Supplementary Materials

for

Methodology Matters:

A Careful Meta-analysis of Climate Damages

SM.1 Extended Discussion of Hypothesis Testing in Section 5.2

Using our preferred model, we test several key hypotheses, as shown in Table SM.5 in the Online Supplementary Material.

First, in our primary dataset and model, we combine damage estimates corresponding to all climate scenarios to improve our estimation power, given our small sample size. This implicit assumption may bias our preferred estimate, as more rapid climate change should lead to greater damages, due to decreased time for natural and human adaptation. Including average annual rate of temperature change (*delta_t*) as a control variable, we find that AICc increases despite the corresponding coefficient's theoretically correct sign, indicating that combining scenarios is currently appropriate. Moreover, when we restrict our dataset to include only estimates consistent with each study's primary climate scenario or to a Business-As-Usual Scenario, we find that our results are consistent with our preferred specification.

Second, in past meta-regressions, there was an ongoing debate about whether climate damage estimates were increasing over time (Howard and Sterner 2017). To test this hypothesis, we include a control variable *Time* measuring the publication date since 1994 in our preferred specification to hold temperature and the estimation methodology mix constant. We find compelling evidence that damage estimates increased over the last 30-years at an average rate of 0.1% annually, as the coefficient is statistically significant at the 10% significance level and AICc declines. In contrast, we find that the inclusion of grey literature does not have an impact on our results. Both findings are consistent with the results in our previous study (Howard and Sterner 2017).

Finally, consistent with our discussion in Section 3.3, we test whether the inclusion of damage estimates that measure the % of change of GDP per capita instead of % change of GDP biases our damage estimates downwards. However, we find evidence of the opposite, though this appears to be driven by the overlap of these estimates with growth studies. Thus, the results are inclusive.

SM.2 Extended Discussion of Sensitivity Analysis in Section 5.3

In addition to the analysis above, we conduct sensitivity analysis to each of the key decisions in our estimation process: our study and estimate selection criteria; our assumptions underlying our forecasting of standard errors for damage estimates; our functional form assumption; our weighting of estimates; and our treatment of outliers. See Tables SM.7 to SM.11 in the Supplementary Material.

As discussed in Section 3, when conducting a meta-analysis, analysts should use a formal search and selection procedure to the extent possible. If an informal process is included, as is standard in the meta-regression of global climate damages, it is important to conduct sensitivity analysis when multiple selection assumptions are justifiable. Given the multitude of possible assumptions, we conduct two types of analyses: we drop each individual study to determine its impacts on our regression results (Figure SM.1); and we impose alternative assumptions that can lead to the inclusion and exclusion of large numbers of estimates (Table SM.7).

With respect to excluding studies one by one, we find that non-catastrophic level impacts are stable, while only three estimates affect either the magnitude of catastrophic impacts (Kikstra et al. 2021) or the magnitude of the growth effects (Dell et al. 2012; Kotz et al. 2024). We did not consider any of these studies *a priori* for exclusion, as we assigned these three studies relatively high subjective quality rankings of 50% to 100%. If we assign all three estimates (Dell et al. 2012; Kikstra et al. 2021; Kotz et al. 2024) low quality status and exclude them, consistent with our selection criteria, the catastrophic and growth coefficients decline by 36% and 20%, respectively, compared to our preferred specification. For a 3°C increase, our ranges of non-catastrophic and total damages shift down to 3.3% to 8.1% for the former and 9.2% to 14% for the latter, with the upper end of the ranges corresponding to growth effects (Table SM.7).

Since our paper's acceptance, it came to our attention that Nature issued an expression of concern regarding Kotz et al. (2024) on November 6, 2024, suggesting it may warrant a lower quality score. Dropping this estimate alone results in a damage function of

$$D = 0.622 \times T^{1.5} + 1.837 \times cat \times T^{1.5} + 1.270 \times Growth \times T.$$

This implies a reduced growth coefficient by 36% relative to our preferred specification, which lowers non-catastrophic damages by nearly a quarter – from 9.2% to 7.0% – for a 3°C increase when accounting for growth effects. See Table SM.7.

Excluding Kotz et al. (2024) from our primary dataset is challenging, because 1.) the quality concerns arose after our literature search's 2023 cutoff date, 2.) editorial action is still pending, and 3.) Kotz et al. (2021, 2022, 2024) are the sole statistical papers to account for climate impact drivers beyond local temperature. Moreover, dropping Dell et al. (2008) – the earliest growth study and one of the three estimates discussed in the previous paragraphs – has an offsetting effect. For these reasons, we leave Kotz et al. (2024) in our dataset.

One potential solution is to replace Kotz et al. (2024) with their earlier estimates. While only Kotz et al. (2024) produces global damage estimates, Waidelich et al. (2024) translates the results of Kotz et al. (2022) into global climate damage estimates. It could serve as a potential replacement, as we excluded it solely on the grounds of duplication. Unfortunately, it is an imperfect substitute, as it does not account for persistence in climate impacts in contrast to Kotz et al. (2024), as Kotz et al. (2022) finds only limited evidence of persistence, with one-year lags observed for only a subset of climate indicators. If we replace Kotz et al. (2024) with Waidelich et al. (2024), assuming a level effect as discussed by the authors, the growth coefficient declines by 39% and the temperature coefficient increases by 4% relative to our preferred specification. This change lowers non-catastrophic damages by nearly a quarter – from 9.2% to 7.0% – for a 3°C increase when accounting for growth effects (Table SM.7).

We conduct sensitivity analysis to the classification of Waidelich et al. (2024) as capturing temporary climate impacts, as it is difficult to determine whether Waidelich et al. (2024) reflects a growth effect. On the one hand, Waidelich et al. (2024) assumes impermanence "to be conservative", noting that they "abstract from the possibility that climatic shifts do not only change GDP growth in a given year but alter a country's long-run growth trajectory persistently." On the other hand, it does account for cumulative impacts, albeit in a very limited way. Therefore, we conduct sensitivity analysis as the cumulative level effect is potentially consistent with our definition of a growth estimate with a very low level of persistence. We find that the coefficient corresponding to growth declines by 31% relative to our preferred specification, which lowers non-catastrophic damages by nearly a fifth – from 9.2% to 7.4% – for a 3°C increase when accounting for growth effects; see results in Table SM.7. Thus, the reclassification of Waidelich et al. (2024) as a growth paper slightly mitigates the decline in the corresponding coefficient and damage estimates.

Finally, in addition to the reasons given above for keeping Kotz et al. (2024) in the primary dataset, another key consideration is that Waidelich et al. (2024) indicates the potential for a similarly large estimate. As Waidelich et al. (2024) finds damages of 10% of GDP for a 2°C increase relative to the current time-period, accounting for persistent growth impacts, as suggested by the authors, "would increase damage estimates substantially". Since incorporating additional lags – along the lines of Kotz et al. (2024) – into Waidelich et al. (2024) could potentially offset the resulting decline from dropping Kotz et al. (2024), we hesitate to completely reject a longer lasting impact.

With respect to including additional studies, we relaxed earlier assumptions to include low quality studies and some duplicate estimates from previous Howard and Stern (2017) and Nordhaus and Moffat (2017) studies and/or to include various estimates that we screened out in the selection process but believed to be relevant enough to include for sensitivity analysis instead of dropping them altogether. We find no significant impact on our preferred results. The same is true when we narrow our selection criteria to focus on estimates preferred by the underlying studies' authors. Finally, when we consider only new estimates published since 2015, which may contain more accurate information and high quality estimation strategies than the older estimates, non-catastrophic level impacts increase. Even so, its value is still within the preferred specification's confidence interval.

Next, we conducted sensitivity analysis over our underlying dataset and functional form assumptions used to estimate the standard errors in Equation (3) and the method for forecasting standard errors; see Table SM.8. In our preferred specification, we use only observed standard errors to estimate a linear spline equation with an intercept and use it to construct standard errors for *all* damage estimates. We relax a combination of three assumptions to conduct sensitivity analysis: (1) we relax our decision to use observed standard errors only by expanding our standard error dataset for estimating Equation (3) to also include standard errors approximated using the minimum and maximum damage estimates in a study provided by the author; (2) we relax our decision to use the linear spline function form with an intercept to consider a polynomial function with an exponent of 1.5; and (3) we relax our assumption of using our estimates of Equation (3) to construct standard error approximations for all damage estimates to instead replace only missing standard error estimates. In general, our results are quite robust, though the growth effect is less stable and our estimate of catastrophic impact declines when we relax the last assumption on only replacing missing standard errors.

Like the standard error function, we also vary the functional form of the damage function. Given the wide range of possibilities, to select the range of potential exponents for each variable, we use the rule of thumb that any specification within two of the minimum AIC (i.e., the best fitting specification) is a strong alternative model candidates (Cavanaugh and Neath, 2019). For our preferred Growth Specification of the damage function, we find that the range of exponents is narrow for the non-catastrophic level and growth effects, while significantly wider for catastrophic impacts. See Table SM.9.

Finally, BN interpret some studies' data differently than us, as well as the relative importance of certain econometric issues. BN emphasize the quality of damage estimates and the risk that outlier estimates can unduly influence results (Nelson and Kennedy 2009), while we focus on heteroskedasticity and omitted variable bias. We explore the impact of emphasizing BN's interpretation of the literature instead of our own. With respect to data, we find that using BN's imputation of data for overlapping studies does not significantly impact our preferred results. In contrast, we find that key differences in our estimators, specifically the use of quality weights and outlier robust estimators, can, but do not necessarily, impact the magnitude of coefficients in our preferred specification.

We explore the impact of adopting BN and our own quality scores. Using Nordhaus' quality weights implies higher growth effects and lower non-catastrophic level and catastrophic impacts. However, the amount of data lost when using his weights makes inference difficult. Instead, when we apply our own quality scores as weights, which are specified for our complete dataset, we find that they have little impact. For the most part, our quality weights are relatively similar to BN for overlapping studies with our weights sometimes being relatively higher (Mendelsohn et al., 2000; Roson and van der Mensbrugghe 2012; Roson and Satori 2016; Kompas et al. 2018) and at other times relatively lower (Dellink et al. 2019; Letta and Tol 2019; Kalkuhl and Wenz 2020).

