equation $r_t = \delta + \eta g_t$, where δ is the pure rate of time preference, η is the elasticity of the marginal utility of consumption, and g_t is the growth rate in consumption in year t. We fix δ and η at values used in similar recent exercises that were calibrated to near-term 2% discount rate[60] and estimate g_t using the global average annual rate of growth in per capita GDP in the perturbed emissions scenario, as described above. Under Ramsey discounting, higher per capita growth rates thus have two competing effects: faster growth leads to larger economies for impacts to act upon, yielding higher total damages, but faster growth also yields higher discount rates, because a society quickly becoming richer would prefer to consume more today at the expense of their wealthier future selves or descendants. In our empirical exercise, we find that these competing factors roughly balance (Fig A8).

For settings where we wish to calculate the present value of damages that have already occurred, we note that discounting in this setting serves to amplify the present cost of past damages, as opposed to the more conventional setting where it reduces the present value of future damages. However, the reasoning is similar. From the time value of money perspective, a given dollar amount yesterday is worth more today, because of generally positive market returns. Similarly, from the perspective of time preference, a later-consumed good is still worth less than an equivalent earlier-consumed good, because of our dislike of having to wait to consume things; something that is worth \$100 to an individual today is worth less than that to her yesterday if she has to wait to today to consume it.

A.3 Estimating temperature-output damage function

To estimate the relationship between location-specific warming and output ($f()$ in equation 17) we follow earlier work[31,61] and use panel fixed effects regression to isolate the contribution of annual temperature fluctuations to variation in growth in real per capita GDP, using national accounts data on country-level GDP from 1961-2019. We estimate distributed lag models of the form:

$$y_{it} = \sum_{k=0}^{n} f(T_{i,t-k}, P_{i,t-k}) + \alpha_i + \delta_t + \theta_i * t + \theta_i * t^2 + \varepsilon_{it} \tag{18}$$

where y_{it} is the first difference of the natural log of real per capita GDP in country i and year t, α_i is a vector of country-specific intercepts (country fixed effects) that account for any time-invariant differences between countries, such as differences in average incomes, average temperatures, or in any other time-invariant factor that could be correlated with both differences in average temperature between countries and differences in average growth rates; δ_t is a vector of year-specific intercepts that account for any shocks or trends in either temperature or growth that are common across countries, such as macroeconomic shocks; $\theta_i * t$ and $\theta_i * t^2$ are country-specific quadratic time trends that additionally flexibly control for locally-trending variables correlated with both temperature and growth. For $f()$, we follow earlier work[31] and use parsimonious quadratic function to allow growth to respond nonlinearly to temperature and precipitation:

$$f(T_{i,t-k}, P_{i,t-k}) = \beta_{1,k} T_{i,t-k} + \beta_{2,k} T^2_{i,t-k} + \lambda_{1,k} P_{i,t-k} + \lambda_{2,k} P^2_{i,t-k} \tag{19}$$

We test robustness to alternate approaches for controlling for time-trending unobservables, including region-by-year fixed effects or linear rather than quadratic country time trends; to a restricted sample of countries with at least 20 years of climate and growth data; and to the use of alternate historical climate data from the Climate Research Unit.

Figure A2 shows the updated pooled response function using the 1961-2019 data. Estimates are largely similar under alternate specification choices and inputs, including using CRU rather than ERA, using only countries with at least 20 years of data, the addition of region x year FE rather than just year FE, using linear country time trends rather than quadratic, and fitting a cubic rather than quadratic polynomial.

Growth versus level effects To distinguish between "level effects", in which output returns to its previous trajectory in the years following a temperature shock, or "growth effects", in which output is permanently lower following a temperature shock, we again follow path-breaking earlier work[61] and estimate distributed lag models where growth is modeled as a function of contemporaneous and lagged values of temperature. The sum of contemporaneous and lagged effects offers insight into whether the effects of temperature on output are persistent or transitory. Because we are estimating non-linear relationships, we evaluate this sum of marginal effects at different points in the temperature distribution, i.e.:

$$\frac{\delta y_{it}}{\delta T_{it}} = \sum_{k=0}^{n} (\beta_{1,k} + 2T_i\beta_{2,k}) \tag{20}$$

A sum of marginals that is significantly different than zero suggests growth effects; a sum not distinguishable from zero suggests level effects. In contrast to earlier work[31], in which the sum of contemporaneous and lagged effects were negative but not statistically different than zero, our updated data provide clear evidence of negative growth effects for most of our sample, with the sum of contemporaneous and lagged effects (up to 5 lags) statistically different than zero for countries with current average temperatures above roughly 14C (Fig A3).

As in BHM, and consistent with recent subnational evidence[62], positive marginal effects in the zero-lag model at the cold end of the temperature distribution get less positive as more lags are added and are no longer statistically significant. This suggests that, with additional warming, we should be much more confident in negative growth effects in hotter regions than we should be in positive growth effects in cooler regions. For nearly all countries on the planet, point estimates on cumulative effects are negative.

Has the pooled response to temperature changed over time? No. We interact our temperature polynomial with dummies for three periods: 1960-1979, 1980-1999, and 2000-2020. If anything, the response curve shifts slightly to the left over time, and shows no signs of flattening - see Figure A2. This rules out the most obvious income or time-driven adaptation stories, as temperatures have warmed +1C during the period, and average per capita incomes have increased nearly three-fold.

Model selection in estimating damage functions Our work builds on earlier results published in Burke Hsiang Miguel[31], which itself built on pathbreaking earlier work by Dell Jones and Olken[61]. Since the publication of both of these articles, many other articles have revisited the question of the aggregate economic impacts of climate change, using alternate panel data or alternate statistical approaches. Many find evidence of non-linear effects of temperature on growth effects that are qualitatively consistent with our findings[62,63].

One paper by Newell, Prest, and Sexton[32] (henceforth NPS) was more skeptical of a temperature/growth link. NPS revisited BHM data and propose to use cross-validation (i.e. training a model on one dataset and evaluating on held out data the model was not trained on) to make key specification choices. Cross-validation is a common statistical approach to evaluating models' predictive performance; its properties are less well known when the goal is causal inference. It is straightforward to show using simulation that, in our panel setting, a model that performs better on a prediction task can perform worse on a causal inference task, and thus that the approach to model selection used by NPS can select models that yield substantially biased estimates of the effect of temperature on aggregate output.

Specifically, consider a data generating process where a location's time series of annual temperatures T_{it} is composed of a location specific mean $\bar{T}_i$, a long term location-specific linear trend $\theta_i * year_t$, and a mean-zero interannual fluctuation $\epsilon_{it} \sim N(0, \sigma)$:

$$T_{it} = \bar{T}_i + \theta_i * year_t + \epsilon_{it} \tag{21}$$

Suppose that per capita growth in each country is a quadratic function of annual temperature, a country specific mean growth rate α_i, a country-specific growth trend ($\lambda_i * year$), and other (unobserved) time-varying sources of growth (ν_{it}).

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \bar{y}_i + \lambda_i * year + \nu_{it} \tag{22}$$

The econometric challenge is to identify β_1 and β_2 in a setting where mean growth rates and mean temperatures could be correlated ($cov(\bar{T}_i, \bar{y}_i) \neq 0$, e.g. if high income countries tend to be cooler) or where temperature trends could be correlated with growth trends ($cov(\theta_i, \lambda_i) \neq 0$, e.g if high latitude countries have warmed more quickly but grown more slowly). Given these potential confounds, a standard approach for identifying β_1 and β_2 is to estimate panel models that flexibly account for time-invariant differences at the country level (typically using unit fixed effects) as well as for time-varying differences that could be country-specific (typically through the inclusion of time fixed effects and/or unit-specific time trends). The goal of these models is not to maximize the accuracy of predicted growth $\hat{y_{it}}$, but instead to isolate the effect of temperature fluctuations from other correlated factors that could affect growth, i.e. come up with unbiased estimates of β_1 and β_2. A model that accurately predicts income growth need not generate unbiased estimates of the impact of temperature, and a model designed to estimate the impact of temperature might not explain the most variation in income growth.

