Cross-Cause Cost-Effectiveness

An Investigation of Climate Change Versus Global Health and Development Interventions

Global Health and
Development Department

Last updated: 2026-May-25 • Report

AUTHORS

Abbie Clare, Thomas R Vargas

MANAGER

Abbie Clare

DIRECTOR

John Firth

Cross-Cause Cost-Effectiveness: An Investigation of Climate Change versus Global Health and Development Interventions

Abbie Clare
Thomas R Vargas

Suggested citation: Clare, A. & Vargas, T. R. 2026. Cross-cause cost-effectiveness: An investigation of climate change versus global health and development interventions. Rethink Priorities. https://rethinkpriorities.org/research-area/climate-change-versus-ghd-interventions

Global Health and Development at Rethink Priorities

The Global Health and Development Department of Rethink Priorities is a multidisciplinary research and consulting group that seeks to disseminate actionable insights and drive positive change in the fields of global health, international development, and climate change.
https://rethinkpriorities.org/global-health-and-development

For all queries, please contact ghd@rethinkpriorities.org.

We thank our anonymous client for commissioning and funding this research report. The views expressed herein are not necessarily endorsed by them.

RETHINK PRIORITIES
530 Divisadero St. PMB #796
San Francisco, California 94117
United States of America

About Rethink Priorities
Rethink Priorities is a research and implementation group that identifies pressing opportunities to make the world better. We act upon these opportunities by developing and implementing strategies, projects, and solutions to key issues. We do this work in close partnership with foundations and impact-focused nonprofits.
www.rethinkpriorities.org

Contents

Editorial Note

This report was commissioned by an anonymous funder and produced by Rethink Priorities from January 2026 to February 2026. We have revised the report for publication. Our anonymous client does not necessarily endorse our conclusions, nor do our expert informants or the organizations with which they are affiliated.

In this report, we provide a framework to evaluate the key questions determining whether an effective altruism (EA)-aligned donor should invest in Global Health and Development (GHD) interventions versus climate change interventions. We explore this "cross-cause comparison" by identifying the primary "cruxes" (key questions or assumptions) that drive differences in estimated cost-effectiveness between the two fields. To do so, we reviewed existing literature and EA community debates and conducted interviews with experts from EA-aligned organizations. While these views informed our work, this does not imply any of these organizations endorse our conclusions.

The report is structured around a progression of quantitative models. We begin by establishing a comprehensive longlist of cruxes, from which we shortlist five key variables for in-depth modeling—ranging from empirical data, like abatement costs, to philosophical preferences, such as the valuation of future lives. We then present three models in ascending order of complexity: first comparing the basic cost per life saved, then incorporating high-certainty economic damages, and finally integrating lower-certainty climate impacts such as natural tipping points and endogenous economic growth effects.

Throughout this report, we refer to standard philanthropic metrics, including the Coefficient Giving (CG) cost-effectiveness "bar" and units of impact, as well as GiveWell's cost per life saved benchmarks. We have tried to flag major sources of uncertainty in our models and the underlying academic literature, and we remain open to revising our views based on new information or further research.

Executive Summary

This work was commissioned by an anonymous funder to evaluate the key questions determining whether an **effective altruism (EA)-aligned** donor should invest in **Global Health and Development (GHD)** interventions versus **climate change interventions**. We refer to this as a "cross-cause comparison." In this report, we analyze EA-style debates, identify the assumptions that shape views on relative cost-effectiveness, and build simple models to test the impact of these assumptions.

What We Did

During the first two weeks, we examined the EA community's existing climate vs. GHD debates and conducted interviews with EA-aligned experts to identify the primary "cruxes" (key questions or assumptions) that drive differences in cost-effectiveness between areas. Specifically, we compiled a longlist of factors influencing cross-cause comparisons and shortlisted five key variables for in-depth modeling, ranging from empirical data (e.g., abatement costs) to philosophical preferences (e.g., sure-bet vs. hits-based giving and valuation of future lives).

In the last two weeks, we used our findings regarding cruxes to build two models that compare the cost-effectiveness of GHD interventions to climate interventions. Given the high level of complexity and uncertainty involved in modeling the combined future impacts of climate change on human life and economic welfare, we first present a calculation of cost per life saved when donating to climate versus GHD causes, thus excluding the broader, more complex and uncertain elements of economic damages attributable to climate change. We then incorporate a series of economic damages into this simplified model in a step-wise manner, starting with the most certain and ending with the least certain, ultimately comparing our best estimate for the social return on investment for philanthropic giving to climate interventions against Coefficient Giving (CG)'s cost-effectiveness bar. This does not imply, however, that CG itself would agree with our analysis.

What We Found

Our models suggest that climate can be competitive with GHD interventions under the following conditions:

- The donation for climate interventions goes towards hits-based climate opportunities
- The cost of abatement is within the range of $0.50–$3.50/tonne CO_2e
- Deaths from air pollution are valued in addition to deaths from rising temperatures
- The life and economic damages caused by climate change are valued using EA-aligned principles, namely, no discounts over deaths and a logarithmic utility function for income gains
- Climate-induced damages from uncertain but significant impacts, such as tipping points and endogenous economic growth effects, are included

In order to arrive at this conclusion, we first created a longlist and subsequently selected a shortlist of five key cruxes that are the most influential in determining the findings from our models. We list these cruxes below, in order of their position along the causal chain from a philanthropist's donation to the valuation of the social impact it creates:

1. Donor preference for sure-bet versus hits-based giving

2. Cost to reduce atmospheric concentrations of CO_2e/PM2.5 by one tonne
3. Valuation of human life over time
4. Valuation of human life and economic damages over space
5. Inclusion of lower certainty climate impacts

We address each of these cruxes in turn, through a process of presenting two models plus a final assessment of how the inclusion of lower certainty climate impacts brings climate intervention close to and in excess of the CG bar.

Results of Model 1: Comparing Cost per Life Saved (CPLS) for Climate vs. GHD When Only Considering Mortality

Model 1 primarily explores the impact of the first two cruxes on our findings: preferences for sure-bet versus hits-based donations, and the impact of CO_2e abatement cost on cost-effectiveness.

The findings from this model indicate that climate cannot compete with GHD interventions purely on a lives saved basis. This is particularly true when comparing sure-bet GHD interventions (e.g., seasonal malaria chemoprevention) with sure-bet climate interventions (e.g., investing in carbon capture and storage projects with a relatively high certainty of abating CO_2e, but also a relatively high cost). In this comparison, GHD was more than 4,000x more cost-effective than climate (median ~$2,759 vs. ~$11.8M per life saved). On this basis, we de-prioritized sure-bet climate interventions for the remainder of the report.

Hits-based climate opportunities that only account for heat-related deaths (i.e., as a result of heat stroke) had an estimated CPLS of ~$44,000, which falls well short of CG and GiveWell benchmarks for high cost-effectiveness. Incorporating averted air pollution deaths shifts the hits-based climate distribution to be roughly 4x more cost-effective (median CPLS ~$10,000). However, climate interventions still fail to clear the high cost-effectiveness bar of top GHD opportunities (~$1600-2550 CPLS for adult and under-5 causes, respectively).

Results from Model 2: Incorporating High Certainty Economic Damages into the Climate Change Estimate

Moving beyond mortality impacts, the next iteration of our model expands to include a set of economic damages that are relatively uncontentious within the scientific literature on climate change. Specifically, we use an Integrated Assessment Model (IAM) called GIVE (Greenhouse Gas Impact Value Estimator) as our central estimate for how to incorporate economic damages from sea level rise, energy use, and agricultural system impacts, alongside mortality impacts. This yields an estimate of the social cost of carbon (SCC) at $185, defined as the estimated economic cost of the damages caused by emitting one additional tonne of carbon dioxide into the atmosphere.

SCC estimates are most often provided in US$ in the climate literature; however, US$ are incomparable with the CG benchmark for philanthropic cost-effectiveness due to differences in the way that lives lost and economic damages are valued. We therefore address the next two of our short-listed cruxes (valuation of life over time, and valuation of human life and economic damages over space) by updating the valuations of damages underlying GIVE's SCC estimates to match CG units (hereafter referred to as CG$). We then also incorporate lives lost from air pollution, as this is not included within the GIVE model. This produces an SCC of ~CG$1600, which translates to a median Social Return on Investment (SROI) of ~800x. This falls well below the 2,000x CG benchmark; however, it is worth noting that 10% of the distribution tail does clear the bar.

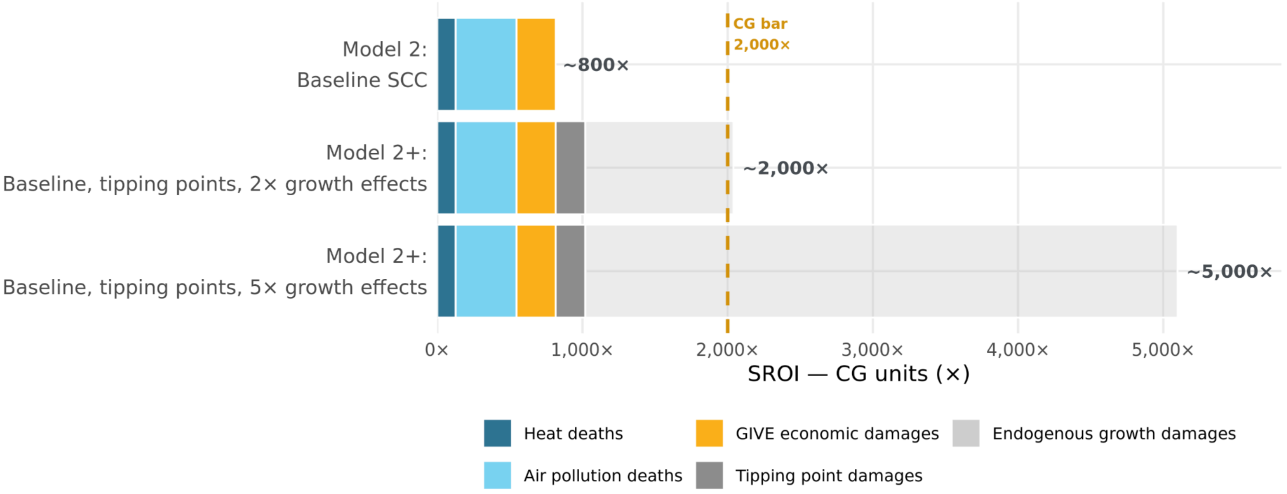
Overall, having translated the SCC into CG$, incorporated air pollution deaths, and accounted for the higher certainty economic damages in the scientific literature, climate interventions continue to look less competitive than GHD interventions.