With respect to outliers, we follow our earlier work to address outliers. First, we drop individual studies one by one and rerun our preferred specification to determine the relative importance of each estimate for the value of each coefficient; see Figure SM.1 and discussion above. Second, we drop each estimation methodology one by one and rerun or preferred specification to determine their relative impacts as well; see Table SM.13 and our discussion in Section 5.4 of the Main Text. Finally, we re-estimate our preferred model using four outlier robust estimators (median regression, m-estimator, s-estimator, and mm-estimator). As discussed in the main text, despite BN's use of the median regression, we focus primarily on the mm-estimator as it is more efficient and performs better in small sample sizes. As discussed in the Supplementary Material in Howard and Sterner (2017), "The mm-estimator was designed to have a high breaking point (i.e., it is relatively robust to a higher percentage of outlier estimates) and to be highly Gaussian efficient (i.e., is efficient if the true distribution is normal) (Verardi and Croux, 2009). The purpose of this design is to address the shortcomings of other estimators: the OLS estimator has a 0 breaking point; the m estimator collapses in the presence of leverage points (i.e., it has a high breaking point relative to vertical outliers only); and the s estimator is relatively inefficient despite having a high breaking point (Verardi and Croux, 2009; Alma, 2011; Jann, 2012)."

Our results are generally robust to these outlier robust estimators, though the magnitude of the damage-temperature relationship is smaller potentially indicating a right-skewed distribution underlying climate damages for a particular temperature increase. We find that that use of Nordhaus' median regression and the m-estimator – one of the three robust estimators used in HS – only slightly mute the impacts of some variables (apart from catastrophic impacts which increase substantially when using the median regression). In contrast, the mm-estimator finds similar results except that catastrophic impacts are much smaller than our preferred regression (Howard and Sterner 2017). Even so, all of the coefficients from the mm-estimator are with the 95th percent confidence intervals of our preferred estimator, while the standard errors for the outlier-robust estimators are relatively smaller.

We choose to focus on our random effects estimator instead of the outlier robust estimators for several reasons. First, we believe that analysts should balance the risk of outliers against the potential information loss from dropping the “outlier” estimates. This is particularly true when the authors of these “outlier” estimates use valid, but underrepresented estimation methodologies or assumptions. Second, the outlier robust estimators reduce our standard error estimates relative to our preferred estimates. Finally, it is unclear to us whether using an outlier robust estimator is preferrable when using the estimate results to calibrate a damage function in a deterministic IAM, such as DICE. In our opinion, expected damage (as measured by our preferred estimate) is the more relevant measurement of impact in this context.

SM.3 Extended Discussion of Synthetic Estimates in Sections 5.4, 5.5, and 6

Overall, the inclusion of methodological controls is critical to measuring climate impacts, given their inclusion improves model fit (according to AICc and BIC) and the joint significance of our model; see Figure 4. While the inclusion of our current set of methodological variables controls for key differences in the treatment effect, particularly differences stemming from varying structural assumptions, there are still unexplained differences between estimation methodologies. Thus, methodological controls may not fully address the implicit weighting of methodologies and their differing underlying structural assumptions.

One potential solution is to use the full theoretically consistent model – Specification 5 in Table 3 instead of Specification 3 – as this controls for additional differences that theoretically should exist. In the future, a more complete analysis controlling for different coverages of economic sectors between estimates is necessary to test whether remaining methodological differences stem completely from different impact coverages.

In another promising direction is to extend the work of William Nordhaus on quality weights (Nordhaus and Moffat, 2017; Barrage and Nordhaus, 2024). Future work could weigh estimation methodologies based on their relative quality to address implicit weighting. However, this would require specifying what makes a high-quality damage estimate and assigning “subjective” quality scores accordingly (Howard and Sterner 2022). It is not clear if there would be a consensus on this issue, as such a large sample survey along the lines of Moore et al. (2024) would be necessary.

SM.3.1 Preferred Synthetic Damage Functions

In the meantime, as estimation methodologies and structural assumptions are highly correlated, we can use the expert elicitation results from Moore et al. (2024) to calculate a synthetic damage function along the lines of what Moore et al. (2024) did for the SCC that implicitly weights methodologies by the relative importance of their structural assumptions.[1] Specifically, Moore et al. (2024) calculates the probability that specific structural assumptions are appropriate when calculating climate damages – such as, tipping point damages (62.1%), growth impacts (60.2%), limited substitutability between market and nonmarket goods (68.2%), and other structural assumptions – using 53 expert responses to questions on whether including specific structural factors improves damage estimates. We apply the probabilities for tipping point damages and growth impacts as ex-post weights to the corresponding components in Equation (5). Specifically, for the catastrophic and growth impacts, we set the values of their corresponding methodological variables in Equation (5) equal to these probabilities, such that $cat = 0.621$ and $Growth = 0.602$.[2] Our resulting synthetic damage function is

$$D = 0.622 \times T^{1.5} + 1.775 \times 0.621 \times T^{1.5} + 1.997 \times 0.602 \times T = 1.202 \times T + 1.724 \times T^{1.5}.$$

For 3ºC and 6ºC increases in global average surface temperature relative to the pre-industrial period, this damage function implies losses of 12.6% and 32.6% of GDP (with 95th percent confidence intervals 0.4% to 24.8% and of -1.4% to 66.5%), respectively. In contrast, a regression without methodological controls produces a damage function of $D = 0.861 \times T^{1.5}$, which implies lower corresponding losses of 4.5% and 12.7%, respectively. To the extent that we omit key methodological controls in our analysis and synthetic damage function, such that we may not fully address the implicit weighting of methodologies (and their structural assumptions), our synthetic damage function may still suffer from omitted variable bias.

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[1] Slightly less than half of enumerative based damage estimates and studies and all scientific-based ones include catastrophic impacts, while other methodologies do not capture tipping points or other catastrophic impacts. Growth impacts are more widely represented in the damage literature across methodologies, but most estimates and studies that account for climate impacts to economic growth are panel-based statistical estimates.

[2] As discussed in our paper, we apply the probability of tipping point damages to our coefficient on catastrophic impacts, though the latter captures a wider set of climate phenomenon and structural assumptions. We test the sensitivity of our results to this assumption below.

As discussed in Section 6 of our paper, there may be reason to prefer the BN approach to catastrophic/tipping damages when constructing a synthetic damage function than our probabilistic weighting of catastrophic impacts. Specifically, Moore et al. (2024) calculates an inclusion probability for damage tipping points based on an expert elicitation on whether "including tipping points in the damage function(s)" affects the mean SCC. As our meta-regression controls for catastrophic impacts – a broader concept than tipping points – it is unclear if the probability applies. Instead, we can probability weight Dietz et al. (2021)'s damage estimate for tipping points, which BN use in their paper, and add it to our preferred meta-regression of non-catastrophic damages to construct an alternative synthetic damage function to Equation (6). Specifically, using Specification 8 in Table 3, we can estimate our preferred synthetic damage function for non-catastrophic impacts

$$D = 0.571 \times T^{1.5} + 1.956 \times (0.602) \times T = 0.571 \times T^{1.5} + 1.178 \times T$$

using the same methods as above. To this we add a probabilistic weighting (i.e., 0.621) of Dietz et al. (2021)'s tipping point damage estimate of 1% of GDP for a 3ºC (i.e., 0.621 ×1%). However, to adjust our synthetic damage function for tipping point impacts, we must calculate the coefficient corresponding to tipping points by rescaling probabilistic damages to account for the temperature increase and the damage functional form, such that $\frac{0.621}{3^{1.5}} = 0.120$. Our new synthetic damage function is

$$D = 0.571 \times T^{1.5} + 1.178 \times T + 0.120 \times T^{1.5},$$

which simplifies to

$$\textbf{(5)}\quad D = 1.178 \times T + 0.691 \times T^{1.5}.$$

This implies total damages of 7.1% for a 3ºC increase, which far exceeds BN's preferred estimate of 3.1%.

SM.3.2 ***Sensitivity Analysis with Respect to the Construction of the Synthetic Damage Functions***

In the above synthetic damage functions, our limited set of methodological controls may not sufficiently address the implicit weighting of methodologies and their differing underlying structural assumptions in our data. As noted above, one potential solution is to use the full theoretically consistent model (Specification 5 in Table 3 instead of Specification 3), which also includes additional methodological controls for market-only impacts and indirect market impacts despite their statistical insignificance according to AICc and BIC, to construct an alternative synthetic damage function. However, simply using the market-only coefficient as a measure of the non-market impacts of climate change is likely inappropriate, as the underlying damage estimates often implicitly assume perfect substitutability between market and non-market goods and services (Hoel and Sterner 2007).[3] In doing so, the damage estimates in our dataset that include non-market impacts generally fail to account for the increase in the relative value of these non-market goods and services over time due to their relative scarcity, which may partially explain the small share (30%) of non-catastrophic damages attributed to climate impacts to non-market goods and services.[4]

Alternatively, we can assume limited substitution, such that climate impacts to relatively scarce non-market goods and services increase their relative value and their prominence in damage estimates over time (Hoel and Sterner 2007; Drupp et al 2024; Moore et al 2024). To account for this increase in value, we follow recent recommendations in Drupp et al. (2024), which recommend that the value of environmental goods and services rise by 2% annually relative to market goods if the quantity of environmental goods and services are relatively stagnant over time. Despite our focus more generally on non-market damages in our context, which includes climate impacts to health in addition to impacts to the environment, we believe that Drupp et al. (2024)'s recommendation applies to our context as well. Specifically, stagnation is a conservative assumption in our case as life expectancy is expected to slowly rise globally over time (Vollset et al 2024) and environmental goods and services, such as for forest area, threatened species, and biodiversity, are likely to slowly decline over time (Drupp et al., 2024). Moreover, to derive their estimate, Drupp et al. (2024) assume an elasticity of willingness to pay for environmental goods and services of one. Similarly, Viscusi and Masterman (2017) find that the elasticity of the value of statistical life with respect

[3] There are some exceptions, particularly for health impacts, such as recent damages estimates using the GIVE model (Rennert et al., 2022).