To show how these prediction and causal inference goals can be in conflict, we simulate a setting where country-specific trends in income growth and temperature are positively and spuriously correlated, and then estimate β_1 and β_2 and evaluate models predicted values of $\hat{y_{it}}$, using panel models that do or do not include country-specific time trends in the regression. Following NPS we evaluate the predictive performance of models using "forecast" cross-validation, where for a panel of length t years, models are trained on the first x years in each country and then evaluated on the final $t - x$ years. We set $t = 50$ and $x = 40$, set values of β_1 and β_2 to match the earlier point estimates in BHM, and choose the variance of v_{it} to yield signal-to-noise ratios (as proxied by "within" r-squared values in the panel regressions) similar to what was reported in BHM. We then estimate two models:

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \gamma_i * year + \alpha_i + \varepsilon_{it} \tag{23}$$

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \alpha_i + \varepsilon_{it} \tag{24}$$

We note that neither model includes year FE, because (as in NPS), the years in the test sample will not have an estimated year intercept and so predictions cannot be made out of sample; in our setting, the lack of year FE do not affect inference as we do not bake in common time-varying sources of bias. We then evaluate recovered marginal effects of temperature on growth from the models with and without trends, as well as calculate RMSE between predicted and observed growth rates in the held out years; we run this simulation 1000 times. Consistent with NPS, we find that the model without time trends (Equation 24) consistently have lower prediction error in held out data (Fig A16a, p=0.04 on a one-sided test), which is presumably because time trends are fit in-sample on limited amounts of data in each country and provide a noisy estimate of how both income growth and temperature will continue to trend out of sample. However, the model without time trends is substantially biased: marginal effects are too positive across the temperature distribution, which is because income growth and temperature (by design) are spuriously trending together. Estimates in the model with time trends, which again would be rejected by NPS in favor of the no time trends model, are unbiased. These results indicate that using predictive performance for model selection in our context can undermine inference.

Nevertheless, as NPS would argue, it might still appear odd to then select the model that does worse in predicting income growth in future years, if our goal is predicting income growth in future years. Critically, however, *neither BHM nor the current analysis use estimated time trends from these models to project forward either trends in temperature or trends in income growth*, precisely because past trends might be a poor guide for future trends. Instead, we rely on decades of research in climate science embedded in global climate models to project future temperature changes, and we rely on output from multiple modeling teams to project future secular growth in income. We do not need our historical models to accurately predict future trends in either of these variables; instead, we need them to credibly isolate temperature from other time-invariant or time varying factors that could affect income growth.

A.4 Non-marginal emissions

Finally, emissions perturbations from large emitters (e.g. the US) are non-marginal: the impact of emissions changes in one year could meaningfully depend on emissions and damages from previous years, for instance because the damage from warming in one year is enough to affect the size of the economy that the next year's warming acts upon. In this case, estimating total or bilateral L&D damages by summing up marginal damages could misstate total damages by not accounting for this dependence. However, we show that errors are likely small: our benchmark approach of estimate per-ton marginal damage using a 1Gt pulse is a close approximation per-ton damages from much smaller or much larger emissions pulses (Fig A7). Nevertheless, to compute the impact of large, multi-year emissions perturbations (e.g. removal of decades of country emissions or carbon major emissions), we calculate damages by feeding the full multi-year emissions perturbation to FaIR rather than estimating marginal damages from pulses in different years and multiplying by tons emitted. Differences between these approaches are likely only a few percent.

A.5 Sensitivity of damage estimates to analytic choices

Estimates of past and future damage are potentially sensitive to analytic choices about how damages are calculated. For historical damages, we compute damages under a range of fixed discount rates. For future damages, and in particular for estimation of the SC-CO_2, we compute sensitivity to a larger set of analytic choices, including the discount rate, for which we use either fixed discount rates (1,2, or 3%) or "Ramsey" discounting calibrated to a near-term rate of 2%, following ref[60]; different time horizons after which impacts cease, using either 2100 or 2300, or alternatively assuming that there are no impacts of temperature on growth after 2100 but the wedge between the economy with the perturbed temperature and the counterfactual temperature remains after 2100; different econometric models, including either the 0-lag model or the 5-lag model; or different baseline growth rates, including a counterfactual rate of 1% or 2% for every country, the use of country-specific growth projections from SSP3, or the latter combined with a "clamping" approach that does not allow future growth rates under climate change to exceed (in absolute value) growth rates in our historical data.

Estimated values of the SC-CO_2 are shown under these choices in Fig A8. Under fixed discount rates, assuming higher baseline growth rates yields much higher estimates of the SC-CO_2, as climate change is acting on a much larger future economy; Ramsey discounting undoes this effect, because higher growth in consumption raises discount rates, limiting the present value of future damages. The time horizon of aggregation also has a large impact on estimates, with damages through 2300 many fold higher than damages aggregated through 2100, depending on the discount rate.

A.6 Estimating unit-specific emissions

To calculate damages caused by specific emitters, we collect emissions data from various sources. For country-level emissions, we use the Global Carbon Budget 2022 datasets. The datasets calculate country-year-level CO_2 emissions (1850-2021) and are divided into data on fossil fuel emissions (with production and consumption emissions) and land use change emissions[64]. For carbon majors, we use data on Scope 1 and Scope 3 emissions (emissions from direct operations and from the use of sold products, respectively) published by the Carbon Disclosure Project (CDP) in 2017 and spanning the years (1988-2015)[40]. The CDP builds on earlier efforts collecting data on emissions by carbon majors[28]. The CDP utilize company-reported scope 1 emissions when disclosed. In cases where companies do not disclose their emissions, the CDP uses production data to estimate emissions. Emissions estimates are reported in carbon dioxide equivalent (CO_2e).

To compare loss and damage associated with company emissions to company revenues, we collected data on company revenues in 2021 from company annual reports or macrotrends.net. Finally, for private jet emissions, we estimate emissions from the flight duration of trips taken by individuals, data on which was scraped from public flight records and posted on Twitter by user Jack Sweeney. We used Twitter's API to collect data on the each flight's duration and used it to estimate emissions, using a constant 503 gallons/hr to calculate fuel burned during a flight. We utilized Ninja API to collect celebrities net worth. We emphasize that flights taken by private jets associated with an individual do not necessarily represent flights taken by that individual.

A.7 Estimating emissions and damages from individual actions

Recent papers have sought to quantify the amount of GHG emissions associated with individual actions[37,38]. To estimate the damages associated with a selected list of individual actions' emissions, we utilize estimates reported by recent studies to calculate the cumulative and future damages (through 2100) of a decade of individual behaviors (2010-2020). Estimates are reported in carbon dioxide equivalent (CO_2e). The list of behaviors includes taking a long-haul flight (2tCO_2e/yr), installing heat pump (-0.8tCO_2e/yr), switching to a vegetarian diet from an average American diet (-0.8tCO_2e/yr), eating one serving of beef a month (0.08tCO_2e/yr), and recycling (-0.06tCO_2e/yr). For comparability, for each of these actions we express damages as a result of doing the more emitting action (taking an additional flight, not eating vegetarian, not installing a heat pump, etc). For emissions associated with driving we utilize the US EPA's estimate of average annual emissions for passenger vehicles. An increase of 10% in driving is associated with an additional 0.5tCO_2/yr emitted.

A.8 Using carbon dioxide removal to alleviate future damages

For a marginal ton of CO_2 emitted in year $t = 0$ (which we set to 2020, as in the SC-CO_2 calculation), we estimate the resulting global damage if the emitting entity uses CDR to remove that ton at some year $t \geq 0$. To do this, we use FaIR to estimate the combined effect on warming of an initial marginal emission in 2020 and then a symmetric removal of the same quantity of emissions in some year after 2020, relative to the same counterfactual emissions pathway described for marginal emissions above; this is depicted in Figure A15. Our approach could overstate the benefits of CDR for reducing global temperature given the asymmetry in carbon cycle response to removing CO_2 as opposed to adding it, but estimates suggest that this asymmetry is modest for small emissions perturbations[65].