Results from Model 2+: Incorporating Lower Certainty Economic Damages from Tipping Points and Endogenous Growth into the Climate Change Estimates

In the final version of our model, we include the life and economic damages that may be posed from two further pathways of climate impact: tipping points and endogenous growth effects. We scanned the literature for estimates of how these two pathways could amplify pre-existing estimates of the SCC. We have medium confidence in the results that we found and apply to the SCC generated in Model 2.

Applying conservative multipliers of 1.25x for damages caused by tipping points and of 2x for damages caused by endogenous growth effects produces a median SCC of ~CG$4000, translating to an SROI of ~2046x, just clearing the CG bar. However, changing the conservative 2x endogenous growth multiplier for a mid-range estimate of 5x produces a median SCC of CG$10,000, translating to an SROI of ~5,000x. This clears the CG bar by more than 3000 SROI units. In other words, a climate intervention would be more than twice as effective as the most effective GHD interventions under these assumptions.

Figure 1: Applying multipliers to our adjusted SCC SROI



Introduction

Both within and outside of the effective altruism community, there is significant interest in being able to make comparisons across cause areas. Cause areas are defined as specific fields to which we could hypothetically allocate resources. Some typical examples are animal welfare, existential risk, global health and development (GHD), and climate change. This report concerns itself with the latter two. We set out to provide a rigorous framework to help inform how donors should think about donating to GHD versus climate change interventions, especially (but not limited to) those with attachments to effective altruism. We conducted this research over four weeks, ultimately producing the following outputs:

- A comprehensive longlist of the cruxes that could be considered to influence cross-cause comparisons between GHD and climate change interventions
- Detailed explanations of and parameter estimates for a shortlist of the five most influential cruxes from the longlist
- A set of BOTECs (back-of-the-envelope calculations) and Monte Carlo simulations illustrating the relative merits of GHD vs. climate interventions based on variation of the short-listed cruxes.

The following sections present each of these outputs in turn.

Longlist of Cruxes

Approach

We began by investigating how effective altruists (EAs) have explored this question before. We spent 1.5 hours reading and following leads from a series of EA forum posts[1] recommended by our anonymous funder. We spent another 30 minutes asking Claude Code to scan the EA forum to identify any other posts related to these matters.[2] We conducted a manual review of the 34 most promising posts since 2020, finding eight additional ones that we read in detail, including the comment threads. Further details can be found in Appendix A. In addition, we interviewed experts from across EA-aligned organizations, though the content of this report and our conclusions do not necessarily reflect any of these organizations' views. We are reasonably confident that our research has allowed us to capture the most important debates in the EA community. Of course, these may not be the only relevant views, and it is possible that additional outreach to other, non-EA-aligned experts would update our views or models in ways that could significantly alter our results.

---

[1] These posts include:

- [updated] Global development interventions are generally more effective than climate change interventions (Hillebrandt, 2019)
- Long-term cost-effectiveness of Founders Pledge's Climate Change Fund (Grilo, 2022)
- Cost Effectiveness of Climate Change Interventions (Richardson, 2022)
- Founders Pledge's Climate Change Fund might be more cost-effective than GiveWell's top charities, but it is much less cost-effective than corporate campaigns for chicken welfare? (Grilo, 2024)

[2] Our prompt on Jan 28, 2026 was: "Hi Claude, I need you to find posts on the cost-effectiveness of climate change interventions compared to global health interventions on the EA Forum. To do so, please write a script to and search for the EA Forum for any posts from 2020-2026 that examine the cost-effectiveness of climate change interventions, especially those that compare them to global health interventions. There is a GraphQL API that will be helpful to you to accomplish this. Do not just look for titles; analyze the text of the posts to ensure they meaningfully discuss cost-effectiveness and comparisons to global health." In further conversation with Claude, we asked it to conduct an initial scan that we could manually check.

Summary of EA Perspectives on Climate vs. GHD Interventions

Based on the approach described, our understanding of current EA debates is that:

- There is significant uncertainty regarding whether climate interventions can be more cost-effective than GHD ones.[3]

- Most of the experts we spoke with, and the posts[4] we examined, indicate that GHD interventions are thought to be more cost-effective than *direct climate interventions* (like reforestation or capture carbon and storage[5]). However, *high-leverage climate interventions*, such as policy advocacy and R&D for neglected technologies, may outperform GHD interventions under some circumstances.

- The extent to which climate interventions can compete for cost-effectiveness with GHD interventions will depend as much on the philosophical viewpoint and risk-tolerance of the donor[6] as on the scientific evidence base for climate and GHD interventions.

The following section presents the longlist of cruxes derived from the literature search and interviews, providing a high-level description of each.

Describing the Longlist of Cruxes

While this cross-cause comparison involves both GHD and climate components, our longlist of cruxes is focused on climate interventions, on the basis that the cruxes related to GHD interventions (e.g., as part of GiveWell BOTEC calculations) are relatively well known and understood in comparison.

Table 1, therefore, describes the longlist of climate-relevant cruxes that we summarized from literature reviews and expert interviews, organized in the roughly chronological order that they become relevant, from the point of initial philanthropic donation all the way through to observing and valuing any resultant health and economic impacts. In addition to describing the cruxes, we also categorize them into those that are pragmatic/empirically testable (i.e., the estimated cost to reduce global concentrations of greenhouse gases by one tonne of CO_2e[7]) versus those that are philosophical/ethical (i.e., the relative value of a life lost today versus a life lost in the future). We feel that this is a useful distinction because empirical cruxes are bound by science and economics, whereas philosophical cruxes are grounded in ethical worldviews and/or individual preferences.

---

[3] From our main sources: Grilo (2024): "I estimated the cost-effectiveness of CCF is: 3.28 times that of TCF, with a plausible range of 0.175 to 30.2 times. So it is unclear to me whether donors interested in improving nearterm human welfare had better donate to GiveWell's funds or CCF." and Hillebrandt (2019): "Because the confidence intervals between climate and development are wide and overlapping, the value of information of reducing uncertainty is high"

[4] For example, from Hillebrandt (2019): "Global development interventions seem generally more effective than climate change interventions. However, under pessimistic modeling assumptions, select climate change interventions might be more effective than global development interventions."

[5] From our main sources: Richardson (2022): "Here's an article about direct carbon capture, where they say the current cost is about $600/tonne, but they're hoping to get it down to $100/tonne" (Service, 2018) and Hillebrandt (2019): "The levelized costs of capturing CO_2 from the atmosphere are projected to be $94-232 per tonne CO_2 and could decrease to $35 by 2050."

[6] E.g. how to value lives across space and time and/or donor comfort with hits-based giving approaches.

[7] CO2e stands for carbon dioxide equivalent, and is a standardized metric to indicate the combined warming effect of all greenhouse gases, e.g., methane and nitrous oxide, in addition to carbon dioxide alone.

Finally, we indicate in Table 1 whether a given crux was shortlisted, and explain the rationale, including its likely influence on the cost-effectiveness calculations for GHD vs. climate interventions. Short-listed cruxes are highlighted with orange shading. As a general rule, cruxes were shortlisted if there was significant uncertainty over their likely values, and if assuming different values within the plausible range could materially affect the conclusions of any given model.

Table 1: Longlist of cruxes organized in roughly chronological order from donation to impact[8]

Step	Crux	Description and Short-List Status
Donor gives money to a philanthropic fund for either climate or GHD causes	*Crux Type: Philosophical* Donor preference for sure-bet versus hits-based interventions	There is a significant difference in the estimated cost-effectiveness of “sure” bets such as GiveWell’s top charities, compared to “hits-based” bets like advocacy for policy change. Hits-based bets may have much greater cost-effectiveness in expectation, however, they are also far more risky/uncertain than sure bets. **Shortlisted:** Donor risk preference can dictate whether GHD or climate is more cost-effective, depending on the type of interventions being compared.
Philanthropic donation reduces atmospheric concentrations of CO_2e and/or PM2.5[9]	*Crux Type: Empirical* Marginal cost to reduce the atmospheric concentrations of CO_2e/PM2.5 by one tonne	The direct financial cost of abating or removing a single unit of pollution. This will be a more certain estimate for sure bets (e.g., solar panels) than hits-based bets (e.g., advocacy for policy change). **Shortlisted:** Our models are very sensitive to assumptions regarding the marginal cost per tonne of reducing atmospheric carbon/PM2.5.
Global average temperatures are reduced	*Crux Type: Empirical* Marginal impact of one reduced tonne CO_2e on global temperatures	Quantifies the physical climate sensitivity for exactly how much avoided warming results from keeping one tonne of carbon out of the atmosphere. **Not shortlisted:** This is a complex scientific calculation that is implicit to the climate models that we integrate into the BOTECs.
Fewer humans die from heat stress[10]	*Crux Type: Empirical* Marginal impact of reduced temperatures on human mortality	At the margin, the relationship between global temperature and direct human mortality (i.e., from heat stress) will depend upon which emissions pathway the world is on (i.e., on track for 2 degrees versus 4 degrees by 2100) and also on how well humans are able to adapt to rising temperatures (e.g., purchasing air conditioning).

---

[8] Existential risk from climate-induced harms was also considered for the longlist of cruxes. However, it was excluded on the basis that the potential astronomical value of future human extinction effectively overwhelms the other nearer-term metrics considered above. In this way, we consider existential risk related to climate as a separate philosophical debate to this specific cross-cause exploration.

[9] While air pollution encompasses a wide variety of harmful emissions (including ozone and nitrogen oxides), we frequently use fine particulate matter (PM2.5) as a proxy for the broader suite of emission types that cause air pollution, because PM2.5 drives the vast majority of the cardiovascular and respiratory health costs of air pollution.

[10] We focus only on mortality from climate change, thereby omitting morbidity from the analysis. This is because the evidence suggests that premature mortality accounts for the vast majority of the total disease burden associated with extreme temperatures (Liu et al., 2025). As a result, many mainstream models of climate impact on human health (including the GIVE model used in this report) only focus on mortality, rather than morbidity and mortality combined.

