

Climate shift uncertainty and economic damages

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Focusing on global annual averages of climatic variables can bias aggregate and distributional estimates of the economic impacts of climate change. We here empirically identify dose-response functions of GDP growth rates to daily mean temperature levels and combine them with regional intra-annual climate projections of daily mean temperatures. We then disentangle, for various shared socio-economic pathways (SSPs), how much of the missing impacts are due to heterogeneous warming patterns over space. Global damages in 2050 are 25% (21-28% across SSPs) higher when accounting for the shift in the shape of the entire intra-annual distribution of daily mean temperatures at the regional scale.

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5 Knowing how future climate damages might be distributed across time and
6 space is an important research frontier and policy issue for climate scientists and
7 economists alike. Projections of endogenous climate damages in macroeconomic
8 models [Fernández-Villaverde et al., 2024] typically rely on reduced-form relation-
9 ships between climate change and the macro-economy, which are generally based
10 on *annual* climatic statistics—e.g. mean annual temperatures. Furthermore,
11 models are generally aggregated for that climate variable to be *global*—mean an-
12 nual global temperatures. In these integrated climate-economy models, carbon
13 emissions are a by-product of regional economic activities. A reduced-form cli-
14 mate module captures endogenously how these carbon emissions turn into global
15 annual mean temperature anomalies, from which regional annual mean tempera-
16 ture anomalies can be statistically down-scaled through a simple linear and time-
17 invariant factor, a process also called ‘pattern scaling’. Lastly, the regional phys-
18 ical impacts are interacted with dose-response functions estimated on global data
19 to measure the economic impacts of endogenous climate change. These macroe-
20 conomic models are either global [Nordhaus, 1994, Barrage and Nordhaus, 2024,
21 Cai and Lontzek, 2019, Traeger, 2023], regional [Nordhaus and Yang, 1996] or
22 gridded, as in spatial integrated assessment modelling (IAM), e.g. Krusell and
23 Smith Jr [2022], Cruz and Rossi-Hansberg [2024] and Desmet and Rossi-Hansberg
24 [2024].

25 The underlying assumption behind these approaches is that the shapes of the
26 spatio-temporal distributions of mean temperatures do not matter. Across time,
27 the intra-annual shape of the distribution of daily mean temperature is assumed
28 to remain constant: temperature increases due to climate change are shape-
29 preserving increases in annual mean. Across space, an average increase in tem-
30 perature at global level is assumed to affect the regional annual distribution by
31 a linear and time-invariant down-scaling factor such as the regional transient re-
32 sponse to cumulative emissions [Leduc et al., 2016].

33 The reality of future regional weather changes, however, is more complex, for

two main reasons. First, natural climate variability over time and space, both from external (e.g. solar cycles) and internal factors (e.g. El Niño-La Niña), might distort future temperature distributions beyond the annual mean [Schwarzwald and Lenssen, 2022]. Second and more fundamentally, the process determining the shape of the weather distribution within a given year for a given regional mean temperature might not be stationary, so that time-invariant relations between annual averages and the intra-annual distribution of weather only imperfectly reflect regional-specific shifts in warming patterns. In North-West Europe, the hottest summer days are warming twice as fast as mean summer days [Patterson, 2023]. Cold extremes are anticipated to warm at a faster rate than both hot extremes and average temperatures for much of the Northern Hemisphere [Gross et al., 2020]. Hot days over tropical land warm substantially more than the average day: for example, warming of the hottest 5% of land days is 21% larger than the time-mean warming averaged across models [Byrne, 2021]. That opens the question around the ‘right’ level of spatial and temporal aggregation for projecting future impacts. Aggregation has advantages, as it comes with statistical robustness, clear identification of causal relationships, and numerical tractability in models where anomaly in climate results from endogenous anthropogenic emissions; it also has shortcomings, such as the risk of averaging contradictory effects between regions both in terms of damage and warming patterns.

Instead of modeling climate change stemming from anthropogenic carbon emissions as an endogenous process, some IAMs use spatially disaggregated projections from global circulation models to infer the costs of climate change with adapting agents [Rudik et al., 2022, Bilal and Rossi-Hansberg, 2023]. In these models, which incorporate credible intra-annual climate projections, climate change remains exogenous to economic activities. As a result, the estimates from the two bodies of literature—endogenous and exogenous—have evolved in parallel, yet the effects of this divergence on the aggregate and distributional estimates of climate impacts remain unclear. We aim to shed light on this apparent gap by testing

63 the impact of including regional projections that sample changes in the entire
64 intra-annual distribution of temperatures.