Figure A1: **Multi-step approach for attributing damages to emissions**. Damages to the Brazilian economy from US emissions since 1990 are used as an example. **a** Total CO_2 emissions from 1900 to 2020 before and after shutting off USA's emissions starting in 1990, **b** temperature response from USA emissions (1990-2020), calculated using FaIR. Black line is median response. Grey interval is temperature response under varying parameters in FaIR. **c** change in temperature in 2020 as a result of US emissions, median estimate from "pattern scaling" the temperature increase using 30 global climate models. **d** Observed Brazil population-average temperature time series (black) and counterfactual temperature absent USA emissions (red), **e** Observed Brazil real GDP 1990-2020 (black) and estimated counterfactual GDP absent USA emissions, calculated using empirical temperature-GDP damage function, f) cumulative damages owed by USA to Brazil (1990-2020).

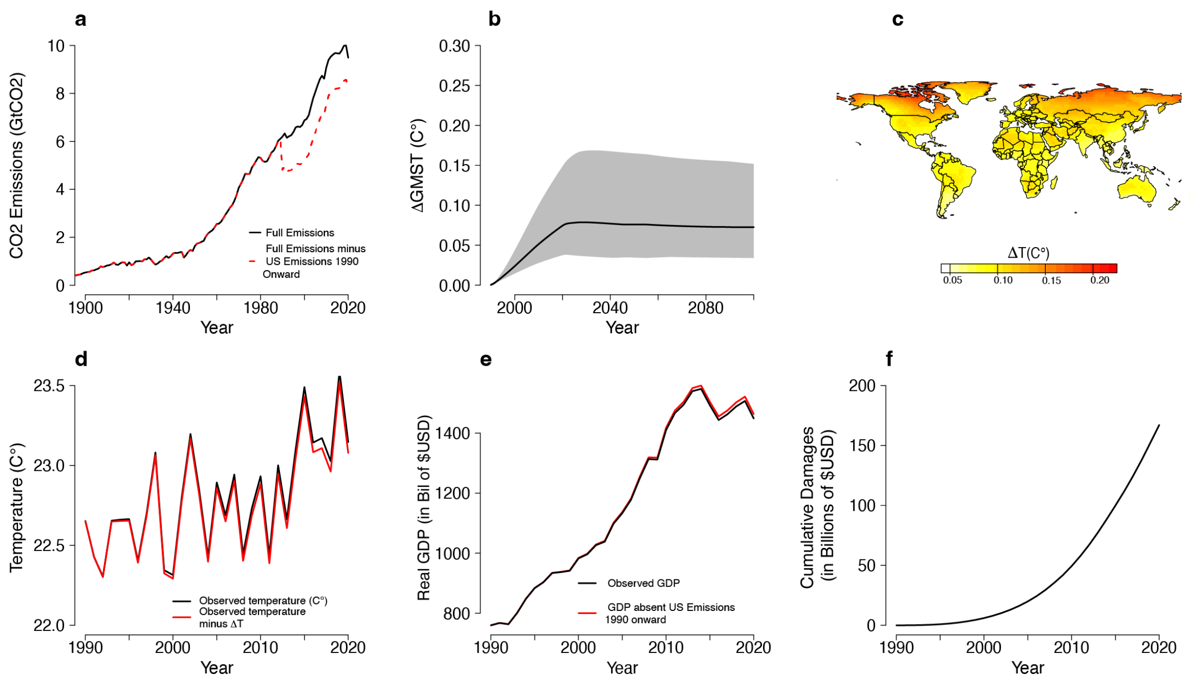


Figure A2: **Nonlinear response of growth to temperature is robust to alternate specifications and data, and is stable over time**. **a** Dark line and blue shaded area are point estimate and 95% bootstrapped confidence interval using ERA-Land climate data. Other lines are estimates under alternate data, FE, or functional forms, as described by the labels. Dotted black line is original pooled estimate from BHM 2015. **b** Global temperature response function has not changed since 1960, despite average per capita incomes nearly tripling during this period. Colors represent period-specific response functions for 1961-1979 (red), 1980-1999 (orange), 2000-2020 (blue). Shaded regions are bootstrapped 95% confidence intervals (1000 bootstraps). Rug plots at bottom show estimated temperature optima for each period and bootstrap.

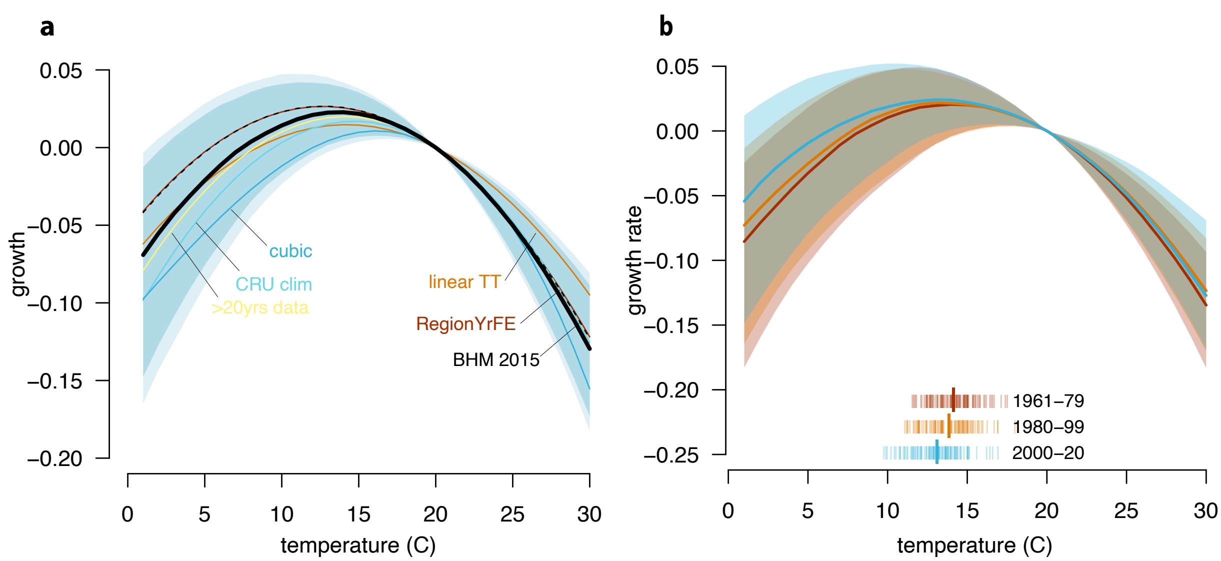


Figure A3: **Distributed lag models show robust evidence of growth effects**. Panels show estimated marginal effects from global pooled regression with 0, 1, 3, or 5 lags of temperature, using ERA-Land data. Light shaded regions are bootstrapped 95% confidence intervals, darker regions are 90% CI (1000 bootstraps). Dotted vertical lines show average temperatures at end of the sample (2016-2020) for select economies globally.