[4] Specification 5 in Table 3 implies a non-market damage function $D_{non-market} = 0.151 \times Market \times T^{1.5}$, such that non-market damages are $\frac{0.151}{0.806-0.296} = 30\%$ of non-catastrophic damages. Though, the non-market impacts are only $\frac{0.151}{0.806} = 19\%$ of direct impacts of climate change.

to income is slightly above one for most of the world, with the exception being the United States with a value below one. Thus, an elasticity of willingness to pay to avoid climate impacts to non-market goods and services with respect to income close to one is also roughly appropriate. Finally, Drupp et al. (2024) assume an annual GDP per capita growth rate of 2%, which is reasonable.[5]

If we include a 2% annual relative price-adjustment to the coefficient corresponding to market only impacts, the non-market damage function becomes $D_{non-market} = 1.02^{(t-2025)} \times 0.151 \times Market \times T^{1.5}$ where t is the year which the temperature increase of T occurs. Thus, the relative value of impacts to non-market goods and services to non-catastrophic damages will increase over time (by approximately $\frac{0.151 \times 1.02^{t-2025}}{0.359+0.151 \times 1.02^{t-2025}}$), such that the ratio rises to 65% in 2100 and 93% in 2200 compared to 30% now. However, to include non-market damages in the synthetic damage function, we set the market-only indicator variable equal to Moore et al. (2024)'s inclusion probability of 68.75% for the structural assumption of limited substitutability between market and nonmarket goods. The resulting synthetic non-market damage function is

$$D_{non-market} = 1.02^{(t-2025)} \times 0.151 \times 0.682 \times T^{1.5} = 1.02^{(t-2025)} \times 0.103 \times T^{1.5}$$

In contrast, no relative price adjustment is necessary for the indirect market component of the theoretically consistent damage function (Specification 5 in Table 3). Moreover, Moore et al. (2024) does not provide an inclusion probability for indirect market impacts, such that we assume it equals one consistent with our implicit weight on all non-catastrophic impacts (except the relative price adjustment). The indirect market damage function is $D_{Indirect} = -0.296 \times T^{1.5}$.

The theoretically consistent synthetic damage function is

$$\textbf{(8)}\ D = (0.806 - 0.151) \times T^{1.5} + 1.629 \times cat \times T^{1.5} + 1.898 \times Growth \times T + 1.02^{(t-2025)} \times 0.103 \times T^{1.5} - 0.296 \times T^{1.5}.$$

[5] If our resulting synthetic damage function is used with a specific GDP per capita forecast, for internal consistency purposes, the analyst should use the corresponding growth rate in their relative price adjustment. For example, in the context of the EPA (2023)'s calculation of the social cost of carbon which uses the RFF-SP, there is an annual GDP per capita growth rate of roughly 1.6% until 2100 on their most likely scenario. In this case, the value of environmental goods and services should rise by 1.6% annually relative to market goods, instead of by 2%.

This simplifies to

$$D = \left[0.359 + 1.629 \times (0.621) + 1.02^{(t-2025)} \times 0.103\right] \times T^{1.5} + 1.898 \times 0.602 \times T,$$

such that

$$\textbf{(9)}\ \ D = \left[1.371 + 1.02^{(t-2025)} \times 0.103\right] \times T^{1.5} + 1.143 \times T.$$

Based on the mean and median damage estimates that include non-market impacts in our dataset, global average temperature increases of 3ºC and 6ºC occur approximately in 2100 and 2200, respectively. For a temperature increase of 3ºC in 2100 and 6ºC in 2200, our synthetic damage equation implies impacts of 12.9% of GDP and 75.4% of GDP, respectively. Critically, compared to Expression (6), the theoretically consistent synthetic damage function produces similar damage estimates for a 3ºC increase, but damages are significantly higher for a 6ºC increase due to relative prices.

Our theoretically consistent synthetic damage function is sensitive to alternative assumptions. First, assuming a growth rate of per capita GDP closer to 1.6% consistent with EPA (2023)'s use of the RFF-SP implies a synthetic damage function of

$$\textbf{(10)} \qquad D = \left[1.371 + 1.016^{(t-2025)} \times 0.103\right] \times T^{1.5} + 1.143 \times T.$$

Consequently, the damage estimates decrease to 12.3% of GDP and 51.3% of GDP for temperature increases of 3ºC in 2100 and 6ºC in 2200, respectively. Second, we can adopt the approach of Barrage and Nordhaus (2023) to tipping point damages discussed above. The theoretically consistent non-catastrophic damage function derived by setting *cat* equal to zero in Equation (8) above is

$$D = 0.359 \times T^{1.5} + 1.898 \times Growth \times T + 1.02^{(t-2025)} \times 0.103 \times T^{1.5}.$$

To this we add a probabilistic weighting of Dietz et al. (2021)'s tipping point estimate, which is equivalent to 0.621% based on the product of the probability (0.621) and the tipping point damage estimate of 1% of GDP for a 3ºC increase. To adjust our synthetic damage function for tipping point impacts, we calculate the coefficient corresponding to tipping points by rescaling probabilistic damages to account for the temperature increase and the damage functional form, such that $\frac{0.621}{3^{1.5}} = 0.120$. This implies a total synthetic damage function of

$$D = \left[0.359 + 1.02^{(t-2025)} \times 0.103\right] \times T^{1.5} + 1.898 \times 0.602 \times T + 0.120 \times T^{1.5}.$$

This simplifies to a total synthetic damage function of

$$\textbf{(11)} \qquad D = \left[0.479 + 1.02^{(t-2025)} \times 0.103\right] \times T^{1.5} + 1.143 \times T.$$

This implies damages of 8.3% and 62.3% for global average temperature increases of 3ºC in 2100 and 6ºC in 2200, respectively.

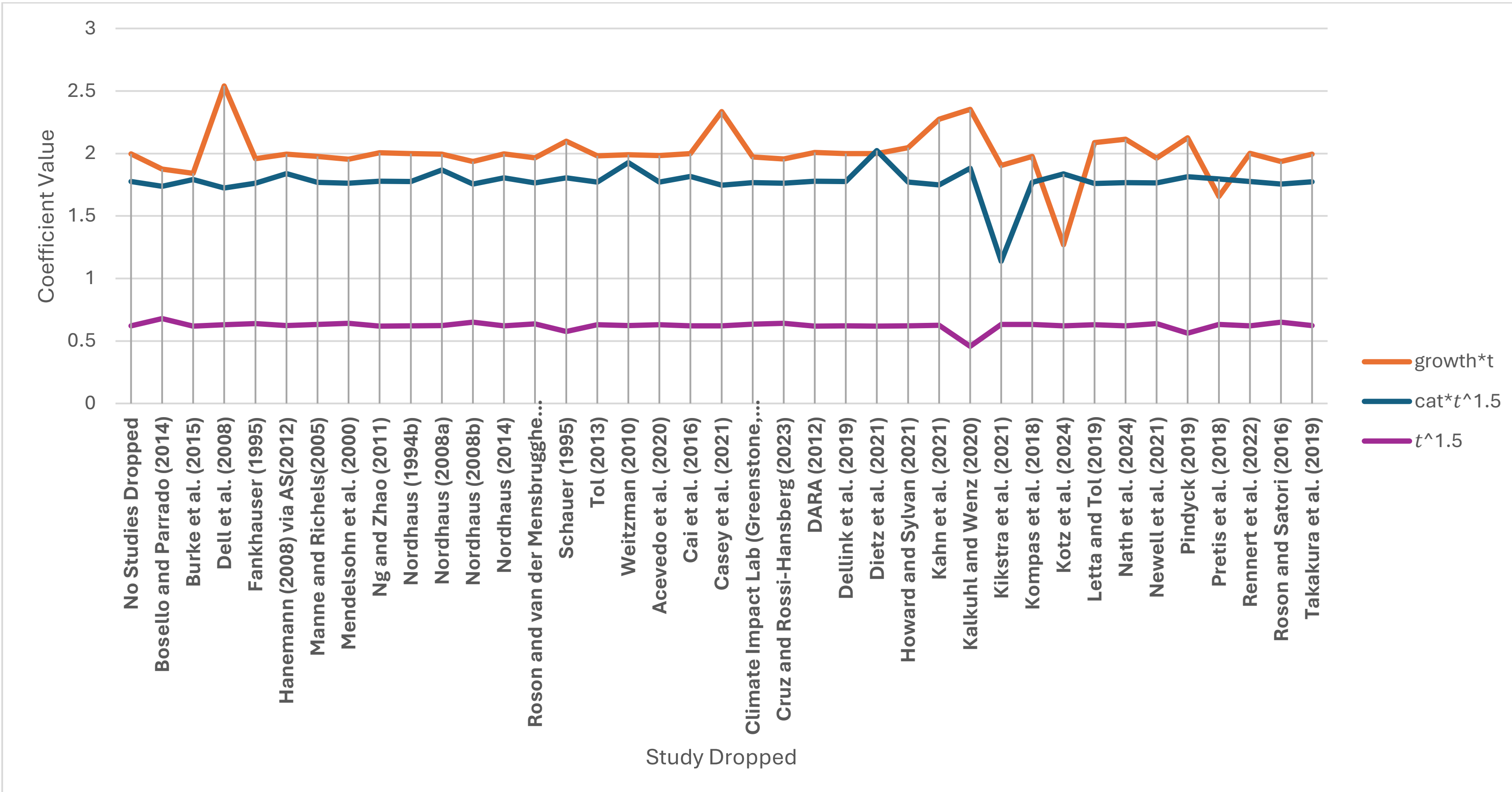

Fig SM.1 Impact of dropping each study on coefficient values of our preferred regression [regression 3 on Table 3], by study dropped and coefficient value. $t^{1.5}$ is temperature change adjusted for its baseline temperature to the 1.5 power, while cat*$t^{1.5}$ is temperature change adjusted for its baseline temperature to the 1.5 power interacted with an indicator variable for whether the estimate includes catastrophic impacts. The variable *growth*t* is an indicator variable for whether the estimate captures a growth effect interacted with temperature change adjusted for its baseline temperature.