		Not shortlisted: We use the globally recognized GIVE model to represent the relationships between rising temperatures, human mortality, and other economic outcomes. The GIVE model is fully probabilistic, and mathematically integrates both the most likely futures and tail-risk scenarios into a single, comprehensive expected value.
Fewer humans die from air pollution	*Crux Type: Empirical* Pollution-linked human mortality	Traditional climate models often overlook the health impacts of co-pollutants, like fine particulate matter (PM2.5), that are emitted alongside CO_2e when burning fossil fuels. Furthermore, quantifying the exact share of mortality attributable to these specific emissions, as well as the overall magnitude of the effect, remains somewhat uncertain. **Not shortlisted**: Mortality linked to air pollution significantly contributes to the overall calculation; however, it is less critical than other cruxes, e.g., inclusion of lower certainty climate impacts
	Crux Type: Philosophical Valuation of human life over time	Often termed "neartermist versus longtermist" in the EA community, this parameter indicates the extent to which you value a life lost in the future less than a life lost now. Longtermists value future lives similarly/the same as current lives, whereas neartermists will apply a "discount" rate to future deaths, effectively valuing them as less important than deaths today. **Shortlisted:** A near-termist donor will value GHD interventions more highly than a long-termist donor.
	Crux Type: Philosophical Valuation of human life and economic damages over space	EA ethical approaches ensure that any life lost is valued the same, regardless of where it is lost. Moreover, economic damages are valued more highly when they accrue to a lower-income individual than a higher-income individual. **Shortlisted:** The ethical valuation of lives lost/economic damages experienced in different countries has a significant impact on the expected value of climate vs. GHD interventions, especially because most lives lost due to climate change will be in low- and middle-income country (LMIC) contexts, where standard economic models will assign much lower values than a typical EA model.
Fewer humans are impacted by significant economic welfare losses due to negative climate impacts	*Crux Type: Empirical and Philosophical* Inclusion of lower certainty climate impacts	Climate change is predicted to affect numerous global systems, both natural and human-made. Existing models that estimate climate damages vary significantly in the "damage modules" that they include, e.g., sea level rise, energy costs, lost productivity, and/or economic growth impacts. **Shortlisted:** The damage modules included and the valuation of their impact have a major bearing on the conclusions of this paper

Shortlist of Cruxes

As indicated in Table 1 above, the following cruxes were shortlisted for in-depth consideration and variation in the cross-cause models:

- Donor preference for sure-bet versus hits-based interventions
- Cost to reduce atmospheric concentrations of CO_2e/PM2.5 by one tonne

- Valuation of human life over time
- Valuation of human life and economic damages over space
- Inclusion of lower certainty climate impacts

The following four sub-sections provide more detail on the five cruxes listed above. Cruxes 3 and 4, regarding ethical approaches to life and economic damage valuation, are combined within a broader discussion regarding the calculation of the social cost of carbon (SCC).

Crux 1: Sure-Bet Versus Hits-Based Giving

Description

The difference in magnitude and certainty of predicted outcomes between sure-bet and hits-based interventions is a critical consideration when comparing GHD against climate giving opportunities. To define these concepts:

- **Sure-bet giving** prioritizes highly certain, easily measurable interventions with predictable near-term benefits (like funding malaria nets).
- **Hits-based giving** intentionally funds high-risk, high-variance projects where most efforts will likely fail, but a single success could yield a massive, transformative payoff.

Table 2 provides illustrative examples of sure-bet and hits-based giving opportunities in the GHD and climate intervention spaces[11].

Table 2: Examples of sure-bet versus hits-based interventions in the GHD and climate spaces

	Global Health and Development	Climate Change Mitigation
Hits-Based	Tech advancement and policy advocacy	Policy advocacy
Sure-Bet	Seasonal malaria chemoprevention (SMC)	Carbon capture and storage (CCS)

To illustrate the importance of this point: A donor might rely on GiveWell recommendations for sure-bet GHD interventions, and Giving Green or Founders Pledge for climate philanthropy. However, this comparison of the GiveWell Top Charities to the Giving Green/Founders Pledge funds is not strictly like-for-like because GiveWell Top Charities (GWTC) makes sure-bet calculations, in comparison to both Giving Green and Founders Pledge that take a hits-based approach to climate philanthropy. This means there is much higher uncertainty surrounding the cost-effectiveness estimates of the Giving Green and Founders Pledge funds compared to GWTC, even though Giving Green and Founders Pledge may appear to offer more cost-effective opportunities.

Modeling the Effect of This Crux on the Results

Incorporating this uncertainty numerically into our models would cause this parameter alone to dominate all other parameters. We therefore specify a model for each of the four cells in

---

[11] It is worth noting that GHD and climate interventions do not all neatly fit into sure-bet or hits-based options. However, we find these categories to be analytically useful in framing the available decision space for donors wanting to give in these spaces. A helpful discussion on hits-based giving from Coefficient Giving can be found here.

Table 2 as part of Model 1, enabling any pairwise comparison to be made as necessary. In practice, the low cost-effectiveness of sure-bet climate donations means that this option is deprioritized for the rest of the report.

Crux 2: The Marginal Cost to Reduce Atmospheric CO_2e/PM2.5 by One Tonne

Description

There is high uncertainty over the cost to reduce atmospheric CO_2e/PM2.5 by one tonne, particularly when considering this from a hits-based giving perspective. Hits-based climate philanthropy funds, such as Giving Green and Founders Pledge, finance high-risk, high-reward avenues such as catalytic technological R&D and/or intensive policy advocacy. These interventions function through high-leverage conditions, in which relatively small philanthropic grants may unlock sizable impact through shifts in, e.g., government funding or market trajectories for clean energy technologies. This means that the values we assign to abatement cost here are fundamentally uncertain; however, we have conducted literature searches and expert interviews to determine our median estimate and value range.

Modeling the Effect of This Crux on the Results

We vary the marginal cost in our models by setting a distribution around plausible costs for the interventions considered, as described here. We then propagate the uncertainty of this parameter throughout our Monte Carlo distributions.

Cruxes 3 and 4: Ethical Valuation of Life and Economic Damages

Description

In the scientific literature, Integrated Assessment Models (IAMs) are used to model the interaction between climate *impacts* (i.e., biophysical or social effects driven by climate change) and climate *damages* (monetized estimates of the social welfare effects of climate change impacts).[12] There are numerous IAMs in existence, each including a different range of damage functions and using different valuation schemes to value the impact of those damages in a way that combines both lives lost and economic impacts into a single value estimate for the social cost of carbon (SCC), i.e., the estimated economic cost of the damages caused by emitting one additional tonne of carbon dioxide into the atmosphere. These cruxes influence SCC calculations as follows:

> **Valuation of human life over time:** Most existing climate models discount the value of lives lost in the future on the assumption that future generations will be significantly wealthier, and on another sometimes contested premise that future wellbeing matters less, simply because it is further away in time. Because human mortality is monetized within these frameworks, saving a future life must compete mathematically against the compounding returns of alternative economic investments. While this makes sense within a certain economic framework, an effective altruist tends to take an alternative approach: valuing lives lost in the future the same as lives lost today, on the basis that the intrinsic moral value of a human life does not diminish simply because a person lives further in the future. The choice of how to value a human life over time is particularly important when making distinctions between climate change and GHD intervention opportunities, as most GHD interventions address issues over the short

---

[12] Views from an internal RP report on IAMs, available upon request.

term and consequently the lives they will save occur in the near future, whereas climate change lives saved occur decades or more from now.

Valuation of human life over space: It is common practice with mainstream SCC models to use the "Value of a Statistical Life" (VSL), which typically uses the GDP of the country in which a life is lost to value that life. Because this metric is tied to a local population's financial "willingness to pay" to reduce mortality risk, standard economic models mathematically assign a significantly lower monetary value to a fatality in a low-income country than to one in a high-income country. While this makes sense within that willingness-to-pay framework, the effective altruism approach would be to value a life lost anywhere in the world exactly the same, on the basis that the intrinsic moral value of a human being is not determined by their local economic output or national wealth. This is important when valuing lives saved as a result of climate and GHD interventions, as the vast majority of lives saved in both categories will be in the lowest-income regions of the Global South.

Inclusion and valuation of economic damages associated with climate change: Each IAM incorporates different modules for estimated climate damages. Most include human deaths combined with some combination of the economic damages from property damage due to sea level rise, crop failure due to rising temperatures, increased energy costs due to air conditioning demands, global economic growth impacts, and/or labor productivity impacts. The damage modules that are included, and the way that those damages are valued, have a strong impact on the ultimate conclusions of this paper. For example, the extent to which it is assumed that climate change will have a negative impact on growth *rate* rather than growth *level* has a significant impact on whether climate change can compete with GHD as a cost-effective philanthropic option. Moreover, whether the welfare impacts of those growth effects are valued in real dollars (i.e., the impact on GDP) rather than estimating their impact on real human welfare (i.e., a $ lost to a poorer person has a much greater welfare penalty than a $ lost to a richer person) further affects whether a donor may consider climate interventions to be more cost-effective than GHD interventions.

Modeling the effect of this crux on the results

Model 2 translates the mainstream estimates of SCC in US$ into EA-equivalent values and assesses how close to the CG cost-effectiveness bar this brings our estimates of climate intervention cost-effectiveness.

Crux 5: Inclusion of Lower Certainty Climate Impacts

Description

Mainstream IAMS (e.g., those used by the US and Germany to calculate their own national social costs of carbon estimates) will typically only attempt to value climate damages for which there is an exceptionally strong evidence base and relatively low uncertainty. For example, damages such as sea level rise, agricultural systems impacts, and heat-related mortality. However, it is highly likely that damages will occur via effects on other systems, e.g., through the triggering of tipping points and/or impacts on economic growth. Although the evidence for these areas is less certain, this does not mean that they pose no risk.

Modeling the Effect of This Crux on the Results

In the final model (Model 2+), we integrate the value of damages from two additional pathways (tipping points and economic growth effects) into our CG-adapted estimate of the SCC.

Summary of Modeling Approach

We present three models, organized in order of ascending complexity and uncertainty:

- Model 1 compares the cost per life saved for GHD and climate interventions, thus excluding the significant economic damages that climate change is predicted to cause. We do this to provide a baseline comparison of the two areas that is relatively high confidence and easily interpretable.
- Model 2 incorporates the best evidenced and most certain economic damage modules into Model 1, and applies an EA-aligned ethically-weighting to make this comparable to the CG bar for cost-effective GHD interventions.
- Model 2+ additionally incorporates the impacts of less certain climate damages caused by nonlinear tipping points and impacts of the rate of economic growth.

Unless stated otherwise, all model findings stem from probabilistic Monte Carlo (MC) simulations.[13] The underlying model is straightforward: we calculate the ratio of the Marginal Abatement Cost (MAC) to the total mortality cost of carbon (MCC) or social cost of carbon (SCC), depending on the model. We set distributions for each of the variables, drawing on the relevant literature or assumptions listed below (see subheadings in this section). The MC simulation then randomly draws one MAC and MCC at a time to calculate a single CPLS estimate, and repeats with replacement for a set number of times (in our case, 50,000). The result is a distribution of CPLS estimates reflecting uncertainty across these two inputs.