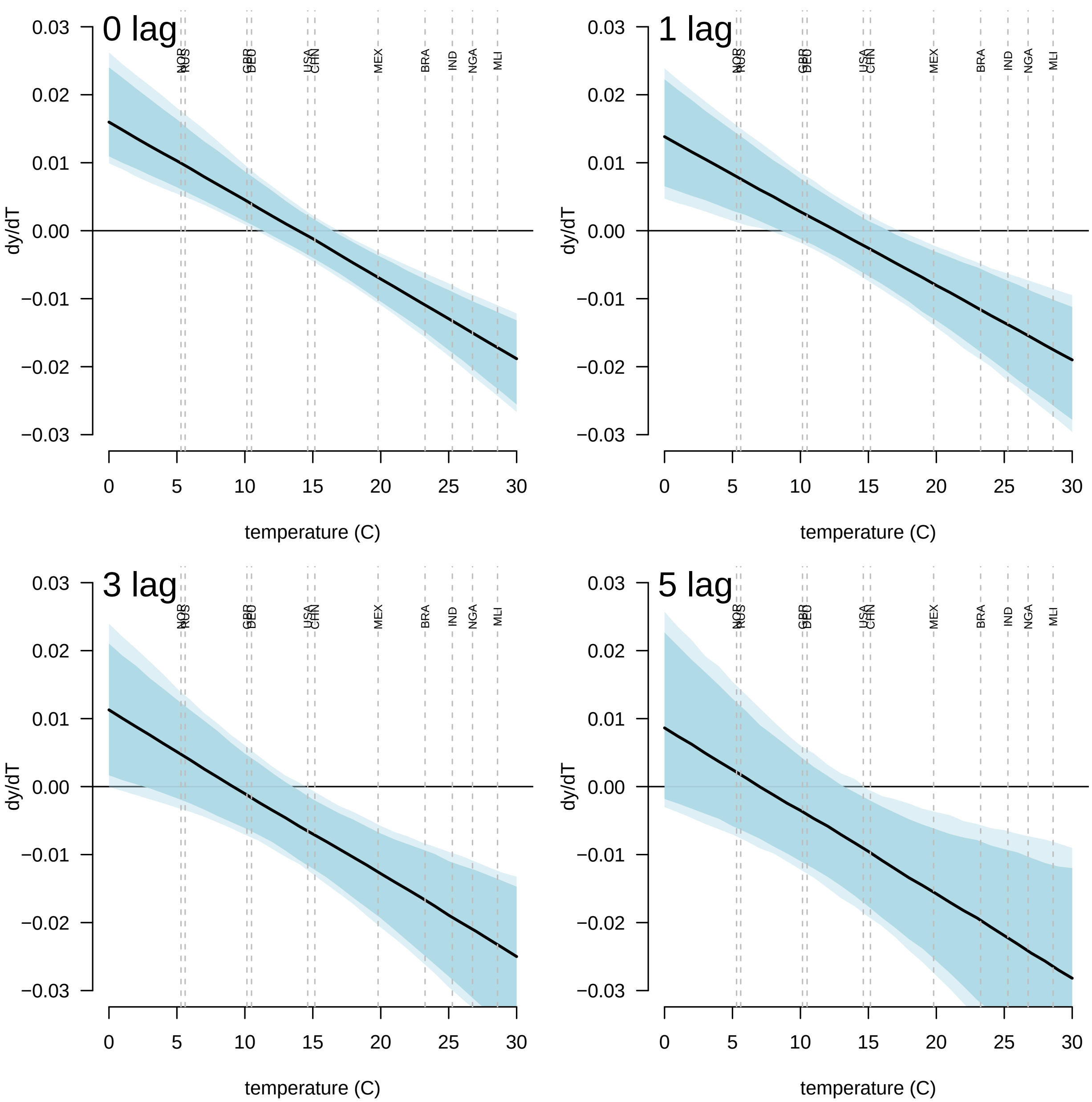


Figure A4: **Total global damages from 1Gt pulse of CO_2 emitted in different years, beginning in 1990**. Numbers correspond to estimates in Figure 2a,b. Left columns show damage accumulated through 2020 under different fixed discount rates, right columns show damage from that same emission between 2021-2100.

	DAMAGES ACCUMULATED THROUGH 2020 (IN BILLIONS OF $USD)					DAMAGES ACCUMULATED 2021-2100 (IN BILLIONS OF $USD)				
	1.5%	2%	3%	5%	7%	1.5%	2%	3%	5%	7%
1990	4	4	3.9	3.6	2.9	416	327	210	99	55
1991	4.1	4.1	4.1	3.9	3.4	412	324	208	98	55
1992	4.4	4.5	4.5	4.5	4.3	408	321	206	97	54
1993	4.7	4.7	4.9	5	5.1	405	318	204	96	54
1994	4.8	4.8	5	5.3	5.5	401	315	202	95	53
1995	4.9	5	5.2	5.6	6	397	312	200	94	52
1996	5.1	5.2	5.5	6	6.6	393	309	198	93	52
1997	5.1	5.2	5.4	6	6.7	389	306	196	92	51
1998	4.7	4.8	5.1	5.6	6.2	384	302	193	90	50
1999	4.4	4.5	4.7	5.2	5.7	379	298	190	89	49
2000	4.1	4.2	4.4	4.8	5.3	374	294	187	87	48
2001	3.9	3.9	4.1	4.5	5	369	290	184	86	47
2002	3.6	3.7	3.8	4.2	4.6	364	286	182	84	46
2003	3.3	3.4	3.6	3.9	4.3	360	282	179	83	45
2004	3.1	3.2	3.3	3.6	3.9	355	278	176	81	44
2005	2.8	2.8	3	3.2	3.5	350	274	173	80	43
2006	2.4	2.4	2.5	2.7	3	344	269	170	78	42
2007	2.1	2.1	2.2	2.3	2.5	339	265	167	76	41
2008	1.8	1.8	1.9	2	2.2	334	261	164	75	40
2009	1.6	1.6	1.7	1.8	1.9	329	257	162	73	39
2010	1.4	1.4	1.5	1.6	1.7	324	253	159	72	38
2011	1.2	1.2	1.2	1.3	1.4	319	249	156	70	37
2012	0.98	0.99	1.02	1.07	1.13	314	244	153	68	36
2013	0.8	0.81	0.83	0.87	0.91	308	240	150	67	35
2014	0.62	0.62	0.64	0.66	0.69	303	235	147	65	34
2015	0.42	0.42	0.43	0.45	0.47	296	230	143	63	32
2016	0.25	0.25	0.25	0.26	0.27	290	225	139	61	31
2017	0.12	0.12	0.12	0.13	0.13	283	219	135	59	30
2018	0.044	0.044	0.045	0.046	0.047	277	214	132	56	28
2019	0.008	0.008	0.009	0.009	0.009	270	208	128	54	27
2020	0	0	0	0	0	263	203	124	52	26

Figure A5: **Understanding the impact of marginal emissions in different years**. **a**. GDP-weighted global average temperature is below the estimated temperature/growth optimum in the early 1990s (indicating that warming would be net beneficial at that time), but exceeds the optimum by the late 1990s (indicating warming would be net harmful); vertical colored lines show the GDP-weighted global average temperature (ERA-Land) every 5 years since 1990, black line is the estimated temperature-growth response function used throughout the paper and shown in Fig A2, zoomed in to show the shape of the function between 12-18C. GDP-weighted global average temperature rises rapidly over time both because the globe is warming and in particular because lower-income countries are on average warmer and are growing faster than higher-income countries, and thus receive increasing weight in GDP-weighted global temperature over time. **b-c** Annual discounted damages from 1Gt CO_2 emissions pulses beginning in 1990, under either a 2% or 7% discount rate. For example, darkest blue line shows the annual global damages (or benefits) from a 1Gt CO_2 pulse in 1990. Annual benefits switch to damages as the GDP-weighted global temperature exceeds the global optimum in (a).