Table SM.1. Damage Studies, Estimates, Estimation Method, and Estimate Weights (That Sum to One Within Studies)

Study	Year	D_new	T_new	Method	Method2	Exclude	New	Study Weight
Nordhaus	1994b	3.6	3	Survey	Survey	0	0	0.33
Nordhaus	1994b	6.7	6	Survey	Survey	0	0	0.33
Nordhaus	1994b	10.4	6	Survey	Survey	0	0	0.33
Fankhauser	1995	1.4	2.5	IAM	Enumerative	0	0	1.00
Meyer and Cooper	1995	11.5	3	IAM	Enumerative	1	0	1.00
Schauer	1995	5.2	2.5	Survey	Survey	0	0	1.00
Mendelsohn et al.	2000	-0.1	2.5	Statistical	Cross-sectional	0	0	0.50
Mendelsohn et al.	2000	0	2.5	Statistical	Experimental	0	0	0.50
Kemfert	2002	1.8	0.3	IAM	CGE	1	0	1.00
Maddison	2003	1.2	2.5	Statistical	Cross-sectional	1	0	1.00
Manne and Richels	2005	1.9	2.5	IAM	Enumerative	0	0	1.00
Rehdanz and Maddison	2005	0.6	1	Statistical	Cross-sectional	1	0	1.00
Dell et al.	2008	0.3	3.4	Statistical	Panel	0	0	1.00
Hanemann via Ackerman and Stanton (2012)	2008	4.2	2.5	IAM	Enumerative	0	0	1.00
Nordhaus	2008a	1.8	2.5	IAM	Enumerative	0	0	1.00
Nordhaus	2008b	0.3	2.1	Statistical	Spatial-panel	0	0	1.00
Horowitz	2009	3.8	0.7	Statistical	Cross-sectional	1	0	1.00
Bluedorn et al.	2010	0	0.7	Statistical	Cross-sectional	1	0	1.00
Weitzman	2010	50	6	Science	Science	0	0	0.10
Weitzman	2010	99	12	Science	Science	0	0	0.90
Ng and Zhao	2011	1.6	0.7	Statistical	Spatial-panel	0	0	1.00
Rehdanz and Maddison	2011	16.3	2.5	Statistical	Cross-sectional	1	0	1.00
DARA	2012	0.7	0.5	IAM	Enumerative	0	0	0.25
DARA[A]	2012	1.1	0.5	IAM	Enumerative	0	0	0.25
DARA	2012	1.8	1	IAM	Enumerative	0	0	0.25
DARA[A]	2012	2.7	1	IAM	Enumerative	0	0	0.25

Roson and van der Mensbrugghe	2012	1.8	2.3	IAM	CGE	0	0	0.50
Roson and van der Mensbrugghe	2012	4.6	4.8	IAM	CGE	0	0	0.50
Tol	2013	-1.4	1	IAM	Enumerative	0	0	1.00
Bosello and Parrado	2014	0.9	2.5	IAM	CGE	0	0	1.00
Nordhaus	2014	4.9	3	Science	Science	0	0	0.10
Nordhaus	2014	10.6	3	Science	Science	0	0	0.90
Burke et al.	2015	23	4.3	Statistical	Panel	0	0	1.00
Hambel	2015	.	.	Statistical	Time-Series	1	0	1.00
Howard and Sylvan	2015	0	1	Survey	Survey	1	0	0.50
Howard and Sylvan	2015	10.2	3	Survey	Survey	1	0	0.50
Cai et al.	2016	0.5	0.6	IAM	Enumerative	0	0	1.00
Roson and Satori	2016	-3.9	3	IAM	Enumerative	0	0	0.30
Kompas et al.	2018	3	3	IAM	CGE	0	0	0.60
Pretis et al.	2018	3	0.6	Statistical	Panel	0	0	0.06
Pretis et al.	2018	5	0.6	Statistical	Panel	0	0	0.06
Pretis et al.	2018	7.3	0.6	Statistical	Panel	0	0	0.25
Pretis et al.	2018	8	0.6	Statistical	Panel	0	0	0.06
Pretis et al.	2018	10	0.6	Statistical	Panel	0	0	0.06
Pretis et al.	2018	6	1.1	Statistical	Panel	0	0	0.06
Pretis et al.	2018	8	1.1	Statistical	Panel	0	0	0.06
Pretis et al.	2018	11.7	1.1	Statistical	Panel	0	0	0.25
Pretis et al.	2018	12	1.1	Statistical	Panel	0	0	0.06
Pretis et al.	2018	15	1.1	Statistical	Panel	0	0	0.06
Dellink et al.	2019	2	1.6	IAM	CGE	0	0	1.00
Lamperti et al.	2019	74	4	IAM	Agent-CGE	1	0	0.20
Lamperti et al.	2019	69	4.2	IAM	Agent-CGE	1	0	0.20
Lamperti et al.	2019	38	4.4	IAM	Agent-CGE	1	0	0.20
Letta and Tol	2019	1.9	3.4	Statistical	Panel	0	0	0.50
Letta and Tol	2019	6.5	3.4	Statistical	Panel	0	0	0.50
Pindyck	2019	10.8	1.5	Survey	Survey	0	0	0.25

Pindyck	2019	12	1.5	Survey	Survey	0	0	0.25
Pindyck	2019	28.4	4.5	Survey	Survey	1	0	0.25
Pindyck	2019	29.2	4.5	Survey	Survey	1	0	0.25
Takakura et al.	2019	0.6	0.8	IAM	CGE	0	0	0.13
Takakura et al.	2019	0.7	0.8	IAM	CGE	0	0	0.13
Takakura et al.	2019	1.8	1.7	IAM	CGE	0	0	0.25
Takakura et al.	2019	2.5	2.2	IAM	CGE	0	0	0.25
Takakura et al.	2019	6.5	3.6	IAM	CGE	0	0	0.25
Acevedo et al.	2020	0.2	1	Statistical	Panel	0	0	1.00
Kalkuhl and Wenz	2020	13.4	2.4	Statistical	Panel	0	0	0.50
Kalkuhl and Wenz	2020	7.4	2.4	Statistical	Spatial-panel	0	0	0.50
Lamperti et al.	2020	16	3.6	IAM	Agent-CGE	1	0	0.20
Lamperti et al.	2020	79	3.6	IAM	Agent-CGE	1	0	0.20
Casey et al.	2021	0.8	1.5	Statistical	Panel	0	0	0.50
Casey et al.	2021	3.4	3.8	Statistical	Panel	0	0	0.50
Dietz et al.	2021	1	2.6	IAM	Meta-analytic IAM	0	0	0.50
Dietz et al.	2021	1.4	5.2	IAM	Meta-analytic IAM	0	0	0.50
Estrada and Botzen	2021	6.2	2.3	IAM	Enumerative	1	0	0.50
Estrada and Botzen	2021	24.7	4.6	IAM	Enumerative	1	0	0.50
Howard and Sylvan	2021	2.2	1.2	Survey	Survey	0	0	0.25
Howard and Sylvan	2021	6.6	3	Survey	Survey	0	0	0.06
Howard and Sylvan	2021	7.4	3	Survey	Survey	0	0	0.06
Howard and Sylvan	2021	8.5	3	Survey	Survey	0	0	0.06
Howard and Sylvan	2021	9.9	3	Survey	Survey	0	0	0.06
Howard and Sylvan	2021	16.1	5	Survey	Survey	0	0	0.25
Howard and Sylvan	2021	25.2	7	Survey	Survey	0	0	0.25
Kahn et al.	2021	7.6	2.9	Statistical	Panel	0	0	1.00
Kikstra et al.	2021	25.1	1	IAM	Enumerative	0	0	0.23
Kikstra et al.	2021	26.8	1.2	IAM	Enumerative	0	0	0.23
Kikstra et al.	2021	6	2.5	IAM	Enumerative	0	0	0.10

Kikstra et al.	2021	36.4	2.5	IAM	Enumerative	0	0	0.23
Kikstra et al.	2021	29.2	3.8	IAM	Enumerative	0	0	0.23
Newell et al.	2021	2.5	4.3	Statistical	Panel	0	0	1.00
Deloitte (Philip et al.)	2022	7.6	1.2	IAM	CGE	1	0	0.10
Rennert et al.	2022	1.6	1.9	IAM	Enumerative	0	0	0.33
Rennert et al.	2022	2.3	2.3	IAM	Enumerative	0	0	0.33
Rennert et al.	2022	2.8	2.6	IAM	Enumerative	0	0	0.33
Climate Impact Lab	2023	-0.4	0.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	-0.1	0.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	-0.6	1.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	-0.2	1.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	-0.1	1.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	-0.1	1.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	0.7	2.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	0.8	2.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	1.8	2.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	3.3	3.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	5.2	3.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	7.4	4.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	7.5	4.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	10.1	4.7	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	13.1	5.2	Statistical	Panel	0	0	0.06
Climate Impact Lab	2023	13.2	5.2	Statistical	Panel	0	0	0.06
Cruz and Rossi-Hansberg	2024	0.5	1.2	IAM	Spatial IAMs	0	0	0.25
Cruz and Rossi-Hansberg	2024	0.4	1.3	IAM	Spatial IAMs	0	0	0.25
Cruz and Rossi-Hansberg	2024	2.1	2.8	IAM	Spatial IAMs	0	0	0.25
Cruz and Rossi-Hansberg	2024	2.7	4.3	IAM	Spatial IAMs	0	0	0.25
Kotz et al.	2024	16.5	0.4	Statistical	Panel	0	0	0.25
Kotz et al.	2024	16.9	0.7	Statistical	Panel	0	0	0.25