Model 1: Comparing Cost per Life Saved for Climate and GHD Interventions

Rationale

This section presents a simplified comparison of the cost-effectiveness of climate change and GHD interventions. Specifically, we limit the damages attributed to climate change to the human deaths arising from 1) increasing temperatures (e.g., as a result of heat stroke/exacerbation of other conditions as a result of prolonged exposure to high temperatures) and 2) air pollution associated with the burning of fossil fuels. Doing so allows us to compare climate and GHD interventions on a cost-per-life-saved basis, rather than a more complex (and arguably more opaque) unit such as Coefficient Giving's philanthropic units, which combines life, health, and economic damages into a single figure.[14] Following preferences among EA-aligned organizations (for example, CG or GiveWell), we do not discount lives.

Because this section relies on fewer assumptions than subsequent models, we treat it as the starting point in this results narrative.

---

[13] A Monte Carlo simulation is a computational tool that helps us understand how variation or uncertainty around key variables produces changes in the underlying model's outcomes.

[14] We do leverage CG's units for later models.

Calculating Cost per Life Saved for Model 1: Climate

Model 1 requires that we compare the cost per life saved of climate and GHD interventions. For climate interventions, this is calculated as follows:

$$Cost\ Per\ Life\ Saved\ =\ \frac{Marginal\ Abatement\ Cost\ (\$\ /\ tCO_2)}{Mortality\ Cost\ of\ Carbon\ (Lives\ /\ tCO_2)}$$

The following sections outline the data and assumptions underlying the calculation of marginal abatement cost and the mortality cost of carbon. A trivial worked example is available here.

Calculating Marginal Abatement Costs

We calculate two separate distributions for marginal abatement costs, because these vary significantly for sure-bet versus hits-based donation opportunities:

- For **hits-based climate mitigation opportunities** (such as the policy advocacy approaches employed by EA climate funds like Giving Green or Founders Pledge), we draw from a uniform distribution with bounds of \$0.50 to \$3.50. Our starting point was to identify opportunities that are generally seen as highly cost-effective by these organizations. In our conversations and research, multiple individuals expressed confidence in being able to find interventions at a cost of roughly \$1/tonne or even lower. However, because we maintain significant uncertainty about how realistically these opportunities might scale, we wanted to apply a reasonable, perhaps slightly conservative, lean to our abatement costs. To reflect this, we placed substantial bounds around this estimate. On the lower end, \$0.50 seemed like a plausible floor.[15] On the higher end, we took note of a 2020 EA forum post (Ben, 2020) and its reading of a Founders Pledge report (Halstead, 2018),[16] that suggested an upper bound of \$5.50. While we weighed these various inputs, we ultimately felt that \$5.50 skewed too high for our purposes. By setting the upper bound at \$3.50, we establish a uniform distribution with a median of \$2/tonne, a figure we believe thoughtfully balances the \$1/tonne optimism with an appropriately conservative buffer.
- For **sure-bet climate mitigation opportunities** (e.g., investing in relatively well-evidenced mitigation technologies such as carbon capture and storage plants), we draw on Sievert et al. (2024) to set the cost per tonne of CO_2e mitigated to be between \$226 to \$835.[17]

Calculating the Mortality Cost of Carbon: Heat-Related Deaths

As outlined in more detail below, we use the GIVE IAM to estimate the marginal deaths per tCO_2e that result directly from the increased exposure of humans to high temperatures. The number of deaths is not directly reported in the Rennert et al. (2022) piece because they are embedded in a larger SCC calculation that also includes economic damages and presents the entire result as one dollar value. However, the GIVE model is modular and open-source,

---

[15] Though we note some individuals suggested it was plausible to get to much lower numbers

[16] We don't put too much weight on these numbers because they don't seem to match the scenarios Founders Pledge describes for Coalition for Rainforest Nations (CfRN). The numbers in the post versus the report are as follows: Optimistic \$0.03 vs. tonne \$0.03/tonne (Exact Match); Realistic \$0.29 vs. \$0.24/tonne (Close Match); Pessimistic \$5.50 vs. \$2.60/tonne (Not a Match.)

[17] We spent relatively little time thinking about this number because the cost is multiple orders of magnitude higher than what the most cost-effective interventions suggest, meaning that even the lower bound will not clear the cost-effectiveness bar.

allowing us to back-calculate how many deaths the model assumes occur over a specified period of time until 2300.[18] This also enables us to separate the number of deaths from the economic valuation that the GIVE model assigns to them based on geographic space (it assumes that deaths in high-income countries are worth more than in low-income countries) and time (it assumes a 2% discount rate, effectively assigning a lower value to deaths in the future than to deaths today). Ultimately, we estimate that the heat-related MCC is 4.31×10^{-5} (95% CI: $2.41 \times 10^{-5} – 8.31 \times 10^{-5}$). Details on our procedures are here.

Calculating the Mortality Cost of Carbon: Air Pollution Deaths

Standard climate IAMs do not include the health impacts of air pollution because they are focused on calculating the long-term damages associated with the warming effects of greenhouse gases in the atmosphere, rather than the health impacts of localized, short-lived co-pollutants (like PM2.5) that are often emitted alongside them. However, we have explicitly incorporated air pollution into our assessment of the benefits that climate mitigation interventions can create, given that most real-world climate interventions will simultaneously avert emissions of both CO2e and particulates. Because particulates likely cause many deaths, it seems important to account for that additional impact.

We calculate the lives lost per tonne of carbon emitted on the basis of air pollution using data from peer-reviewed estimates. Because using a single paper would provide a false sense of precision, and we have some uncertainty regarding the most appropriate model, we select three highly cited, peer-reviewed publications in reputable journals: Vohra et al. (2021), Lelieveld et al. (2023), and McDuffie et al. (2021). We used these papers because they represent varied reasonable ranges of the types of damages resulting from air pollution, but also reflect reasonable differences in how these should be modeled.[19] We combine information from across all papers via a Bayesian hierarchical model, using researcher-assigned weights. Ultimately, we estimate that the air-pollution MCC is 1.46×10^{-4} (95% CI: $2.48 \times 10^{-5} – 4.28 \times 10^{-4}$). This is about 3x the heat-related mortality. Details on our procedure are here.

Calculating Cost per Life Saved for Model 1: GHD Interventions

Estimates of cost per life saved are clearer in the GHD literature than for climate, particularly within the EA community, where organizations such as GiveWell and Coefficient Giving have spent significant time and resources on these calculations. We therefore use the three benchmarks derived from these literatures to provide a range of sure-bet and hits-based cost-per-life-saved comparator points, as follows:

- For **hits-based GHD intervention opportunities**, we use three benchmarks derived from the CG valuation of disability-adjusted life years (DALYs).[20] The CG bar is 2000x (Berger and Reid, 2025). CG values U5 deaths at 51 DALYs, and adult deaths at 32 DALYs. 1 DALY is worth 100K in CG terms. On this basis, the cost has to be $2,550[21] for a young child under five and $1,600[22] for an adult to be considered highly cost-effective by CG (or ~$50 per DALY averted). These benchmarks are shown as vertical lines in Figure 1, representing the threshold for high cost-effectiveness.

---

[18] Note that this is different to the PM2.5 deaths, which are a one shot reduction per tonne abated.

[19] The papers differ with respect to which diseases they count as being affected by emissions, and how they model the effects of PM2.5, among other differences.

[20] An explanation of CG units can be found here.

[21] 51*100K;5.1m/2000

[22] 32*100K; 3.2m/2000

- For **sure-bet GHD intervention opportunities**, we use GiveWell's CPLS estimates for Seasonal Malaria Chemoprevention as the sure-bet benchmark. We draw from GiveWell's reported estimates across sub-Saharan Africa, including their own simulation standard errors, and then combine them using an averaging procedure. We then use the model's analytical distribution as the benchmark to beat. Details on our procedure are here.

Model 1 Results

Before focusing on results for hits-based interventions, which remain the focus of our report moving forward, we briefly turn our attention to the difference between sure-bet interventions: giving to a Seasonal Malaria Chemoprevention (SMC) intervention versus a carbon capture intervention. The results are shown in Table 3.

Table 3: Comparison of CPLS for sure-bet interventions in the GHD and climate spaces

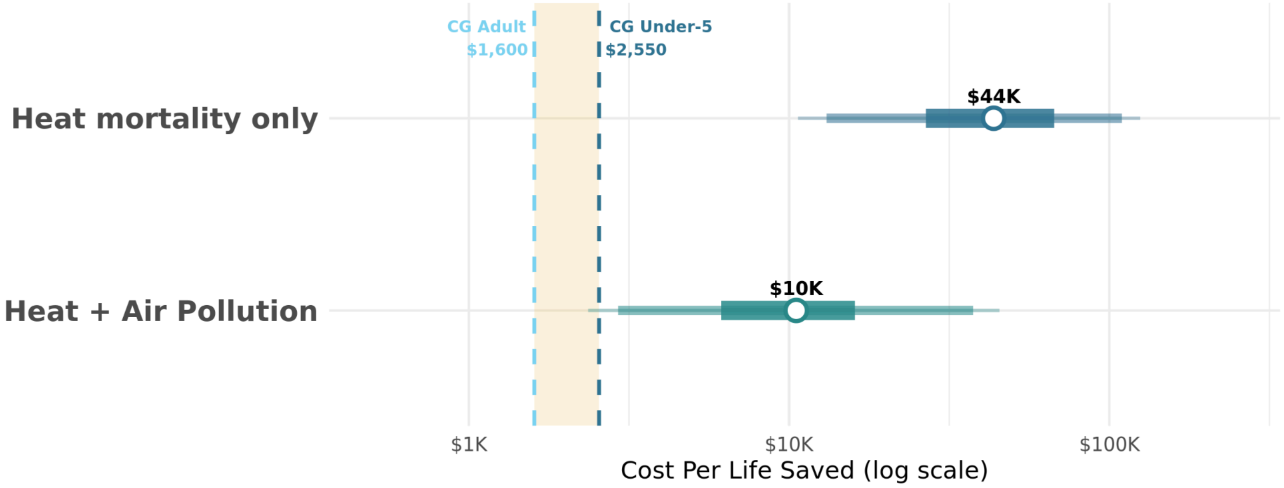
Intervention	Median CPLS	95% Confidence Interval (CI)
GiveWell SMC: Pooled CPLS Estimates	$2,759	[$1,798–$4,206]
Carbon Capture Intervention	$11,871,881	[$3,820,012–$30,973,487]

It is clear from this table that sure-bet climate interventions perform poorly against highly cost-effective, identified sure-bet GHD interventions when only considering mortality associated with rising temperatures. The difference is quite large; our SMC estimates are approximately 4,000x more cost-effective than carbon capture technologies. In short, climate opportunities are not competitive when comparing sure bets. For this reason, we set these comparisons aside for the rest of this report.