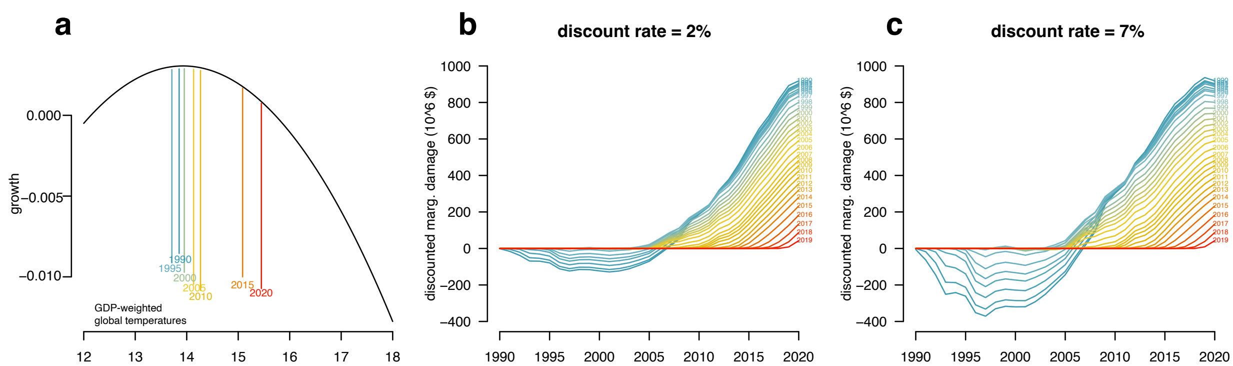


Figure A6: **Schematic of SC-CO_2 calculation under different time horizons**. A marginal emission in year 2020 generates subsequent warming and slows growth in a hypothetical economy, relative to a counterfactual where that emission did not occur. Slower growth through 2100 generates a ”wedge” of damages to total GDP shown in black. In our first scenario, where we assume no damages after 2100, the SC-CO_2 is the black wedge, discounted back to 2020. We then consider two additional scenarios where damages occur past 2100. The first of these, ”no growth impacts after 2100”, assumes that growth returns to its counterfactual rate in 2100 and thereafter (for instance, because a new technology is invented or practice adopted that eliminates the impact of temperature on growth), but this resumed growth is now acting on an economy that is smaller in 2100 than it would have been without the emission; this generates the blue shaded regions of damages. The SC-CO_2 in this scenario is then the discounted sum of the black and blue wedges. In the last scenario, ”growth impacts through 2300”, we assume warming continues to affect the growth rate through 2300 and impacts end in that year. That generates the additional damages shown in green, and the SC-CO_2 in this scenario is the discounted sum of the black, blue, and green regions. The black lines provide the trajectory of GDP under each scenario. The drawing is schematic and the relative size of the wedges is not to scale. Quantitative estimates of the SC-CO_2 under these different scenarios are provided in Fig 2e.

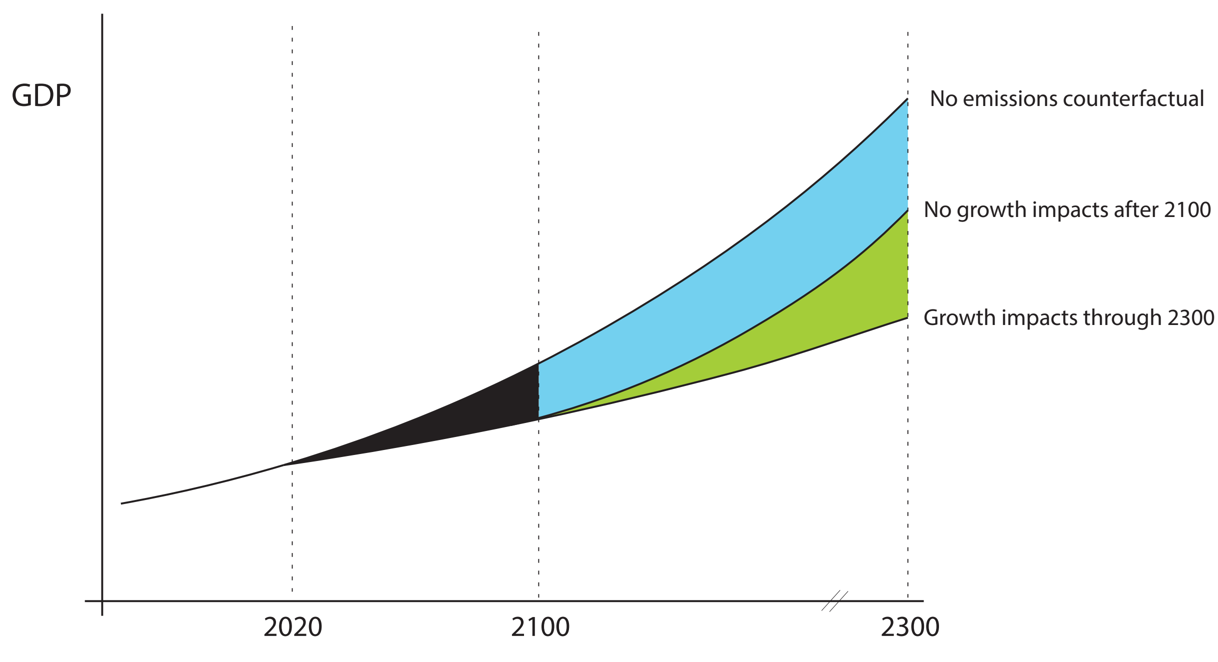


Figure A7: **Estimated damages per ton of CO_2 vary only slightly with the size of the emissions pulse**. Our baseline approach to calculating marginal damages is with a 1Gt emissions pulse. Using the same 1990 emissions year, estimated per-ton damages using pulses of dramatically smaller or larger size yield damages that differ by only a few percent, both for $HDCO_2$ damages (left two columns) and for $FDCO_2$ (right two columns). All estimates assume a 2% discount rate, and $FDCO_2$ estimates assume impacts end in 2100.

	Per tonne HD	% Difference relative to 1GtCO2 pulse	Per tonne FD	% Difference relative to 1GtCO2 pulse
1000tCO2	$4.13	103%	$323	99%
1MtCO2	$4.02	100%	$327	100%
1GtCO2	$4.02	100%	$327	100%
10GtCO2	$3.99	99%	$328	100%
100GtCO2	$3.75	93%	$335	102%

Figure A8: **$SC\text{-}CO_2$ under different discounting schemes, baseline growth scenarios, and time horizons**. Scenarios with "Growth at 2100 rate" use SSP3 estimates of country-year-level growth through 2100 as the baseline growth rate, extending the estimates in 2100 through 2300 to estimate impacts during that time period. "Clamping" scenarios do not allow future growth rates to exceed (in absolute value) observed historical growth rates for any country. "No impacts > 2100" assumes impacts stop in 2100, and "No growth effects > 2100" assumes that temperature does not impact the growth rate after 2100 but that the accumulated wedge by 2100 in the perturbed versus baseline GDP level is sustained. See Fig A6 for a schematic. Ramsey discounting uses values calibrated to a 2% near term rate, following ref[60]. The column "post-2100 growth" indicates the counterfactual growth rate assumed for economies after 2100. Reported $SC\text{-}CO_2$ estimates in this table do not precisely match those in Fig 2e, as Fig 2e estimates are median estimates from a distribution that considers full climate and regression (damage function) uncertainty. For computational tractability, the values reported here combine median estimates from the climate model ensemble with regression point estimates.

	DISCOUNT RATE						
SCENARIO	DISCOUNT RATE AT 1%	DISCOUNT RATE AT 2%	DISCOUNT RATE AT 3%	RAMSEY DISCOUNT (0.2%,1.24)	TIME HORIZON	POST-2100 GROWTH	REGRESSION MODEL
Growth at 2100 rate	$2,910	$680	$242	$1,459	through 2300	SSP 2100 growth rate	0-lag BHM model
Growth at 1%	$4,276	$854	$270	$2,008	through 2300	1% growth rate	0-lag BHM model
Growth at 2%	$14,482	$1,966	$422	$1,626	through 2300	2% growth rate	0-lag BHM model
Growth at 2100 + clamping	$2,577	$591	$206	$1,296	through 2300	SSP 2100 clamped rate	0-lag BHM model
Growth at 2100 + 5lag BHM	$15,111	$3,301	$1,153	$8,059	through 2300	SSP 2100 rates	5-lag BHM model
Growth at 2100 + 5lag BHM + No impacts > 2100	$1,617	$975	$612	$1,421	through 2100	SSP 2100 rates	5-lag BHM model
No growth effects > 2100	$1,607	$482	$203	$907	through 2300	SSP 2100 rates	0-lag BHM model
No impacts > 2100	$346	$203	$124	$275	through 2100		0-lag BHM model

Figure A9: **Sources of uncertainty in estimation of SC-CO_2.** Estimates show influence of different estimation components on uncertainty in estimates of SC-CO_2, fixing other components at their median.