Kotz et al.	2024	23.2	0.8	Statistical	Panel	0	0	0.25
Nath et al.	2024	0.4	0.9	Statistical	Panel	0	0	0.13
Nath et al.	2024	0.8	0.9	Statistical	Panel	0	0	0.13
Nath et al.	2024	3.2	2	Statistical	Panel	0	0	0.13
Nath et al.	2024	5.4	2	Statistical	Panel	0	0	0.13
Nath et al.	2024	7	2	Statistical	Panel	0	0	0.13
Nath et al.	2024	6.8	3.7	Statistical	Panel	0	0	0.13
Nath et al.	2024	11.5	3.7	Statistical	Panel	0	0	0.13
Nath et al.	2024	15	3.7	Statistical	Panel	0	0	0.13

[A] *DARA (2012) provides estimates of market impacts and health impacts of climate change in terms of lost human lives. Using the EPA (2023) methodology, we estimate the monetary value of health impacts of climate change according to the report. Therefore, the lower damage estimates for a temperature increase cited here match the study, as they include only market impacts. The two higher estimates for each temperature change reflect our calculations.*

Table SM.2. Variable Definitions

Variable	Definition
D_new	Climate damage as a % of GDP
Damage	Non-catastrophic damages (*D_new* with catastrophic damages removed)
SE	Standard error of the climate damage estimate
T_new	Increase in average surface temperature (°C) relative to base year
t	Increase in average surface temperature (°C) adjusted for study's base period (equal to 0 if catastrophic only impacts)
delta_t	Average annual rate of temperature change (°C/year)
T_Base	Temperature increase (°C) in base year relative to pre-industrial
Base_Year	(Central) year when base temperature increase occurs
Impact_Year	Year when final temperature increase occurs
Market	Indicator variable equal to 1 if estimate includes only market damages
cat	Indicator variable equal to 1 if estimate includes catastrophic damages
prod	Indicator variable equal to 1 if estimate captures the impacts of climate change on GDP through economic productivity
cross	Indicator variable equal to 1 if study uses cross-sectional data without country fixed Effects
indirect	Indicator variable equal to 1 if the estimate captures indirect market damages
Growth	Indicator variable equal to 1 if estimate captures growth effect
Level	Indicator variable equal to 1 if estimate captures growth effect and uses temperature level variable(s)
Change	Indicator variable equal to 1 if estimate captures growth effect and uses temperature change variable(s)
Time	Year published minus 1994
Grey	Indicator variable equal to 1 if study is drawn from grey literature
GDPPC	Indicator variable equal to 1 if study measures damages in terms of % change in GDP per capita
m_iam	Indicator variable equal to 1 if estimate uses an IAM (enumerative or CGE) to derive damages
m_science	Indicator variable equal to 1 if estimate uses the science-based method to derive damages
m_stat	Indicator variable equal to 1 if estimate uses the statistical-based method to derive damages
m_survey	Indicator variable equal to 1 if estimate uses the survey-based method to derive damages

m2_cge	Indicator variable equal to 1 if estimate uses a CGE-IAM to derive damages
m2_cross	Indicator variable equal to 1 if estimate uses the cross-sectional statistical method to derive damages
m2_enum	Indicator variable equal to 1 if estimate uses the enumerative method to derive damages
m2_other_stat	Indicator variable equal to 1 if estimate uses a non-panel statistical method to derive damages
m2_panel	Indicator variable equal to 1 if estimate uses the panel-based statistical method to derive damages
m2_science	Indicator variable equal to 1 if estimate uses the science-based method to derive damages
m2_survey	Indicator variable equal to 1 if estimate uses the survey-based method to derive damages

Table SM.3 Functional Forms

Functional Form	Equation	Dependent Variable
Quadratic Function	$g(T) = \alpha_1 T + \alpha_2 T^2$	Damage
Sextic Function	$g(T) = \alpha_1 T^2 + \alpha_2 T^6$	Damage
Power Function	$g(T) = \alpha T^\lambda$ with $0 < \lambda \leq 6$	Damage and Standard Error
Linear Spline / Piecewise Linear	$g(T) = \alpha_1 T + 1[T > \lambda] \times \alpha_2 T$ with $0 < \lambda \leq 6$	Damage and Standard Error
Linear Spline with Constant	$g(T) = \alpha_1 + 1[T > \lambda] \times \alpha_2 T$ with $0 < \lambda \leq 6$	Standard Error
Constant	$g(T) = \alpha_1$	Standard Error

Table SM.4. Standard Error Regressions (Estimating Equation 3 in our paper) using OLS with Cluster Robust Standard Errors at the Estimation Method Level, by Data and Model Assumption

a. Data Used In Regressions Are Only Observed Standard Errors

Specification	Observed Standard Errors Only					
	All SE Estimates				SE Estimates Corresponding to Temperature Changes Less Than or Equal to 4°C	
	SE Estimates Corresponding to Non-Catastrophic Damages		SE Estimates Corresponding to Total Damages		SE Estimates Corresponding to Non-Catastrophic Damages	SE Estimates Corresponding to Total Damages
	Poly-nomial	Spline	Poly-nomial	Spline	Constant	
	Alternative	Best	Alternative	Preferred	Best	Best
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES[A]	SE	SE	SE	SE	SE	SE
$t^{1.5}$	1.369***		1.366***			
	(0.072)		(0.075)			
1[t>2.7]*t		6.604***		6.546***		
		(1.253)		(1.193)		
$cat*t^{0.5}$			16.815***	19.043***		21.072***
			(0.540)	(1.407)		(1.835)
1[t>2.6]*t						
Constant		4.150**		4.196**	4.744**	4.717**
		(1.556)		(1.517)	(1.537)	(1.562)
Observations	30	30	35	35	23	28
Likelihood	-101.1	-99.94	-119.8	-118.6	-63.49	-84.01
R2	0.6	0.357	0.643	0.42	0	0.461
Adjusted R2	0.586	0.334	0.621	0.383	0	0.44

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] See variable definitions in Tables 1A and SM.2.

b. Data Used In Regressions Are Both Observed and Calculated Standard Errors

Specification	Observed and Calculated Standard Errors					
	All SE Estimates				SE Estimates Corresponding to Temperature Changes Less Than or Equal to 4°C	
	SE Estimates Corresponding to Non-Catastrophic Damages		SE Estimates Corresponding to Total Damages		SE Estimates Corresponding to Non-Catastrophic Damages	SE Estimates Corresponding to Total Damages
	Poly-nomial	Spline	Poly-nomial	Spline	Constant	
	Alternati ve	Best	Alternative	Preferred	Best	Best
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES[A]	SE	SE	SE	SE	SE	SE
$t^{1.5}$	0.948***		0.947***			
	(0.045)		(0.047)			
1[t>2.7]*t						
$cat*t^{0.5}$			19.819***	20.838***		22.235***
			(0.335)	(1.235)		(1.494)
1[t>2.6]*t		3.620**		3.612**		
		(1.396)		(1.374)		
Constant		3.551*		3.563*	3.740**	3.727**
		(1.484)		(1.459)	(1.256)	(1.272)
Observations	38	38	43	43	29	34
Likelihood	-129.4	-128.5	-148	-147.1	-78.33	-99.13
R2	0.443	0.181	0.527	0.299	0	0.468
Adjusted R2	0.428	0.159	0.503	0.264	0	0.451

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] See variable definitions in Tables 1A and SM.2.

Table SM.5 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3) with Hypothesis Tests for Impact of Scenario, Publication Date, Inclusion of Grey Literature, and GDP Per Capita, by Hypothesis

Specification[A]	Random Effects Modeling Using All Data and Forecasted SE Using Linear Spline with Intercept, Varying by Methodological Controls						
	Preferred	Delta[B]	Primary Scenario[B]	BAU Scenario[B]	Time Linear	Grey	GDP Per Capita
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES[C]	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.406	0.608**	0.695**	0.170	0.620**	0.429
	(0.265)	(0.430)	(0.250)	(0.279)	(0.370)	(0.267)	(0.281)
$cat*t^{1.5}$	1.775	2.199	1.236	1.050	1.817	1.780	2.024
	(1.858)	(2.042)	(1.780)	(2.553)	(1.858)	(1.860)	(1.862)
*Growth*t*	1.997*	2.005*	2.404**	1.776	1.774	1.959	0.990
	(1.130)	(1.133)	(1.110)	(1.177)	(1.138)	(1.266)	(1.232)
Cross	-2.559	-2.096	-2.504		-1.456	-2.550	-1.794
	(6.026)	(6.071)	(6.016)		(6.059)	(6.027)	(6.037)
delta_t		39.252					
		(60.272)					
Time					0.114*		
					(0.065)		
Grey* $t^{1.5}$						0.103	
						(1.540)	
GDPPC* $t^{1.5}$							1.147**
							(0.559)
Observations	105	101	79	45	105	105	105
F-statistic	4.763	3.932	5.575	5.989	4.422	3.811	4.652
Prob>F	0.001	0.003	0.001	0.002	0.001	0.003	0.001
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AICc	760.942	732.741	588.41	338.57	750.209	760.927	745.8819
Damages at 3ºC							

Non-catastrophic/Level	3.2%	2.1%	3.2%	3.6%	0.9%	3.2%	2.2%
Growth	9.2%	8.1%	10.4%	8.9%	6.2%	9.1%	5.2%
Catastrophic	9.2%	11.4%	6.4%	5.5%	9.4%	9.2%	10.5%

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[A] Specification (1) is our preferred random effects model estimated using all selected damage estimates and corresponding forecasted standard errors (approximated using a linear spline model in temperature with an intercept) and with variances estimated using the Knapp–Hartung estimator. Specification (2) includes average rate of temperature change as an additional control variable. Specification (3) only keeps estimates that correspond to the author's preferred scenario(s). Specification (4) only keeps estimates that correspond to Business-As-Usual scenarios. Specification (5) includes a linear time trend. Specification (6) includes an indicator variable for whether the estimate was from the grey literature interacted with the temperature variable to the power of 1.5. Specification (7) includes an indicator variable for whether the estimate measured damages in terms of % of change of GDP per capita (instead of % change of GDP) interacted with the temperature variable to the power of 1.5.