Moving on, Figure 1 compares our calculations of CPLS for hits-based climate interventions versus hits-based GHD intervention benchmarks. It considers two variants: 1) a model with heat-based mortality only, and 2) a model incorporating both heat and air pollution mortality.

As the figure demonstrates, heat mortality alone is quite far away from the CG benchmarks (median $43,471), implying that averted heat-related mortality from climate interventions is not competitive when compared to highly cost-effective health opportunities. However, when incorporating air pollution deaths, the distribution moves significantly to the left (median $10,517, which is roughly 4x more cost-effective than the heat-only model). Factoring in air pollution deaths substantially raises the mortality benefit per tonne of CO_2e abated, making climate look much more competitive. This makes sense given our discussion of the magnitude of the air pollution effect previously.

Figure 1: Comparison of hits-based interventions, across mortality scenario



Note. Simulation details. Both models use 50,000 Monte Carlo draws. Heat Mortality Only: the MCC is bootstrapped by resampling with replacement from 50 GIVE model runs (Rennert et al., 2022); abatement cost is drawn from a uniform distribution with bounds of $0.50 and $3.50/tCO₂, reflecting a hits-based carbon removal portfolio. Heat + Air Pollution: the combined MCC adds an independent air pollution drawn from a three-source Bayesian mixture. Bars show 50% (thick), 90% (medium), and 95% (thin) credible intervals; dot = median. Benchmark lines: $1,600 per adult life saved and $2,550 per under-5 life saved, derived from CG moral weights (32 and 51 DALYs, respectively) at CG's $100,000/DALY valuation.

Despite this shift, both distributions indicate a CPLS substantially higher than the cost-effectiveness bar. (Under extreme scenarios, where the cost of abatement is extremely cheap and the MCC is very high, our Heat + Air Pollution model may *just* clear the CG U5 benchmark.) We conclude on this basis that climate interventions are not competitive with GHD interventions when only considering the mortality component of climate change. This remains true:

- Regardless of whether the philanthropic donation takes a hits-based or sure-bet approach
- Even if lives lost now versus in the future are not valued differently
- If we assume a relatively competitive, but perhaps not uniquely optimistic, distribution of mitigation costs (i.e., $0.50–$3.50 / tCO_2e abated)
- When the climate damages accounted for include *only* lives lost due to air pollution and rising temperatures, but exclude economic damages (e.g., from sea level rise, rising air conditioning costs, and impacts on economic growth).

Model 2: Comparing the Broader Lives Lost and Economic Damage Values of GHD vs. Climate Change Interventions

Rationale

This section presents results from a more comprehensive model in which we account for the averted damages of climate change beyond mortality. For example, the economic costs of failing crops, protecting property from sea level rise, and increased bills from air conditioning. To do so, we leverage IAMs,[23] which are explained below.

Calculations of climate damages that include both lives lost and economic impacts attempt to put a single numerical value on the "social cost of carbon" (SCC), defined as the estimated economic cost of the damages caused by emitting one additional tonne of carbon dioxide into the atmosphere. The SCC is usually expressed in US$, which requires putting a dollar cost value on the lives lost, and adding this to the economic costs of damages to, e.g., agricultural systems, energy systems, and sea-level-rise damages. This is typically calculated through a combination of a series of IAMs, some of which focus purely on modeling bio-physical systems, some on modeling human social systems, and others on combining the prior two categories to arrive at an estimate of SCC.

Introducing the GIVE Model

A leading IAM today is the GIVE model (Greenhouse Gas Impact Value Estimator). It was built by Resources for the Future in response to a US National Academies of Sciences, Engineering, and Medicine (NASEM) report, which stated that older legacy IAMs were based on outdated approaches to climate modeling and needed updating.[24] GIVE was subsequently used by the US EPA in 2023 as part of its federal climate valuation and produces SCC estimates using an open-source framework that separates socioeconomics, climate science, economic damages, and discounting into distinct, customizable modules. The version of GIVE used by the US EPA and cited throughout this report includes climate damage modules for:

- **Human mortality:** uses global actuarial data to estimate the relationship between temperature and death rates. It accounts for the ability for humans to adapt to higher temperatures (e.g., as regions get richer, they buy more air conditioning units/solutions/hours, and die less from heat).
- **Agriculture:** models yield changes for maize, wheat, rice, and soy based on temperature and rainfall, and account for trade and market adjustments
- **Energy consumption:** Calculates the net cost of changes in energy demand (e.g., more summer air conditioning and less winter heating)
- **Sea level rise:** Estimates the cost of sea level rise, including loss of land and the costs of building defenses such as protective sea walls

GIVE is a fully probabilistic model providing a mean SCC estimate of $185[25]/tCO$_2$e. The lower 5% bound is $44, representing a world in which the climate has low sensitivity to increasing concentrations of GHGs in the atmosphere and where humans are able to adapt relatively easily to any climate-induced impacts. Conversely, the 95th percentile estimate is $413,

---

[23] The first set of IAMs (now sometimes termed "legacy models") were DICE (developed by Nobel laureate William Nordhaus), FUND (by Richard Tol and David Anthoff), and PAGE (by Chris Hope). These models took a top-down approach to estimating climate impacts, focusing on translating global temperature rises into a percentage loss of global GDP, but with little to no consideration of the spatial distribution of losses around the world, or even of human health and mortality damages from climate change (in the case of DICE and PAGE). However, modern IAMs take a bottom-up, granular approach to estimating climate damages, incorporating huge volumes of location-sensitive data on numerous natural and social systems, and modeling interactions between them under various climate scenarios. Moreover, these latest IAMs are open-source and modular, meaning that researchers around the world can develop speciality modules for e.g., sea level rise or labor productivity, and incorporate them into the model to explore how this affects the outcomes.

[24] National Academies of Sciences, Engineering, and Medicine (NASEM). (2017). Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide. Washington, DC: The National Academies Press.

[25] This is far higher than the prior estimates of the legacy IAMs FUND, DICE and PAGE, which each released central estimates in 2010 of $6, $28 and $30/tCO2e, respectively.

representing a world where the climate is highly sensitive to increasing greenhouse-gas (GHG) concentrations and humans have low adaptation capacity to the resultant temperatures. There are two reasons that the GIVE estimate may underestimate climate change damages:

- GIVE does not include modules on climate impacts such as labor productivity or economic growth, and it also does not explicitly model the risks from tipping points or extreme tail risks, such as conflict or widespread famine due to agricultural system collapse.
- From an EA perspective, the GIVE model SCC valuation will be lower than expected due to the valuation approaches it takes to both human and economic damages.

The following section explains this latter point in more detail.

Valuing human life and economic damages in the GIVE model

Standard climate change IAMs, such as GIVE, take a very different approach to valuing the impacts of climate damages compared to the EA community. For example, the most widely cited application of the GIVE model is that published by Rennert et al. (2022), which formed the basis of the US EPA estimate, finalized under the Biden administration. The valuations of human lives lost and economic damages sustained vary compared to the EA approach as follows:

- **Valuation of life across space:** Rennert et al. (2022) adopt a standard income-elastic Value of Statistical Life (VSL), assigning a higher monetary value to lives lost in wealthier countries than in poorer ones. A typical EA approach, such as that of CG, would convert the lives lost into DALYs and then apply a moral weight of valuing each DALY at $100,000. This values all lives lost equally, no matter where they are lost.
- **Valuation of life across time:** Rennert et al. (2022) apply a market-based discount rate of ~2% to lives lost in the future, thus valuing future lives less than present lives. CG typically uses a more conservative rate of ~0.2% for long-term considerations such as climate change, on the basis that they only discount the future based on a background probability of existential risk. [26]
- **Valuation of economic utility across space:** Rennert et al. (2022) value $1 of damages in a wealthy nation exactly the same as $1 of damages in a poorer nation. In contrast, CG's approach applies an equity weighting, such that financial damages occurring in poorer regions are weighted more highly than those occurring in richer regions, on the basis that $1 lost to a poor individual carries a much higher welfare burden than $1 lost to a richer individual.

Combined with well-established assumptions about the spatial distribution of climate damages (namely, that it will hit the poorest in lower-income countries the hardest[27]) and the fact that most climate-related mortality is projected to occur in the future,[28] the median SCC of $185 provided by Rennert et al. (2022) is far lower than it would be under an EA valuation framework. Our intuition is that if an EA framework were applied to the underlying lives lost and economic damages predicted by the core GIVE model, the resulting valuation would be significantly higher. Consequently, this $185 figure cannot be directly compared to either the

---

[26] Income is another matter entirely. While CG does not discount percentage increases in utility, absolute dollars are discounted at the expected income growth rate.

[27] Dell et al. (2012); Burke et al. (2015)

[28] Both Bressler (2021) and Rennert et al. (2022) report that mortality accumulates over time and so deaths are concentrated in the future. For example: "These [deaths] are concentrated at the end of the century when global average temperatures are highest and marginal changes to temperatures are most damaging." (Bressler, 2021, p.6)

GW or CG funding bars, as it relies on fundamentally different approaches to valuing those damages.

We address this comparability challenge through a bottom-up approach. Essentially, we calculate an “ethically-weighted” SCC, using EA-style valuations of the GIVE model outputs and adding air pollution, to produce a metric that can be compared (roughly) with the GW and CG bars. In the appendix, we also produce a threshold approach that uses a BOTEC to work backwards from the established philanthropic benchmarks of CG and GW to calculate the extent of economic damages averted that would be required for a climate intervention to be considered highly competitive with a GHD intervention. Both methods yield similar results.

Bottom-Up Approach: Calculating an Ethically-Weighted SCC

The task is to take Rennert et al.’s (2022) estimate of SCC using the GIVE model, and apply EA-aligned weights to it; namely, to weight deaths equally over time and space, and to express economic damages as welfare-equivalent income gains. The German Environment Agency (UBA) has produced estimates that already incorporate this approach. According to their Methodological Convention 3.2 document, they recommend: “[u]sing 880 €2024 / t CO_2-eq when weighting the welfare of current and future generations equally (0% pure rate of time preference)” (Matthey et al., 2024, p. 8).

At a high level, our approach is to take their overall numbers at face value with some minor currency and other adjustments, and scale the mortality benefits to account for air pollution. We ultimately arrive at an adjusted SCC of **€1,809/tCO_2** (~CG$1,600 when adjusted for currency and inflation). We then translate this into a CG SROI metric, where *Benefits per tCO_2e* are divided by the *cost per tCO_2e abated*. Details on our procedures are here.