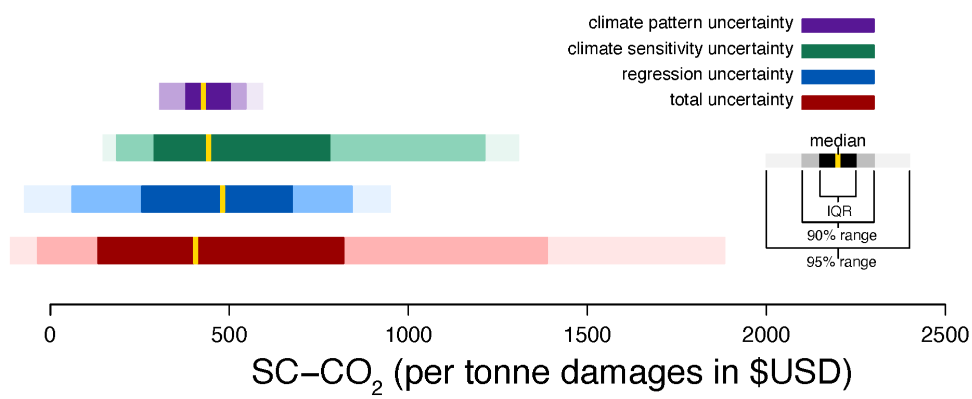


Figure A10: **Estimated damages from emissions related to individual behaviors or firm output over varying time periods**

a. CUMULATIVE DAMAGES (THROUGH 2100) OF A DECADE (2010-2020) OF INDIVIDUAL BEH VIORS A

	DAMAGES THROUGH 2020	DAMAGES 2021-2100
ADDITIONAL LONG-HAUL (8000KM) FLIGHT PER YEAR	$20	$5,490
EATING AN AVERAGE AMERICAN DIET INSTEAD OF VEGETARIAN DIET	$8	$2,196
USING A GAS FURNACE INSTEAD OF A HEAT PUMP	$8	$2,196
DRIVING 10% MORE THAN AVERAGE AMERICAN	$5	$1,373
A SERVING OF BEEF/MONTH	$0.8	$215
NOT RECYCLING	$0.6	$165

b. PRESENT VALUE OF FUTURE CUMULATIVE DAMAGES (THROUGH 2100) OF CELEBRITIES PRIVATE JET EMISSIONS IN 2022 (THOUSANDS OF $)

	DAMAGES THROUGH 2100
BILL GATES	$400k
JEFF BEZOS	$291k
FLOYD MAYWEATHER	$282k
ELON MUSK	$266k
PUMA/JAY-Z	$260k
TAYLOR SWIFT	$231k
STEVEN SPIELBERG	$193k
KIM KARDASHIAN	$192k
A-ROD	$187k

c. ACCUMULATED DAMAGES BY 2020 OF EMISSIONS OF CARBON MAJORS 1988-2015 (SCOPE 1 AND 3, $T)

	DAMAGES THROUGH 2020	DAMAGES 2021-2100
SAUDI ARABIAN OIL COMPANY (ARAMCO)	$0.24T	$13.09T
GAZPROM OAO	$0.23T	$11.63T
NATIONAL IRANIAN OIL CO	$0.12T	$6.61T
EXXONMOBIL CORP	$0.12T	$5.92T
PETROLEOS MEXICANOS	$0.11T	$5.52T
COAL INDIA	$0.09T	$5.31T
ROYAL DUTCH SHELL PLC	$0.1T	$4.95T
BP PLC	$0.09T	$4.57T
CHINA NATIONAL PETROLEUM CORP (CNPC)	$0.08T	$4.56T
CHEVRON CORP	$0.08T	$3.95T
PETROLEOS DE VENEZUELA SA (PDVSA)	$0.07T	$3.65T
ABU DHABI NATIONAL OIL CO	$0.06T	$3.46T
PEABODY ENERGY CORP	$0.06T	$3.17T
SONATRACH SPA	$0.05T	$2.88T
KUWAIT PETROLEUM CORP	$0.05T	$2.86T

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Figure A11: **Carbon debt estimates for scope 1 emissions of carbon majors**. Estimates show cumulative historical damages (through 2100) from carbon majors' emissions occurring between 1988 and 2015. Cumulative damages are discounted at 2%. Estimates for Scope 1+3 are given in Fig 3.

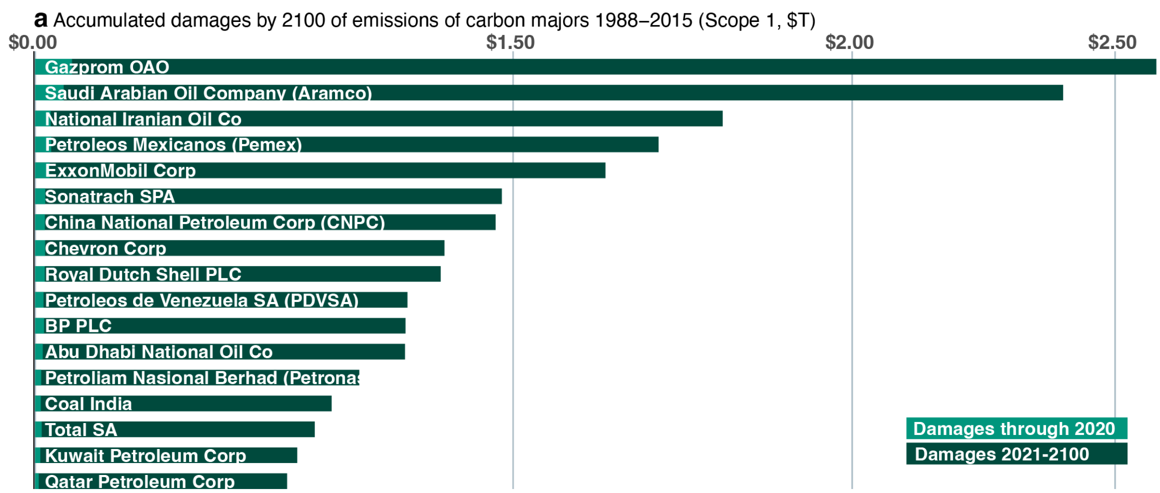

Figure A12: **Attribution of climate damages or benefits since 1980 to specific emitters (Fossil fuel + LUCF emissions).**