[B] We cannot compare the AICc from Regression 2 to 4 with the AICc from Regressions 5 to 7.

[C] See variable definitions in Tables 1A and SM.2.

Table SM.6 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3), by Standard Error Specification, Whether Dropped Damage Estimates Corresponding to Temperature Increases Below 1ºC, and Whether Bootstrapped Standard Errors

Specification	All Damages Estimates				Damages Estimates Above 1ºC Temperature Change (t≥1ºC)				Double Bootstrap (2,000 Draws)
	Spline SE		Polynomial SE		Spline SE		Polynomial SE		Polynomial (Boxcox) SE[A]
	Non-catastrophic	Total	Non-catastrophic	Total	Non-catastrophic	Total	Non-catastrophic	Total	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES[B]	damage	D_new	Damage	D_new	damage	D_new	damage	D_new	D_new
$t^{1.5}$	0.571	0.622**	0.576	0.578	0.580	0.627**	0.512*	0.497	0.674***
	(0.348)	(0.265)	(0.354)	(0.368)	(0.348)	(0.266)	(0.300)	(0.314)	(0.196)
cat*$t^{1.5}$		1.775		1.633		2.129		2.272	1.011**
		(1.858)		(1.681)		(2.033)		(1.900)	(0.834)
Growth*t	1.956	1.997*	3.748***	3.838***	1.646	1.456	2.201*	2.334*	5.599***
	(1.390)	(1.130)	(1.317)	(1.322)	(1.404)	(1.151)	(1.244)	(1.248)	(1.237)
Cross	-2.359	-2.559	-2.379	-2.383	-2.391	-2.578	-2.124	-2.066	
	(9.440)	(6.026)	(8.868)	(8.872)	(9.440)	(6.027)	-7.744	(7.736)	
Observations	93	105	93	105	76	85	76	85	85
F-statistic	3.56	4.763	7.511	6.331	3.09	3.918	3.972	3.678	-
Prob>F	0.017	0.001	0.000	0.000	0.032	0.006	0.011	0.008	-
Tau2	0	0	18.11	18.28	0	0	0	0	-
I2	0	0	0.229	0.148	0	0	0	0	-
Q	16.1	31.48	116.8	118.6	10.56	17.65	17.03	18.73	-
Chi corrected	0	0	40.74	41.09	0	0	0	0	-

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] In Specification (9), we estimate two-level bootstrapped standard errors randomly drawing observations with replacement in both the standard error and damage regressions. In the first stage, we assume a polynomial function for the standard error model in equation (4) and run a box-cox regression to allow functional form to vary.

[B] See variable definitions in Tables 1A and SM.2.

Table SM.7 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3), by Alternative Selection Criteria

Specification	Preferred	Include Low Quality and Some Superseded Studies	Include Estimates Screened Out in Selection Process	Jointly Include Both Sets of Estimates Added in the Previous Two Columns	Focus Exclusively on Estimates Preferred by Authors	Focus Exclusively on Studies Published After 2015	Drop Dell et al. (2012); Kikstra et al. (2021); and Kotz et al. (2024)	Drop Only Kotz et al. (2024)	Replace Kotz et al. (2024) with Waidelich et al. (2024)	Replace Kotz et al. (2024) with Waidelich et al. (2024) Assuming the Latter Is a Growth Paper
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
t_5	0.622**	0.705***	0.647**	0.636**	0.583**	0.820**	0.637**	0.622**	0.647**	0.621**
	(0.265)	(0.250)	(0.260)	(0.244)	(0.243)	(0.370)	(0.265)	(0.265)	(0.263)	(0.265)
cross	-2.559	0.460	-2.657	-0.796	-		-2.619	-2.560	-2.659	-2.555
	(6.026)	(2.011)	(6.023)	(2.007)	-		(6.026)	(6.026)	(6.025)	(6.026)
growth_t	1.997*	1.909*	1.944*	2.053**	2.544**	1.979	1.605	1.270	1.216	1.379
	(1.130)	(1.032)	(1.125)	(1.006)	(1.153)	(1.360)	(1.224)	(1.147)	(1.145)	(1.123)
cat_t_5	1.775	2.162	1.759	2.202	1.743	2.383	1.133	1.837	1.821	1.829
	(1.858)	(1.636)	(1.858)	(1.635)	(1.837)	(3.104)	(2.070)	(1.858)	(1.858)	(1.858)
Observations	105	124	111	145	81	79	95	101	104	104
F-statistic	4.763	6.767	4.930	6.385	7.249	5.764	3.48	3.547	3.681	3.776
Prob>F	0.001	0.000	0.001	0.000	0.000	0.001	0.011	0.010	0.008	0.007
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[A] See variable definitions in Tables 1A and SM.2.

Table SM.8 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3), by Assumptions Underlying Standard Error Regression and Construction of Standard Error Approximations

Specification[A]	Use Observed Data, Spline Function & Approx. All SE (Preferred)	Use Observed Data, Alternative SE Function (Polynomial) & Approx. All SE	Use Calculated Data, Spline Function & Approx. All SE	Use Calculated Data, Polynomial Function, & Approx. All SE	Use Observed Data, Spline Function & Keep Observed SE	Use Observed Data, Poly. Function & Keep Obs. SE	Use Calculated Data, Spline Function & Keep Obs. and Calc. SE	Use Calculated Data, Poly. Function & Keep Obs. and Calc. SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES[A]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.578	0.609***	0.575*	0.560***	0.551***	0.558***	0.551***
	(0.265)	(0.368)	(0.216)	(0.291)	(0.077)	(0.077)	(0.076)	(0.075)
Cross	-2.559	-2.383	-2.509	-2.374	-2.312	-2.276	-2.308	-2.277
	(6.026)	(8.872)	(5.111)	(7.192)	(6.020)	(7.696)	(5.137)	(5.383)
Growth*t	1.997*	3.838***	1.982**	3.294***	1.297	1.775*	1.245	1.818**
	(1.130)	(1.322)	(0.889)	(1.051)	(0.892)	(0.924)	(0.760)	(0.739)
cat*$t^{1.5}$	1.775	1.633	1.771	1.742	0.731	0.635	0.854	0.696
	(1.862)	(1.681)	(1.677)	(1.659)	(1.299)	(1.219)	(1.227)	(1.208)
Observations	105	105	105	105	105	105	105	105
F-statistic	7.795	6.331	7.421	8.382	15.60	15.84	16.77	16.31
Prob>F	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tau2	0.000	18.280	0.000	22.38	0.937	0.830	0.914	1.012

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[A] We run all possible combination of three alternative assumptions to conduct sensitivity analysis: observed standard errors Versus observed and calculated standard errors; linear spline function with an intercept Versus polynomial function with an exponent of 1.5; and construct standard error approximations for all damage estimates Versus constructed standard error approximations only for damage estimates missing SE values (i.e., only replace missing standard errors).

[B] See variable definitions in Tables 1A and SM.2.

Table SM.9 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3), by Range of Alternative Functional Form Assumptions

Specification[A]	Total Damages							
	Simple		Extended Simple		Growth		Extended Growth	
	(1)		(2)		(3)		(4)	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
VARIABLES[B]	Damage	Damage	damage	damage	damage	damage	damage	Damage
t	1.572***		1.347**		1.210**		1.241**	
	(0.438)		(0.591)		(0.497)		(0.489)	
t^2		0.441***		0.428***		0.326**		0.340**
		(0.117)		(0.140)		(0.142)		(0.138)
prod*$t^{0.5}$			1.678					
			(2.311)					
prod*t^6				0.000				
				(0.000)				
Growth*$t^{0.5}$					5.247*			
					(2.744)			
Growth*t^5						0.827		
						(0.532)		
Level*$t^{0.5}$							7.610	
							(5.409)	
Level*t^5								0.781
								(0.866)
Change*$t^{0.5}$							4.828	
							(3.276)	
Change*t^5								0.858
								(0.649)
cat*$t^{0.5}$	6.576		6.700		6.463		6.129	
	(9.448)		(9.453)		(9.449)		(9.464)	
cat*t^3		0.020		0.021		0.028		0.027
		(0.058)		(0.058)		(0.058)		(0.058)
Cross			-3.468	-2.778	-3.126	-2.140	-3.201	-2.227
			(6.115)	(5.998)	(6.063)	(6.000)	(6.059)	(5.997)
Observations	105	105	105	105	105	105	105	105
F-statistic	6.877	7.563	3.690	3.858	4.472	4.443	3.611	3.523
Prob>F	0.002	0.001	0.008	0.006	0.002	0.002	0.005	0.006
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] See variable definitions in Tables 1A and SM.2.

Table SM10 Preferred Random Effects Estimator (Regression 3 on Table 3) and Outlier Robust Estimators for Total Damages Assuming Growth Model Specification, by Alternative Nordhaus Assumption, Inclusion of Quality Weights, and Outlier Robust Estimator

Specification	Preferred	Consistent Data	Quality Weights		Outlier Robust[A]			
		For Overlapping Studies, Replace Our Damage & Temp. Data with Nordhaus' Damage & Temp. Data	Use Nordhaus' Quality Weights	Use Our Own Quality Weights	Median Regression	M-estimator (Huber 1973)	S-estimator (Salibian-Barrera and Yohai 2006)	MM-estimator (Yohai 1987)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES[B]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.672**	0.289	0.544*	0.481***	0.497***	0.341***	0.410***
	(0.265)	(0.263)	(0.346)	(0.297)	(0.123)	(0.094)	(0.068)	(0.084)
Cross	-3.275	-2.756	0.434	-2.252	-2.000	-2.066***	-1.448***	-1.719***
	(6.084)	(6.025)	(5.866)	(6.049)	(0.000)	(0.370)	(0.268)	(0.330)
Growth*t	1.997*	2.001*	3.188*	2.337*	1.634	1.601***	1.751***	1.454***
	(1.130)	(1.118)	(1.848)	(1.300)	(2.604)	(0.588)	(0.274)	(0.323)
cat*$t^{1.5}$	1.775	1.733	0.166	1.560	5.212	0.328*	0.137***	0.187**
	(1.862)	(1.858)	(5.269)	(1.976)	(3.602)	(0.172)	(0.036)	(0.079)
Observations	105	103	31	105	102	105	105	105
F-statistic	7.795	5.275	1.498	3.543	-	0.153	0.0719	0.144
Prob>F	0.001	0.001	0.231	0.010	-	0	0	0
Tau2	0.000	0.000	0.000	0.000	-	-	-	-

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[A] We use STATA's robreg command to generate these outlier robust estimators, except for the median regression. See discussion in "Extended Discussion of Sensitivity Analysis in Section 5.3" above.