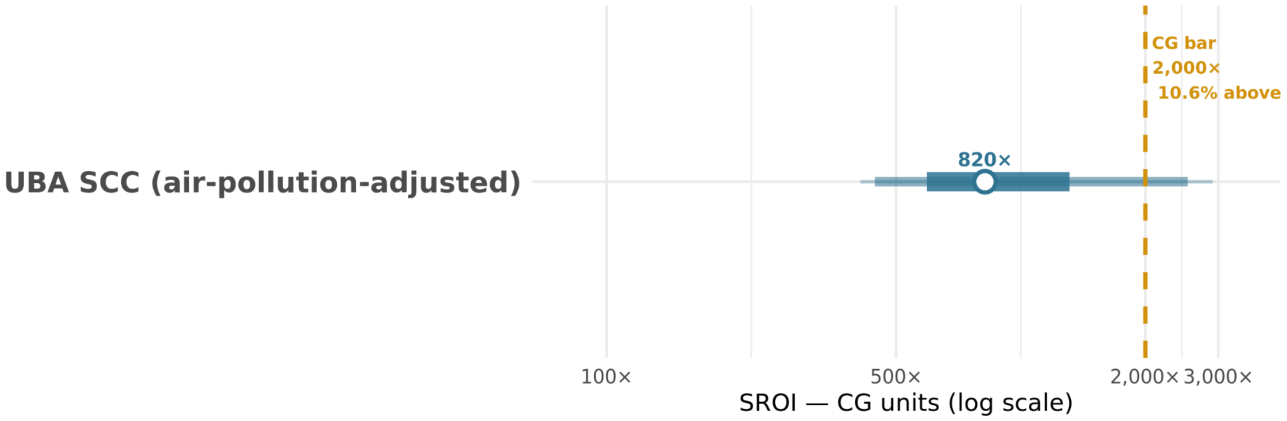
The results show that a full SCC model incorporating the discussed mortality and economic benefits can be competitive with a GHD intervention, albeit only in an upside scenario.[29] The median draw is 820x, which is 2.4 times away from the bar. As a further sense check, the results are broadly consistent with our threshold approach in the appendix, which generates a value 3x lower than the CG bar.[30]

---

[29] A brief aside regarding risk tolerance: while these results suggest there is a universe where hits-based climate interventions meet or surpass the cost-effectiveness of top GHD programs, pursuing them carries inherent uncertainty. Because of this layered risk, some donors may disprefer climate interventions relative to a 2,000x GHD intervention (which may itself be a hits-based or sure-bet opportunity).

[30] Readers might be interested in noting that our estimate of the GW bar is around 800x in CG SROI, which would imply that UBA SCC is competitive with the best GW opportunities—though we have not spent much time doing this translation and have not double-checked with GW.

Figure 2: UBA adjusted SCC in CG SROI



Note. Results are from 100,000 Monte Carlo draws. The UBA SCC baseline of €880/tCO_2e (0% PRTP; [Matthey et al., 2024](#)) is first adjusted for air pollution co-mortality: the 32% mortality share is scaled up by a pollution multiplier derived from the Model 1 heat-to-combined MCC ratio, raising the adjusted mean. Four stochastic inputs are then propagated: (1) UBA SCC; (2) EUR/USD exchange rate; (3) GDP deflator; (4) abatement cost. The dashed amber line marks the 2,000× CG return threshold; the annotation reports the share of draws exceeding that bar.

Model 2+: Incorporating the Impact of Tipping Points and Endogenous Growth Effects on the Cost-Effectiveness of Climate Change Interventions

The results above indicate that the social cost of carbon (SCC) would need to be in the order of **CG$~4,000** (if CG$1,600 = 820x; then ~CG$4000= 2000x**)** in order to meet the CG bar for cost-effectiveness. In this section, we assess how likely this is based on the inclusion of estimates for climate damages that are generally considered too uncertain for inclusion in mainstream IAMs such as GIVE, but that are nonetheless likely to occur to some extent. Specifically, the literature highlights two[31] areas that are worth consideration in the context of this calculation:

1) The likelihood of and damages caused by natural **tipping points**
2) The extent to which increasing temperatures impacts the rate of **economic growth**

The following subsections assess the implications of each of these for SCC estimates, based on the latest scientific literature.

Tipping Points Increase the SCC by at Least a 1.25x Multiplier

The GIVE model is based upon a "smooth damage function," i.e., the damages modeled within its mortality, agriculture, sea level rise, and energy demand modules assume that as temperature increases by a fraction of a degree, the associated damages increase by a predictable and proportional amount. This means that GIVE effectively ignores the risks posed

---

[31] Initially, we planned to add labor productivity as a further area alongside economic growth and tipping points in this section, on the basis that the Data-driven Spatial Climate Impact Model (DSCIM) model (also used as part of the US EPA's SCC estimate) includes a damage module on labor productivity, and GIVE does not. However, the DCSIM model produces a similar estimate of SCC ($190) because it predicts lower damages for agriculture and energy than GIVE while estimating high labor productivity costs. Moreover, including labor productivity alongside economic growth effects would risk significant double counting. We therefore exclude it from this section but note that some models include this module in some detail.

to human life and welfare by climate-induced tipping points, such as the thawing of Arctic permafrost or the collapse of the Amazon rainforest, where crossing a critical temperature threshold triggers sudden, nonlinear, and irreversible catastrophic shocks to the global climate system.

We use the Model for Economic Tipping point Analysis (META) model, developed by Dietz et al. (2021)[32], to incorporate the likely value of these impacts into our estimates.[33] The META model estimates national-level climate damages from rising temperatures and sea levels for 180 countries, and assesses the collective economic damages that could arise from eight major climate tipping points, including carbon-cycle and temperature feedbacks; ice sheet disintegration; and changes in large-scale circulation systems. Taken together, Dietz et al. (2021) estimate that the impact of including these tipping points into existing climate models would increase the SCC by 25%. However, these authors and others note that this is likely an underestimate, given that some additional tipping points, tipping point interactions, and impact channels have not been sufficiently researched to be included in their model (Keen et al., 2022). For example, Dietz et al. (2021) report that there is a ~10% chance of climate tipping points more than doubling the SCC.[34]

On the basis of this evidence, we consider it reasonable to increase our SCC estimate by 25% from ~CG$1600 to ~CG$2000.

Endogenous Economic Growth Effects Could Multiply the SCC by 2x to 15x, Though This is Uncertain

Standard IAMS, including GIVE, tend to assume that any climate impacts on economic growth take the form of “level effects.” For example, if a climate shock like a severe drought occurs, the model registers a drop in economic output for that specific period. Crucially, however, it assumes that the underlying engine of economic growth continues at its original rate from that newly lowered baseline.

In contrast, a growing subset of the macroeconomic literature argues that climate change may affect the *rate* of growth, leading to so-called endogenous growth effects, initially prompted by empirical evidence[35] that temperature shocks persistently reduce economic production rates, particularly in poorer nations. For example, if extreme heat persistently lowers labor productivity, the economy may grow more slowly every single year thereafter. When this is represented over time, the mathematics of compounding interest means that even a small impact on the annual economic growth rate can expand into large long-term economic damage, significantly increasing associated SCC estimates.

---

[32] Dietz et al. (2021)

[33] Earlier stochastic models estimated the theoretical risk premium of climate tipping points by treating them as probabilistic events that impose calibrated but ultimately assumed GDP losses (see, e.g., Cai et al., 2015). Following the methodological guidance of Kopp et al. (2016) and the U.S. Environmental Protection Agency’s 2023 review of unquantified climate impacts, we opted to use the META model from Dietz et al. (2021). The META model resolves the limitations of older models by physically coupling actual geophysical tipping elements (e.g., permafrost thaw, ice sheet disintegration) directly into the economic damage functions. This provides a structural, evidence-based central estimate rather than the previous top-down models whose results depend on more subjective risk-aversion parameters.

[34] Our team is currently developing models to understand or estimate the likelihood of damages from tipping points and feedback loops.

[35] Burke et al. (2015)

The precise impact of endogenous growth on climate damages remains hotly debated within the climate community. Arguing in favor of accounting for endogenous growth impacts, eminent climate scientists and economists, such as Nicholas Stern and Joseph Stiglitz, state that the current IAM assumptions of smooth, uninterrupted economic growth are "absurd," particularly at higher temperatures:

> *[IAMs] have underlying growth processes which essentially embody standard growth models with exogenous growth of 1-2% p.a. over the indefinite future. Given the extraordinary disruption likely at 3-6 degrees Celsius, this assumption would seem to be absurd given the deterioration of productive opportunities likely to arise with a transformation of the environment which likely results in immense loss of life, destruction of capital, collapses in biodiversity, and a recasting of where was habitable.* (Stern et al., 2021, p. 54)[36,37]

In line with these comments, many other papers conclude that endogenous growth effects should be included and that they will have a sizable impact on SCC estimates. Table 4 summarizes the approaches of recent academic papers on this topic, in addition to their estimates on how endogenous growth effects should influence estimates of the SCC.

It should be noted that most papers do not report the isolated effect of endogenous growth alone, as they also model other assumptions that differ from our baseline SCC generated by the GIVE model. We therefore specify the value(s) of the SCC multiplier(s) they report or that their results imply, and detail the number and nature of the parameters that drive these multiplier effects.

Only Dietz et al. (2021) report the isolated impact of endogenous growth versus exogenous growth, while Dietz and Stern (2015) report a range of 2x for pure endogenous growth and up to 7x when assuming endogenous growth plus severe climate damage convexity and sensitivity risk. The remaining estimates are presented in ascending order of SCC multiplier value, with brief explanations of the factors within the models that drive the ultimate figures.

Table 4: Summary of recent academic literature estimating the impact of climate-induced endogenous growth impacts on SCC values

Academic paper	SCC multiplier	Driver(s) of the multiplier
Dietz et al. (2021)	1.87x[38]	Endogenous growth: assumes 100% of climate damages operate through compounding GDP rather than static output levels

---

[36] Stern et al. (2021)

[37] For reference, the GIVE model puts the probability of a 3 degree temperature rise by 2100 at the ~75-80th percentile of its distribution, providing a roughly 1-in-4 or 1-in-5 chance that the world would meet or exceed 3 degrees average global temperature rise by the end of the century. The probability would of course be much higher if longer time horizons (e.g., to 2200 or 2300) were considered.

[38] See p. 61 of Supplementary information for Dietz et al. (2021)

Dietz and Stern (2015)	2x - 7x[39]	Mixed: The lower bound (~2x) represents pure endogenous growth. The upper bound (~7x) combines growth with severe damage convexity and climate sensitivity risk.
Bilal and Känzig (2024)	>5x[40]	Combined: Persistent growth effects plus a methodological shift to capture global macroeconomic interactions of damages rather than isolated local effects.
Moore and Diaz (2015)	~6.6x[41]	Combined: Endogenous growth plus updated empirical baseline damage functions for poorer nations, highlighting significant negative growth effects in poorer countries.
Kikstra et al. (2021)	15x[42]	Combined: Assumes 10% of economic shock damage persists and combines this with the empirical data of Burke et al. (2015), which predicts extremely high damages to economies in the Global South.