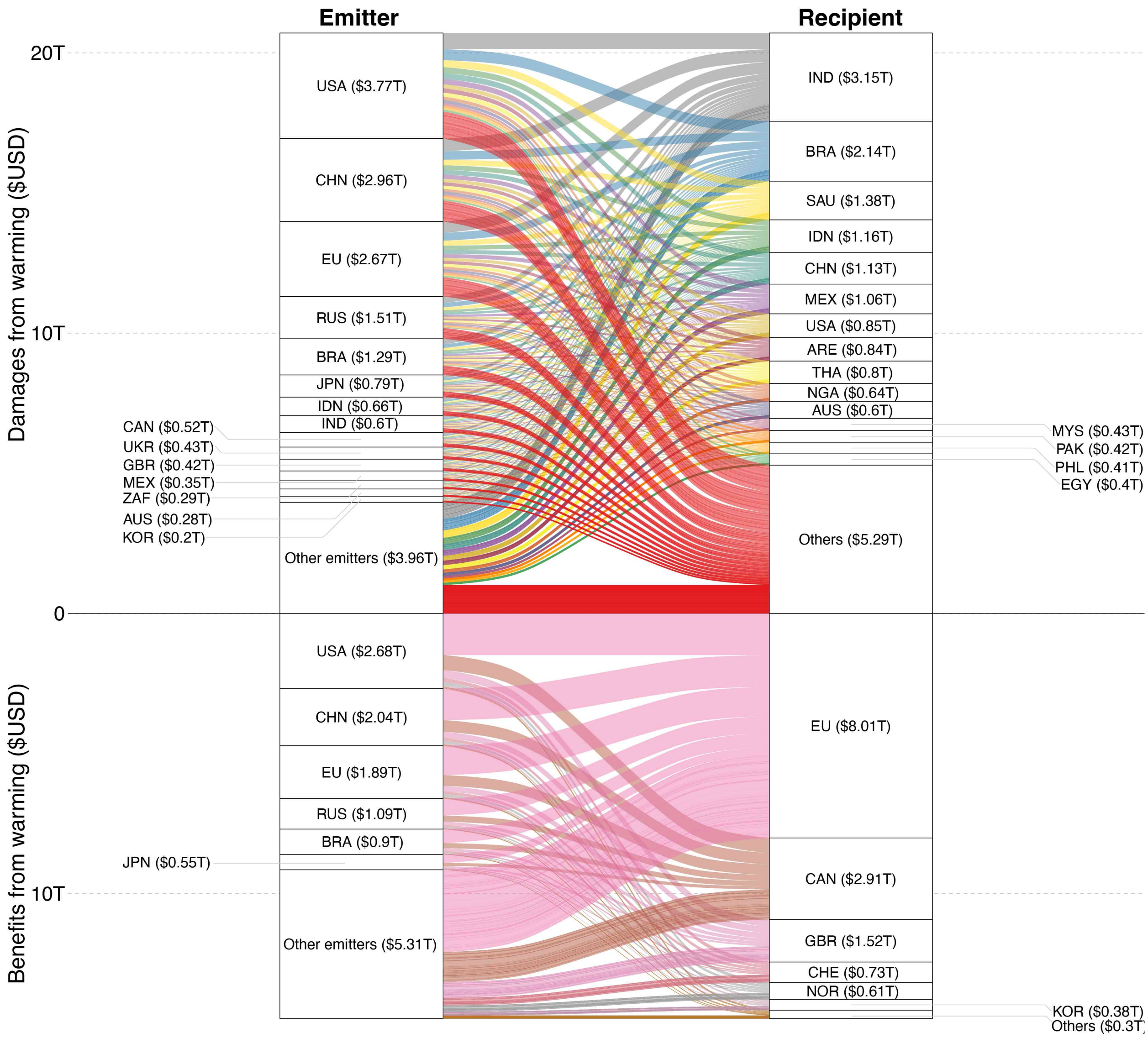

Figure A13: **Attribution of climate damages or benefits since 1990 to specific emitters (consumption emissions) excluding LUCF emissions**

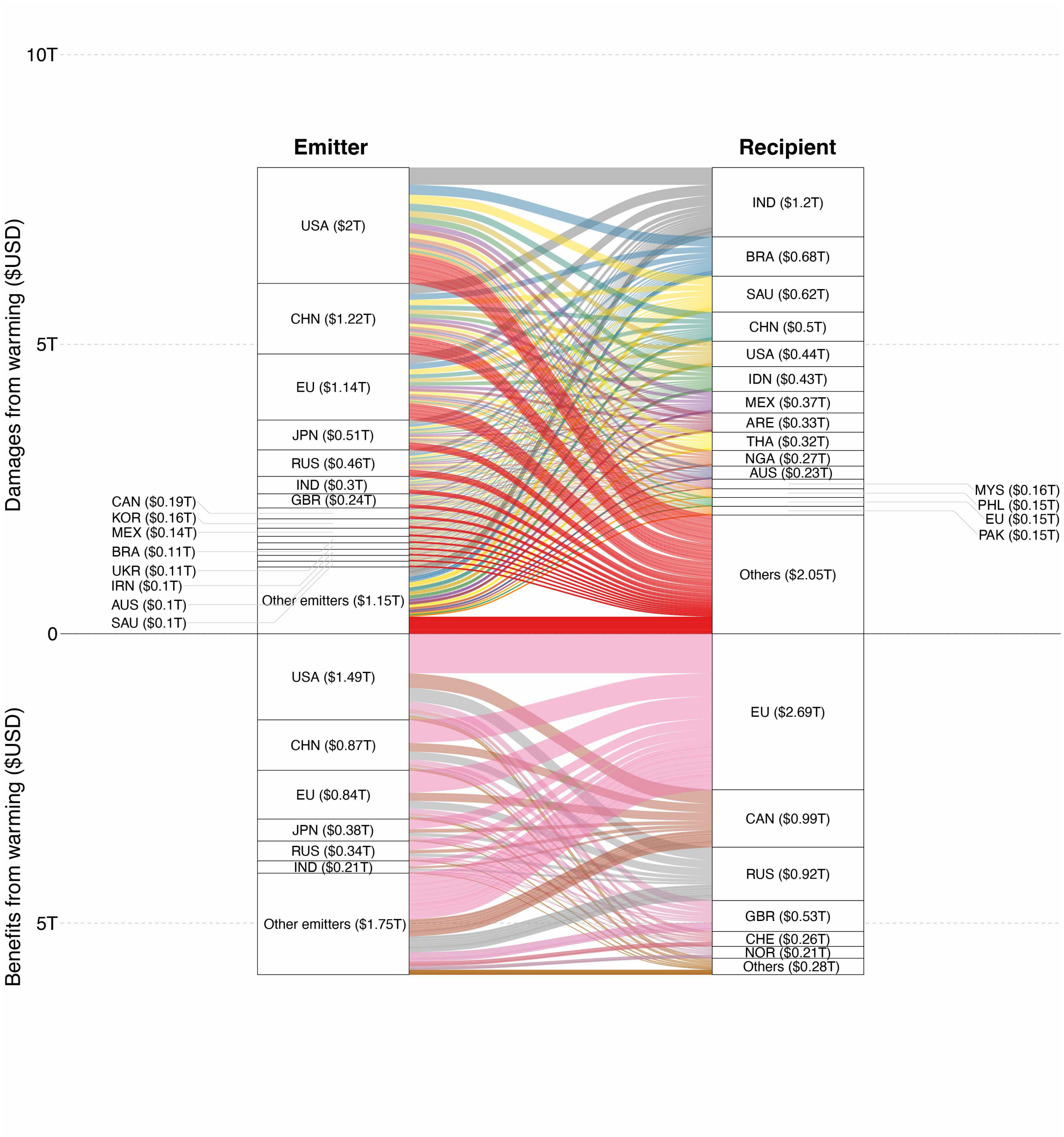

Figure A14: **Attribution of climate damages or benefits since 1990 to specific emitters (production emissions) excluding LUCF emissions**