[B] See variable definitions in Tables 1A and SM.2.

Table SM.11 Method-Specific Meta-Regression for Non-Catastrophic Damages Using a Random Effects Estimator And Assuming Simple Model Specification, by Estimation Method

Specification	Aggregate	Method Specific Regression Using General Classification of Estimation Methodologies			Method Specific Regression Using Detailed Classification of Estimation Methodologies			
	All Methods	IAM	Statistical	Survey	Enumerative	CGE	Panel	Survey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES[A]	damage	damage	damage	damage	damage	Damage	Damage	damage
$t^{1.5}$	0.834***	0.375	1.077***	1.288	0.366	0.382	1.143***	1.288
	(0.285)	(0.463)	(0.398)	(0.862)	(0.714)	(0.609)	(0.410)	(0.862)
Weighted Studies	31.4	12.9	15	3.5	7.3	5.6	14	3.5
Observations	93	27	53	13	13	14	51	13
F-statistic	8.564	0.655	7.311	2.231	0.263	0.393	7.762	2.231
Prob>F	0.004	0.426	0.009	0.161	0.618	0.542	0.008	0.161
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Proportion of Weight	1.000	41.1%	47.8%	11.1%	24.0%	18.4%	46.1%	11.5%
Weighted Impact	-	0.154	0.514	0.144	0.088	0.070	0.526	0.148
Sum	-	0.812			0.833			

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[A] See variable definitions in Tables 1A and SM.2.

Table SM.12 Method-Specific Meta-Regression for Total Damages Using a Random Effects Estimator And Assuming Growth Model Specification, by Estimation Method[A]

Specification	Preferred	Method Specific Regression Using General Classification of Estimation Methodologies				Method Specific Regression Using Detailed Classification of Estimation Methodologies				
	All Methods	IAM	Science	Statistical	Survey	Enumerative	CGE	Science	Panel	Survey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES[B]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.361	2.206	0.778	1.519*	0.353	0.382	2.206	0.864*	1.519*
	(0.265)	(0.353)	(2.487)	(0.472)	(0.783)	(0.583)	(0.609)	(2.487)	(0.497)	(0.783)
Cross	-2.559			-3.177						
	(6.026)			(6.220)						
Growth*t	1.997*	13.067		1.616	-0.003	13.083			1.427	-0.003
	(1.130)	(12.472)		(1.472)	(3.346)	(12.489)			(1.512)	(3.346)
cat*$t^{1.5}$	1.775	0.049				0.053				
	(1.858)	(3.658)				(3.662)				
Observations	105	35	4	53	13	21	14	4	51	13
F-statistic	4.763	1.085	0.787	4.397	2.279	0.856	0.393	0.787	6.744	2.279
Prob>F	0.001	0.369	0.440	0.008	0.149	0.482	0.542	0.440	0.003	0.149
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] We use the Growth Specification, though we can only include the variables that are consistent with each methodology, hence the complete set of control variables is not included in any of the method-specific regressions. Only statistical methodologies include cross-sectional studies (*cross*). Similarly, only IAM estimates corresponding to the enumerative method, statistical estimates corresponding to the panel method, and survey-based estimates can account for growth effects. While both IAM estimates corresponding to the enumerative method and science-based estimates can include catastrophic impacts, only the IAM/enumerative regressions can include the interaction of the catastrophic indicator variable (*cat*) and the temperature variable, as there is a portion of these studies that exclude catastrophic impacts. In contrast, all science-based estimates are classified as catastrophic, so the impact of non-catastrophic and catastrophic impacts are captured in the coefficient corresponding to $t^{1.5}$.

[B] See variable definitions in Tables 1A and SM.2.

Table SM.13 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3), by Dropped Estimation Method

Specification	Preferred	Dropped Estimation Method Using General Classification of Estimation Methodologies				Dropped Estimation Method Using Detailed Classification of Estimation Methodologies				
	All Methods	IAM	Science	Statistical	Survey	Enumerative	CGE	Science	Panel	Survey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES[A]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.977**	0.624**	0.552*	0.505*	0.700**	0.765**	0.624**	0.528*	0.505*
	(0.265)	(0.404)	(0.265)	(0.321)	(0.282)	(0.298)	(0.331)	(0.265)	(0.314)	(0.282)
Cross	-2.559	-3.962	-2.566		-2.095	-2.867	-3.123	-2.566	-2.185	-2.095
	(6.026)	(6.145)	(6.026)		(6.038)	(6.050)	(6.077)	(6.026)	(6.062)	(6.038)
Growth*t	1.997*	1.154	1.988*	2.388	2.302*	1.756	1.689	1.988*	2.429	2.302*
	(1.130)	(1.315)	(1.133)	(2.968)	(1.202)	(1.174)	(1.209)	(1.133)	(2.966)	(1.202)
cat*$t^{1.5}$	1.775	1.229	2.011	1.800	1.847	1.506	1.682	2.011	1.817	1.847
	(1.858)	(2.520)	(2.769)	(1.878)	(1.859)	(2.505)	(1.863)	(2.769)	(1.878)	(1.859)
Observations	105	70	101	52	92	84	91	101	54	92
F-statistic	4.763	4.469	4.570	2.010	3.999	4.382	4.72	4.570	1.475	3.999
Prob>F	0.001	0.003	0.002	0.125	0.005	0.003	0.002	0.002	0.224	0.005
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] See variable definitions in Tables 1A and SM.2.

Table SM.14 Preferred Random Effects Estimator for Total Damages Assuming Growth Model Specification (Regression 3 on Table 3) with Temperature-Method Interactions, by Model Specification

Specification	Constructing Temperature Method Interactions Using General Classification of Estimation Methodologies				Constructing Temperature Method Interactions Using Detailed Classification of Estimation Methodologies			
	Simple	Extended Simple	Growth	Extended Growth	Simple	Extended Simple	Growth	Extended Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES[A]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
m_iam*$t^{1.5}$	0.376	0.195	0.374	0.374				
	(0.352)	(0.464)	(0.352)	(0.352)				
m_science*$t^{1.5}$	-0.345	-0.337	-0.060	-0.027	-0.336	-0.159	-0.083	-0.051
	(3.724)	(3.724)	(3.732)	(3.745)	(3.735)	(3.745)	(3.744)	(3.757)
m_stat*$t^{1.5}$	1.093***	0.991**	0.807*	0.853**				
	(0.324)	(0.422)	(0.451)	(0.426)				
m_survey*$t^{1.5}$	1.519**	1.466**	1.373*	1.380*	1.519**	1.442**	1.388*	1.394*
	(0.711)	(0.717)	(0.723)	(0.727)	(0.711)	(0.721)	(0.724)	(0.727)
m2_enum*$t^{1.5}$					0.390	0.387	0.386	0.386
					(0.582)	(0.582)	(0.582)	(0.582)
m2_cge*$t^{1.5}$					0.367	-0.044	0.367	0.367
					(0.443)	(0.778)	(0.443)	(0.443)
m2_panel*$t^{1.5}$					1.206***	0.968*	0.888*	0.928**
					(0.340)	(0.502)	(0.473)	(0.444)
m2_other_stat*$t^{1.5}$					-0.013	-0.000	-0.000	-0.000
					(1.062)	(1.501)	(1.501)	(1.501)
prod*$t^{1.5}$		0.284				0.412		
		(0.475)				(0.640)		
Cross		-4.016	-3.292	-3.472		-0.100	-0.100	-0.100
		(6.164)	(6.196)	(6.168)		(8.392)	(8.392)	(8.392)
Growth*t			1.489				1.327	
			(1.339)				(1.370)	

Level*t				1.660				1.494
				(2.090)				(2.109)
Change*t				1.415				1.273
				(1.521)				(1.540)
cat*$t^{1.5}$	2.551	2.543	2.266	2.233	2.542	2.365	2.289	2.258
	(2.771)	(2.771)	(2.783)	(2.800)	(2.787)	(2.800)	(2.799)	(2.815)
Observations	105	105	105	105	105	105	105	105
F-statistic	3.781	2.835	2.960	2.587	2.872	2.28	2.338	2.105
Prob>F	0.004	0.010	0.007	0.013	0.009	0.023	0.020	0.031
Tau2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[A] See variable definitions in Tables 1A and SM.2.

Table SM.15 Climate Impact-Specific Meta-Regressions for Total Damages Using a Random Effects Estimator And Assuming Simple Model Specification, by Impact Type

Specification	Preferred	Type of Impact			
	All Impact Types	Non-Catastrophic Level	Non-Catastrophic Level (without Cross-Sectional)	Catastrophic Only	Non-Catastrophic Growth
	(1)	(2)	(3)	(4)	(5)
VARIABLES[A]	D_new	D_new	D_new	D_new	D_new
$T^{1.5}$	0.622**	0.619**	0.639**		
	(0.265)	(0.262)	(0.267)		
$Cat*t^{1.5}$	1.775			0.218	
	(1.858)			(4.582)	
Growth*t	1.997*				3.303***
	(1.130)				(1.000)
Cross	-2.559				
	(6.026)				
Observations	105	56	55	3	35
F-statistic	4.763	5.563	5.753	0.002	10.92
Prob>F	0.001	0.022	0.020	0.966	0.002
Tau2	0.000	0.000	0.000	0.000	2.919
I2	0	0	0	0	0
Q	31.48	8.741	8.551	0.001	21.33
Chi corrected	0.000	0.000	0.000	0.000	0.015

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[A] See variable definitions in Tables 1A and SM.2.