Arguing against the case for the inclusion of endogenous growth effects are scientists who claim that these estimates are extremely uncertain and vulnerable to the assumptions of the modelers. For example, Newell et al. (2021) conducted a cross-validation of multiple growth models, concluding that the results were extremely vulnerable to assumptions regarding the background economic time trends. By adjusting these, they report no statistically significant impacts on growth rates in poor countries. Moreover, the huge variation in the estimates their model produced regarding 2100 GDP impacts (anywhere from -84% to +349%) led them to conclude that we simply do not have enough certainty to draw policy conclusions from this data. A further line of argument against the inclusion of endogenous economic effects is that societies should be able to adapt their systems to gradual shifts in climatic conditions over time. For example, a critique from Aufhammer (2018) of the empirical data cited above (Burke et al., 2015) is that this is indicative of shock events that catch individuals (e.g., farmers) by surprise, and that this should not be conflated with the impacts of long-term, more gradual increases that governments/societies can better foresee and adapt to.

We agree that calculating the effect of endogenous growth on SCC estimates includes high uncertainty. However, there also seems to be growing consensus that at least some economic damage will persist, rather than recovering after each climatic shock event. We note that the lower range estimates of Dietz et al. (2021) and Dietz and Stern (2015) start from very low baseline SCC figures (due to their use of the highly conservative DICE IAM, which estimates an SCC of $40 as standard). As a result, these multipliers may represent a lower bound. Likewise,

---

[39] The baseline DICE model gives an SCC of $40. Introducing endogenous growth damages alone roughly doubles this estimate. When further assuming that damages scale exponentially at higher temperatures, the SCC estimate increases drastically to $280 (7x).

[40] The Bilal paper outputs a SCC of $1056, which is just over 5x the Rennert SCC of $185

[41] Ran the DICE IAM climate model, split into "rich" and "poor" regions. Assuming exogenous (level) growth produces a SCC of $33. Assuming endogenous growth assumes a SCC of $220, approximately 6.6x.

[42] 15x number presented at Kikstra et al. (2021), Climate-economy feedbacks, temperature variability, and the social cost of carbon (Kikstra et al., 2020, p. 8).

the Kikstra paper is an outlier in its estimate of a 15x SCC multiple, with some versions of its model effectively predicting the collapse of economies in the Global South. We therefore feel there is insufficient additional supporting evidence for us to justify applying a multiplier of 15x. Taking an average across all multipliers displayed in the above table gives an estimate of 6.3x, which we reduce to 5x, given the significant uncertainty inherent in these models.

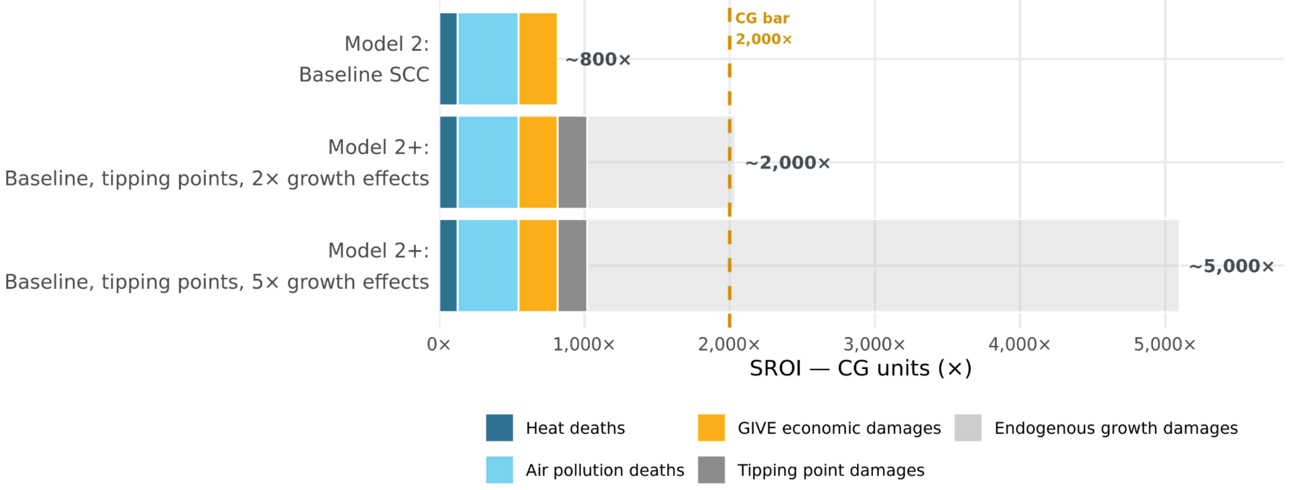
We apply this multiplication to the previous valuation of ***~CG$2,000*** *(incorporating tipping points), which yields an SCC value of* ***~CG$10,000****, and an* ***SROI of ~5,000x, far clearing the cost-effectiveness bar****.*

Concluding Remarks

When accounting for the SCC multipliers of 1.25x for tipping points and 5x for the impacts of endogenous growth effects, climate change interventions easily clear the CG bar. In a deterministic model using our median SCC, the bar is cleared by more than 3,000 SROI units; in other words, a climate intervention would be more than twice as effective as the most effective GHD interventions.

Figure 3 displays the approximate value of the contributions of human life plus various economic damage types to the ultimate estimate of value, expressed in CG$. For comparison, we also include a 2x multiplier for endogenous growth effects and note that this also enables climate interventions to clear the CG bar.

Figure 3: Applying multipliers to UBA-adjusted SCC SROI



Note. Component shares follow [Matthey et al. (2024)](): agricultural damage 59%, mortality 32%, energy consumption 7%, sea level rise 2% of the €880/tCO_2 baseline. The air pollution mortality segment is estimated by applying the Model 1 pollution multiplier to the 32% mortality share; the non-mortality components are held at their original absolute values. All values are converted to 2020 USD and expressed as SROI units at a central abatement cost of \$2.00/tCO_2. Reading the chart: colored segments represent the original UBA component values, identical in absolute terms across all three rows. The gray extension (left tail) shows the additional SCC that would be required to reach 1.25*2× or 1.25*5× the baseline. The dashed amber line marks the 2,000x CG threshold.

We therefore conclude that philanthropic donations to climate change causes can be competitive with some GHD causes under the following conditions:

- The donation goes towards hits-based climate funds, such as Giving Green or FoundersPledge, which aim to provide high-leverage opportunities for climate-based giving through advocacy channels and catalyzing technological innovation
- Such hits-based climate funds offer donation opportunities, where the cost of abatement is within the range of $0.50–$3.50
- Deaths from air pollution are included in the model, in addition to deaths from increased temperatures
- The life and economic damages caused by climate change are valued using CG's principles
- Estimates of the ultimate social cost of carbon account for uncertain but potentially highly significant impacts, such as tipping points and mid-range estimates of the damages arising from endogenous economic growth effects

Contributions and acknowledgments

Abbie Clare and Tom Vargas jointly researched and wrote this report. Vargas also served as project lead. Clare supervised the project. Thank you to John Firth and Ruby Emerson for comments.

Special thanks to Shane Coburn for copyediting, to Thais Jacomassi for bibliography support, and to Elisa Autric for help with publishing this report.

An anonymous client provided funding for this report, but they do not necessarily endorse our conclusions.

Appendix A: Additional Sources from EA Forum

- "If someone identifies as a longtermist, should they donate to Founders Pledge's top climate charities than to GiveWell's top charities?" by Brian Tan
- "Clean cookstoves may be competitive with GiveWell-recommended charities" by Sanjay
- "Introducing our Newest Charity Recommendations—From Reducing Brick Kiln Emissions to Securing Scale-up Funding for Alternative Proteins" by Ambitious Impact
- "Climate research in effective altruism" by Rethink Priorities
- "Metaculus Launches Space Technology & Climate Forecasting Initiative" by christian
- "[Notes] Could climate change make Earth uninhabitable for humans?" by Ben
- "How We Think about Expected Impact in Climate Philanthropy" by jackva
- "Better weather forecasting: Agricultural and non-agricultural benefits in low- and lower-middle-income countries" by Rethink Priorities

Appendix B: GIVE Model Calculations

Rennert et al. (2022) report that the SCC attributable to heat-related mortality is approximately $90 per tonne of CO_2e. This is a monetized figure that weights deaths according to local income at a 2% discount rate. *This is not a standard EA framework* because it values lives differently across space or time. Still, since the GIVE model is open source and modular, we are able to run it directly and extract the exact number of deaths in the model, which allows us to value them directly. The actual code is written in Julia. Because we are unfamiliar with this coding language, we asked Claude Code to rerun the model with 50 trial runs (instead of 10,000), given time and computing constraints. We set the run configuration following the parameters given in Rennert et al. (2022) for their preferred model:

Table B1: Key GIVE Model Parameters

Parameter	Value
Preferred near-term discount rate	2.0%
Pulse year	2020
Pulse size	1e-4 GtC (= 366,667 tCO_2e)
Damage period	2020–2300
Number of countries	184

The logic of the Julia model is:

- Run the model to get the number of global deaths.
- Inject a small amount of CO_2 in the year 2020 to estimate how this changes the total number of global deaths for the entire period (1×10^{-4} GtC).
- Obtain the difference and divide by the pulse, which is the marginal mortality cost of carbon for heat-related deaths for one extra tonne of CO_2.

The model run took around six hours in our Claude Container (implemented via Docker). We checked Claude Code's output at various times to ensure that it did what it said it was doing, asked it to produce auditable CSV files, and fed the code and results to Gemini for confirmation. Aside from passing these tests, the output produced from our small run largely reconstructs the one provided by Rennert et al. (2022) (see table below). In short, we are reasonably confident that this output is a meaningful and faithful implementation of the GIVE model. As such, we have high confidence in the marginal mortality estimates it provides.