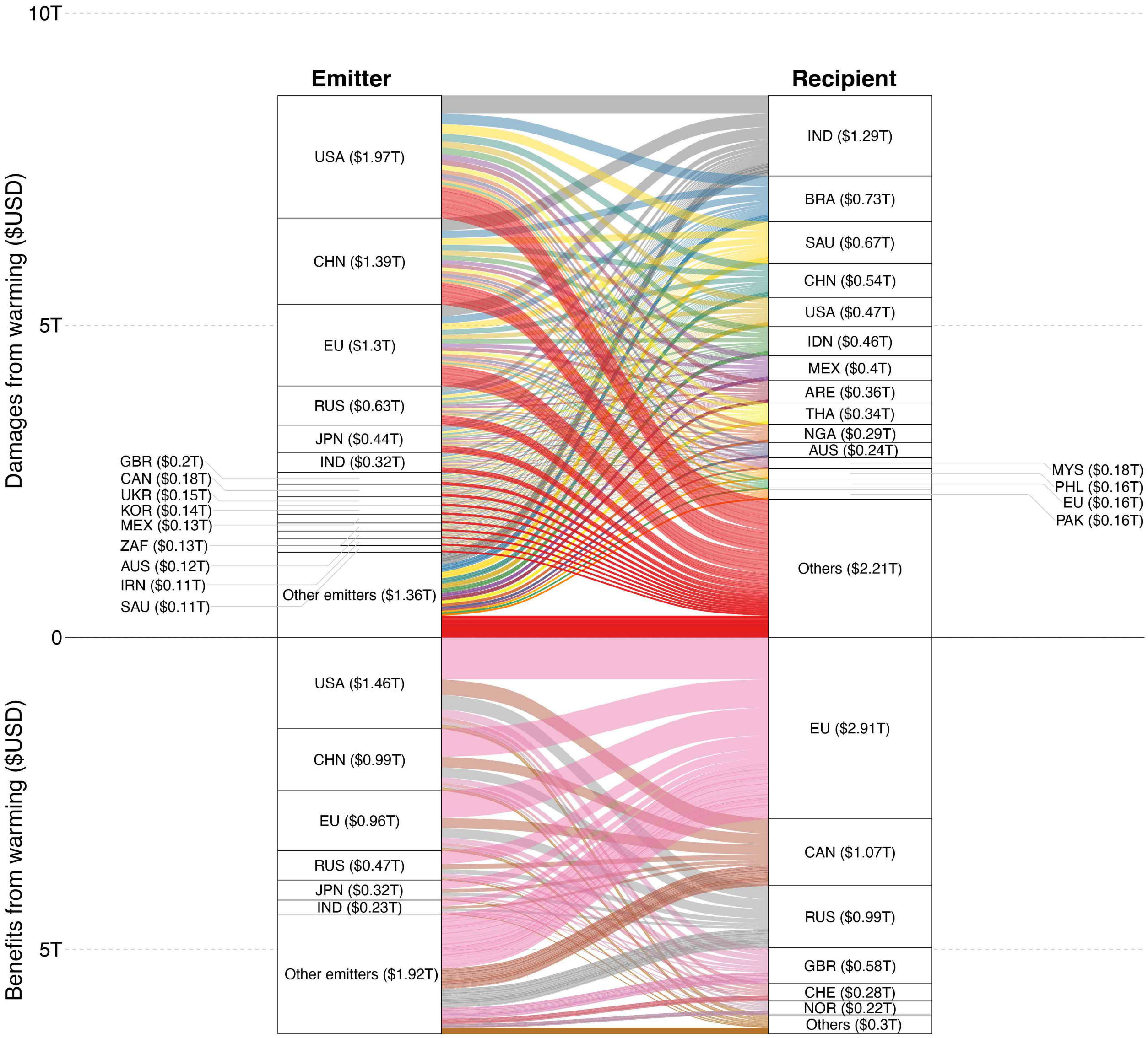

Figure A15: **Effectiveness of carbon removal for reducing damages declines as a function of time between emissions and capture**. **a.** Example of pulse experiment, where 1t pulse of CO2 is emitted in t_e=2020 and 1t removed with CDR in future year t_{CDR} (here, 2030). **b.** FaIR estimate of warming as a result of this pulse and subsequent capture. **c.** Schematic of impact on GDP in a hypothetical economy. Warming from initial pulse makes the economy grow more slowly, driving a wedge between GDP without the emission and GDP with the emission, up through time of removal. Damage between t_e and t_{CDR} is represented by orange triangle. If a ton is removed at time t_{CDR}, the economy resumes growing at its original pace but from a lower initial value in t_{CDR}, and the wedge is sustained into the future, creating the damage in the yellow polygon. Put simply, damage continues to occur after removal, due to the wedge that was created before removal. If the ton was never removed, the additional damages is in blue. The SC-CO2 is the sum of the colored triangles (discounted annually back to 2020). Increasing delay between t_e and t_{CDR} increases both the orange and yellow triangles. Drawing is schematic and for visual clarity, polygon sizes are not to scale. **d.** Quantitative estimates of the percent of damage averted through 2100, for a 2020 emissions year and a $t_{CDR} > 2020$, assuming all damages end in 2100. Removal in 2030 reduces damages by 80%. Removal in 2050 reduces damages by roughly half.

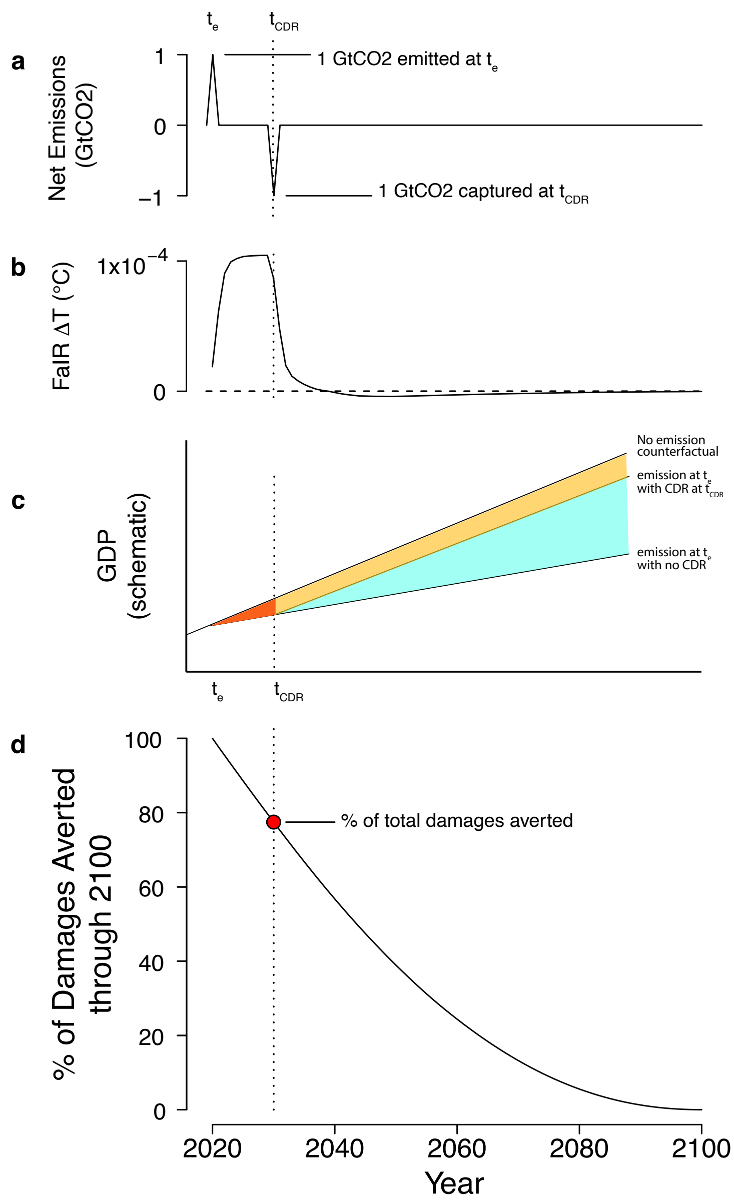

Figure A16: **Selecting regression controls based on model predictive performance can bias estimates of parameters of interest**. Simulation results of estimating regression models with and without time local time trends in a setting where both outcomes (growth) and independent variable (temperature) are spuriously trending. Left panel: model with trends has higher RMSE than model without trends on temporally-held-out outcome data. Center panel: model with trends correctly estimates the marginal effect of temperature on growth. Right panel: model without trends has a bias estimate of the marginal effect of temperature on growth, because it did not remove the spurious unit-specific trends. Black link in both panels is the true effect, colored lines are 100 bootstrapped estimates of the two regression models.