Table SM.16 Breakdown of Step (6) in Table 4 in the Main Text into Sub-steps, by Sub-step

Specification	Adopt BN's Alternative Damage and Temperature Data[A]	Drop Grey Literature	Include Studies in BN's Dataset and Excluded in Our Preferred Regression[A]	Switch to BN's Set of Studies Exclusively[A]
	(5)	(5a)	(5b)	(6)
VARIABLES[B]	D_new	D_new	D_new	D_new
T_new^2	0.649***	0.647***	0.591***	0.389***
	(0.050)	(0.055)	(0.075)	(0.063)
Observations	103	63	79	31
Adjusted R2	0.616	0.684	0.437	0.548
Likelihood	-380.1	-231.2	-328.1	-91.08
R2	0.62	0.689	0.444	0.563

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[A] BN refers to Barrage and Nordhaus (2024)

[B] See variable definitions in Tables 1A and SM.2.

Table SM.17 One-by-One Regression Modifications Using Our Preferred Damage Specification (Regression 3 on Table 3)

Specification[A]	Preferred Model (with Knapp–Hartung Variance Estimator	Drop Method-ological Controls	Change Exponent	Drop Base Temp-erature Adjustment	Drop Standard Errors Weights and Stop Clustering SE	Adopt BN's Alternative Damage and Temp-erature Data for Overlapping Estimates	Switch to BN's Set of Studies	Adopt BN's Quality Weights	Adopt Median Reg-ression
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES[B]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
$t^{1.5}$	0.622**	0.861***			0.673***	0.546**	0.601*	0.527**	0.481***
	(0.265)	(0.225)			(0.155)	(0.208)	(0.301)	(0.226)	-0.123
cat* $t^{1.5}$	1.775				1.513***	2.050	-0.145	1.842	5.212
	(1.858)				(0.203)	(1.990)	(8.684)	(1.361)	-3.602
Growth*t	1.997*				2.649***	2.090*	1.782	2.784***	1.634
	(1.130)				(0.572)	(1.083)	(1.646)	(0.761)	-2.604
Cross	-2.559		-2.176	-2.834	-2.761	-2.256	0.279	-2.184	-2
	(6.026)		(6.000)	(6.063)	(7.751)	(5.991)	(2.726)	(9.741)	0
t^2			0.332**						
			(0.142)						
cat* t^2			0.451						
			(0.655)						
Growth* t^2			0.359						
			(0.254)						
$T\_new^{1.5}$				0.692**					
				(0.315)					
cat* $T\_new^{1.5}$				-1.488					
				(4.988)					
Growth* T_new				2.220**					
				(1.109)					

Observations	105	105	105	105	105	103	31	105	102
F-statistic	4.763	14.69	4.399	4.243	78.96	5.128	2.249	12.13	
Prob>F	0.001	0.000	0.003	0.003	0	0.001	0.090	0.000	
Tau2	0	0	0	0	57.7	0	0	6.062	
I2	0	0	0	0	0.943	0	0	0	
Q	31.48	35.84	32.93	33.56	1778	30.33	9.523	84.25	
Chi corrected	0	0	0	0	1414	0	0	2.186	
Non-catastrophic damages for a 3ºC									
Damages (% GDP)	3.2%	4.5%	3.0%	3.6%	3.5%	2.8%	3.1%	2.7%	2.5%
% Change From Previous Column	-	38%	-8%	11%	8%	-12%	-3%	-15%	-23%
Non-catastrophic damages for a 6ºC									
Damages (% GDP)	9.1%	12.7%	12.0%	10.2%	9.9%	8.0%	8.8%	7.7%	7.1%
% Change From Previous Column	-	38%	31%	11%	8%	-12%	-3%	-15%	-23%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[A] Specification (0) is our preferred random effects model estimated using all selected damage estimates and corresponding forecasted standard errors (approximated using a linear spline model in temperature with an intercept) and with variances estimated using the Knapp–Hartung estimator. Specification (1) drop methodological controls. Specification (2) changes the temperature exponent from 1.5 to two. Specification (3) drops adjustments to temperature that account for the base period of the study. Specification (4) drops random effects weights and clustering. Specification (5) adopts BN's interpretation and imputation of damage and temperature data for overlapping studies. Specification (6) switches to BN's set of studies dropping and adding studies accordingly. Specification (7) adopts Barrage and Nordhaus' (2024) quality weights. Specification (8) adopts median regression

[B] See variable definitions in Tables 1A and SM.2.

Table SM.18 One-by-One Regression Modifications Using Barrage and Nordhaus' (2024) Weight-OLS Estimates

Specification[A]	BN Model (Weighted OLS)	Add Methodological Controls	Change Exponent	Add Base Temperature Adjustment	Add Standard Errors Weights and Stop Clustering SE	Adopt our Damage and Temperature Data for Overlapping Estimates	Switch to Our Set of Studies	Replace Quality Weights with Estimate Weights That Sum to One Within Studies
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES[B]	D_new	D_new	D_new	D_new	D_new	D_new	D_new	D_new
T_new^2	0.350***	0.239***			0.299**	0.360***	0.647***	0.494***
	(0.057)	(0.051)			(0.098)	(0.074)	(0.032)	(0.065)
cat* T_new^2		-0.039						
		(0.151)						
Growth* T_new^2		0.536***						
		(0.105)						
Cross		1.921						
		(2.738)						
$T\_new^{1.5}$			0.751***					
			(0.144)					
t^2				0.312***				
				(0.057)				
Observations	31	31	31	31	31	31	102	31
Adjusted R2	0.545	0.749	0.458	0.485	0.38	0.421	0.797	0.648
Likelihood	-93.72	-82.85	-96.45	-95.65	-92.28	-97.76	-387.2	-92.46
R2	0.56	0.782	0.475	0.502	0.4	0.44	0.799	0.659
Non-catastrophic damages for a 3ºC								

Damages (% GDP)	3.2%	2.2%	3.9%	2.8%	2.7%	3.2%	5.8%	4.4%
% Change From Previous Column	-	-32%	24%	-11%	-15%	3%	85%	41%
Non-catastrophic damages for a 6ºC								
Damages (% GDP)	12.6%	8.6%	11.0%	11.2%	10.8%	13.0%	23.3%	17.8%
% Change From Previous Column	-	-32%	-12%	-11%	-15%	3%	85%	41%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[A] Specification (0) is our replication of BN's Weighted OLS Regression. Specification (1) adds methodological controls. Specification (2) changes the temperature exponent from two to 1.5. Specification (3) adds adjustments to temperature that account for the base period of the study. Specification (4) adds random effects weights and clustering. Specification (5) adopts our interpretation and imputation of damage and temperature data for overlapping studies. Specification (6) switches to our set of studies dropping and adding studies accordingly. Specification (7) replace BN's quality weights with estimate weights that sum to one within studies.

[B] See variable definitions in Tables 1A and SM.2.

Supplementary Material (Additional References)

Ackerman, F., E. A. Stanton., and R. Bueno. 2012. CRED v. 1.4 Technical Report. Stockholm Environment Institute, Somerville

Cavanaugh JE, Neath AA (2019) The Akaike information criterion: Background, derivation, properties, application, interpretation, and refinements. Wiley Interdiscip Rev: Comput Stat 11(3):e1460

DARA (2012) Climate Vulnerability monitor-A guide to the cold calculus of a hot planet. In DARA and Climate Vulnerable Forum, Madrid

Hanemann WM (2008) What is the economic cost of climate change? University of California, Berkeley. http://repositories.cdlib.org/are_ucb/1071/. Accessed 09 Jan 2014.

Huber PJ (1973) Robust regression: asymptotics, conjectures and Monte Carlo. The annals of statistics 1(5):799-821

Kemfert C (2002) An Integrated Assessment Model of Economy-Energy-Climate: The Model Wiagem. *Integrated Assessment* 3(4):281–98

Ng P, Zhao X (2011) No Matter How It Is Measured, Income Declines with Global Warming. *Ecological Economics* 70(5):963–70

Nordhaus, W. D., and J. Boyer. 2000. *Warning the World: Economic Models of Global Warming.* MIT Press, Cambridge

Nordhaus WD (2008a) A Question of Balance: Weighing the Options on Global Warming Policies. Yale University Press, New Haven

Nordhaus WD (2008b). New Metrics for Environmental Economics: Gridded Economic Data. Integrated Assessment Journal 8(1):73-84

Schauer, M. J. 1995. Estimation of the Greenhouse Gas Externality with Uncertainty. *Environmental and Resource Economics* 5(1): 71–82.

Salibian-Barrera M, Yohai VJ (2006) A fast algorithm for S-regression estimates. Journal of computational and Graphical Statistics 15(2):414-427

Tol, R. S. 2014. Correction and Update: The Economic Effects of Climate Change. *Journal of Economic Perspectives* 28(2): 221–26.

Viscusi WK, Masterman CJ (2017) Income elasticities and global values of a statistical life. J Benefit-Cost Anal 8(2):226-250

Vollset SE, Ababneh HS, Abate YH et al (2024) Burden of disease scenarios for 204 countries and territories, 2022–2050: a forecasting analysis for the Global Burden of Disease Study 2021. Lancet 403(10440):2204-2256

Waidelich P, Batibeniz F, Rising J et al (2024) Climate damage projections beyond annual temperature Nature Clim Change 14(6):592-599

Yohai VJ (1987) High breakdown-point and high efficiency robust estimates for regression. The Annals of statistics 15(2):642-656.