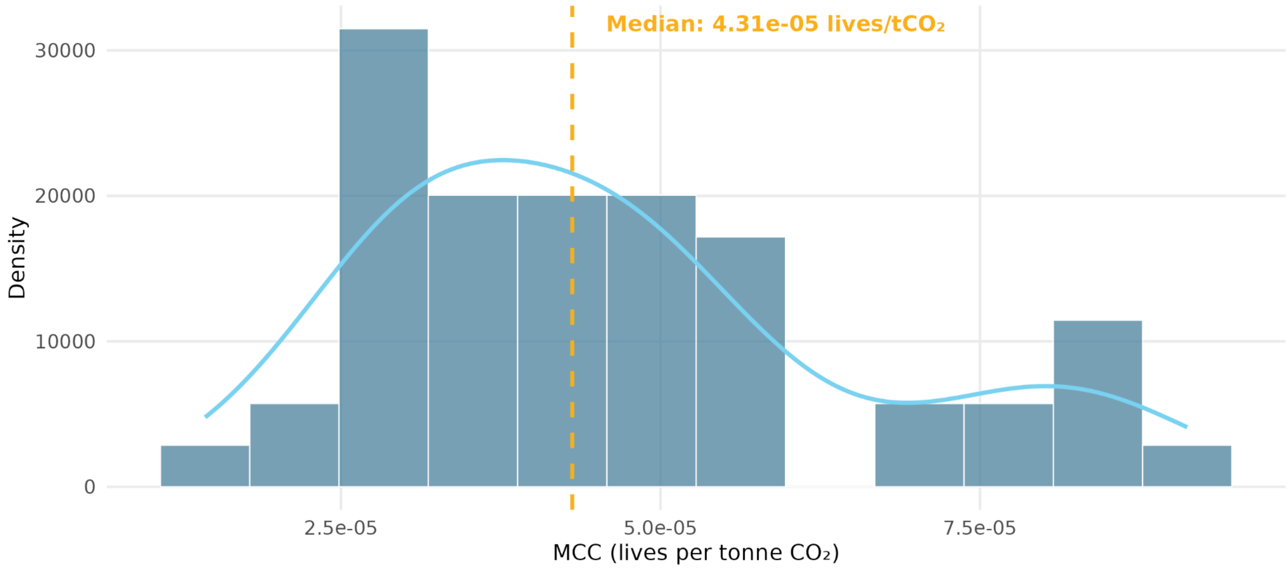
Table B2: Comparison of GIVE implementation

	Rennert et al. (2022) reported values ($/$tCO_2e$)	Our GIVE model implementation ($/$tCO_2e$)	Difference (%)
Total SCC (Mean)	185	192.7	+4.2%
Components			

Mortality	90	90.16	+0.2%
Agriculture	84	91.3	+8.7%
Energy	9	8.92	-0.9%
SLR	2	2.36	+18.0%

The figure below shows the output of the model in MCC (lives per tonne CO$_2$e). Note that because of our limited draws, the tails might not be well represented.

Figure B1: Heat mortality cost of carbon according to our runs of the GIVE model



Appendix C: Air Pollution Calculations

No paper reports the MCC attributable to air pollution. To do so, we take each paper's estimated fossil fuel attributable PM2.5 death per year and divide it by the respective emissions released globally for that year. The paper estimates and our calculation are in the table below:

Table C1: Estimated fossil fuel attributable PM2.5 death per year across the literature

Paper	Estimate in millions (95% CI)	Year	Calculated Air Pollution MCC
Vohra et al. (2021)	10.2 (5.03 – 15.36 M)	2012	2.93e-04 (1.45e-04 – 4.41e-04)
Lelieveld et al. (2023)	8.34 (5.63 to 11.19)	2019	1.47e-04 (1.21e-04 – 1.73e-04)
McDuffie et al. (2021)	1.05 (0.74–1.36)	2017	3.00e-05 (2.42e-05 -3.58e-05)

This Air Pollution MCC is a simplification in two key ways. First, not all CO_2e is equally deadly (abating coal, for instance, eliminates far more particulate matter per tonne than abating natural gas). Second, our estimate represents the average MCC rather than the marginal. We think this is likely acceptable because, unlike the convex heat-damage function, the pollution-damage function is generally concave, meaning the first few particles cause more harm than additional ones in a saturated environment. If anything, we are likely overstating the return to climate interventions, meaning that a more accurate measure would make climate look less appealing. Given that abatement occurs across a mix of clean and polluted regions globally, the average provides a reasonable estimate of the marginal benefit.

Bayesian Implementation

The pollution MCC is modeled as a Bayesian-weighted combination of three air pollution MCC distributions (one per paper). The prior over the air pollution MCC is:

$$p(\mathrm{MCC}_{\mathrm{poll}}) = \sum_{i=1}^{3} w_i \cdot \mathcal{N}^{+}(\mu_i, \sigma_i^2)$$

where w_i are researcher-assigned mixture weights (Vohra 20%, Lelieveld 60%, McDuffie 20%), μ_i and σ_i are the mean and standard deviation from each paper's MCC. Rather than averaging the three estimates into a single point, we assigned weights given our intuitions regarding the mainstreaminess of each paper. The reason is that Vohra feels too high to us and McDuffie seems too low. But a different implementation with equal weight would not change the results meaningfully.

Appendix D: GiveWell Seasonal Malaria Chemoprevention MC

To obtain a firm estimate of the SMC CPLS, we look to GiveWell's spreadsheets. Specifically, we draw from their Confidence intervals sheet the median and confidence intervals associated with the following data: cost per under-5 child reached, under-5 malaria mortality rate, proportion of mortality falling within the SMC season, SMC efficacy on under-5 deaths, over-5 mortality, and grantee-level adjustments. We analytically derive the standard deviations and set normal distributions around these parameters. We then draw with replacement 10,000 to estimate:

$$CPLS = \text{cost-per-child} \times [1 \div (\text{mortality rate} \times \text{seasonal proportion} \times \text{efficacy})] \times \text{over-5 adjustment} \times \text{grantee adjustment}.$$

We then use a simple sampling procedure to create a distribution around the CPLS. Effectively, we treated the 16 location-specific median values as exact data points. We calculated the simple average and standard deviation of those 16 medians, and then assumed a standard normal distribution with that shape. We then drew 100,000 analytical samples for both the grand mean (scaling the variance for our sample size) and the predictive distribution. After exponentiating those draws back into real dollars, we obtain a simple and fast "posterior," though this is not technically a posterior, since it is a closed-form approximation. (Another user might prefer using a full Bayesian hierarchical model to account for, among other things, the nested nature of the data and to profit from shrinkage, but we thought this model was simple enough to make our stark point). The distributions' mean posterior CPLS serves as the GHD benchmark in Table 3.

Appendix E: Threshold Approach to Calculating the Extent of Economic Damages to Make Climate Competitive with GHD

We developed a deterministic BOTEC to estimate the economic benefits required to make a climate change mitigation intervention competitive with GHD, as follows:

1. *Find the allowable emissions:* We take each of the benchmarks and divide them by the intervention cost (which we set at the median abatement cost of $2) to determine how many tonnes we need to reduce to save one life.
2. *Calculate the target MCC:* We take the reciprocal of this number to obtain the required Mortality Cost of Carbon (MCC) in lives per tonne.
3. *Determine the gap:* We subtract the median MCC estimate from our Model 1 Heat + Air Pollution (1.90E-04) from the target to arrive at the remaining benefit required to hit the benchmark (for the median draw).
4. *Find the multiplier:* Finally, we divide this difference by our actual median MCC to obtain exactly how many times larger the total MCC needs to be.

Table E1: Multipliers required to reach benchmarks

	CG U5	CG Adult	GW	Average of all three benchmarks
Multiplier	2.61x	4.76x	1.49x	~3x

Table E1 above shows the results of the BOTEC, which suggests that the aggregated economic benefits would have to be roughly 3x the size of the mortality benefits so that the median simulation draw meets the average benchmark. We consider the size of these multipliers in this section.

Appendix F: Methodological Details on SCC Adjustment

With medium-high certainty, we believe that the UBA SCC estimates are roughly aligned with what a CG evaluation would be. This is true insofar as:

- Mortality is not discounted at all.
- Income/economic gains are evaluated using a log utility function for income (in the UBA case, anchored on the median income in Germany ~50,000 EUR).
- Moral weights are similar (e.g., a DALY is equal to doubling of income).

We have least confidence in the last bullet, but believe the other two items align across methods. If we are right, then we need only account for *air pollution* to express UBA's estimate in CG units, our preferred units when mixing health and economic benefits.

Adding air pollution benefits to the UBA SCC is straightforward using some simplifications. UBA already notes that mortality benefits account for 32% of their SCC. From Model 1, the air pollution component is roughly three times the heat-only component. We therefore scale only the mortality slice of the UBA SCC by this multiplier, leaving the remaining 68% (non-mortality damages) unchanged. This yields an air-pollution-adjusted central estimate of **€1,809/tCO$_2$**. A deterministic BOTEC using median values is shown here; the resulting SROI is roughly 800x, which is below the 2,000x CG bar. We implement a Monte Carlo simulation with noise around the adjusted €1,809 central estimate[43] alongside uncertainty in abatement costs, yielding the distribution depicted in Figure 2.

---

[43] Alongside trivial uncertainty in exchange rates.

Appendix G: A Note on CG Units

CG units of impact[44] are defined as the utility of giving $1 to someone earning $50,000 per year in the United States (approximately the median national income). This serves as a baseline to which all income gains, regardless of where they occur globally, are compared. To make universal comparisons, CG relies on a logarithmic utility function. This model acknowledges that the wellbeing derived from additional income is not linear: the more money one has, the less additional wellbeing is gained from each extra dollar. Under CG's conversion formula,[45] giving $1 to a person making $100 annually is therefore significantly more impactful than giving it to someone making $50,000. This model has two specific mathematical consequences:

1. An additional dollar is proportionally more valuable to a lower-income individual. For instance, a $1 increase for a person earning $500 per year represents a 0.2% raise (1/500 = 0.002). For a person earning $50,000 per year, that same dollar represents only a 0.002% raise (1/50,000 = 0.00002). Therefore, the impact of that single dollar is 100 times greater for the lower-income individual. (0.002/0.00002=100)
2. A fixed percentage increase in income generates the same *value* regardless of the initial income. Because the model values proportional gains rather than absolute dollar amounts, a 10% raise generates the same utility for a person making $100 as it does for one making $500. When converted back into CG units (baseline dollars), this value is constant. The calculation for both individuals is: 50,000 * ln(1 + 0.10) = ~4,765 CG units.

Finally, CG benchmarks DALY-denominated health gains against income. Specifically, each DALY averted is valued at 100,000 CG units. This allows for direct comparison between health and economic interventions. For example, if an intervention averts one DALY for a cost of $1,000, it delivers 100 CG units of impact for every dollar spent (100,000 impact/1,000 cost). By using these inputs, we can consolidate deaths, DALYs, and economic effects into a single metric.

---

[44] Technically, this is our language. CG uses $ impact or philanthropic value when referring to their valuations.

[45] The formula is $v = 50{,}0000 \cdot w \cdot y \cdot \ln(1 + z)$ where v is the philanthropic value of a z% increase in income for w people over y years (in the calculation of short-term benefits, y is 1 year).