65 To disentangle these spatial and temporal effects, we follow a two-step approach.
66 First, we switch from annual average temperatures to the complete daily tempera-
67 ture distribution over a year and show how this affects the heterogeneous distribu-
68 tion of warming patterns between regions, compared to a setting where we assume
69 a shape-preserving shift in mean annual temperatures under a synthetic changing
70 climate. Second, we interact these regional-specific shifts in warming patterns
71 with intra-annual damage patterns, comparing them to a setting where damage
72 are inferred from annual mean temperature. Building on work on the non-linear
73 effects of temperature on economic activity using temperature bins [Dell et al.,
74 2014, Hsiang, 2016, Auffhammer, 2018], we use non-linear dose response functions
75 in intra-annual temperatures to capture some of the regional idiosyncrasies in the
76 climate-society relationship by considering changes in the intra-annual shape of
77 temperature distributions for each aggregate Köppen-Geiger climatic zone: arid,
78 continental, polar, temperate, tropical.

79 We further probe the consequences of this spatio-temporal aggregation of cli-
80 mate projections on quantifying the uncertainty surrounding any best-guess esti-
81 mate of future climate damages. Uncertainties abound [Rising et al., 2022, Moore
82 et al., 2024, Waidehlich et al., 2024]. The quantifiable variance of future projec-
83 tions of climate impacts is affected by scenario uncertainty (differences in Shared
84 Socioeconomic Pathways, SSPs), model uncertainty (differences in Earth System
85 Models’—ESMs’—responses to the SSPs), internal variability (spatio-temporally,
86 due to the chaotic nature of the climate and due to regional differences that
87 may be hidden by regional aggregation), choices made in post-processing or bias-
88 correcting ESM output (including how finely to apply projected changes in cli-
89 mate distributions from ESMs), regression uncertainty from the dose-response
90 functions, and differences between observational data products used to fit the
91 dose-response function and act as a baseline to which future ESM output is com-

pared. Historically, many studies have relied on global annual average climate variables to estimate and project climate damages, thereby overlooking significant sources of internal variability. These include regional disparities in climate conditions and the tendency to extract only mean changes from ESM projections. This limitation is further exacerbated by the inherent constraints of endogenous reduced-form climate models, which struggle to capture future changes in intra-annual weather patterns—an aspect that might be better addressed through the development of climate emulators [Eftekhari et al., 2024]. We focus on two of these uncertainties and their interaction: the sensitivity of economic impact projections to an improved sampling of internal variability (through capturing regional differences in impacts) and an improved treatment of ESM output (by capturing changes in the full shape of the temperature distribution instead of annual averages). We further uncover some of the model uncertainties between ESMs using the full shape of warming patterns that is usually reduced by the aggregation procedure on a global and annual scale. Lastly, we provide a framework based on mean temperature distributions that can be applied to other climate data, for instance precipitation patterns [Waidehlich et al., 2024], and a quantification to show how much the regional-specific shift in the shape of warming patterns interacting with intra-annual damage patterns matters empirically. We do so both at the aggregate level and in the distribution of impacts, with the year 2050 as a case study.

We also contribute to the recent literature and ongoing debate on the appropriate estimation of future climate change damages. In a sense, we take the opposite approach of Bilal and Känzig [forthcoming], who deliberately avoid disaggregation and rely on global annual average temperature to infer future damages. While we share their concern that time fixed effects may wash out the common component of a shock in the estimation—thereby focusing only on the idiosyncratic regional part—we take the opposite stance by zooming in on intra-annual weather changes both for the estimation and for climate projections. Our aim is to highlight the

121 importance of accounting for both intra-annual variability and regional hetero-
122 geneity when assessing idiosyncratic climate damages. Our core intuition is akin
123 to a Jensen’s inequality argument: if intra-annual damages are convex in tem-
124 perature, then annual averages may be misleading (i.e., temporal heterogeneity
125 matters). A next step beyond our current approach would be to develop a frame-
126 work that preserves both the idiosyncratic and common components of climate
127 shocks in estimation and aggregation, while also moving beyond annual means
128 and the global scale to fully capture the spatial and temporal heterogeneity of
129 climate impacts from past weather shocks [Lemoine, 2018].

130 All this yields two main conclusions. First, switching from annual global mean
131 temperature to the regional annual distribution of daily mean temperatures af-
132 fects the magnitude of the estimates of economic damages: in 2050, using damage
133 patterns interacted with the shift in the whole shape of the distribution of daily
134 temperatures yields climate damage at the global scale that are around 25% larger
135 than the damage obtained under the assumption of a shape-preserving shift in
136 annual mean daily temperature. Standard aggregation leads to an underestima-
137 tion of future climate damages. We test this result across a range of SSPs, from
138 the least (SSP1-2.6) to the most carbon-intensive (SSP5-8.5), finding a range of
139 of 21-28%. Second, we show that the distributional effect is far from clear-cut.
140 Uncertainty in the change in the shape of the temperature distributions has wildly
141 different effects across regions. In particular, we show that the omitted damages
142 are not primarily driven by tail effects. Extreme events alone do not explain the
143 intra-annual pattern of damages; rather, the entire distribution of temperatures
144 plays a critical role. This effect holds consistently across different temperature
145 pathways, both at the regional level and in the aggregate.

I. Climate and economic data

A. Warming patterns

Our main concern is that shifts in the intra-annual distribution of daily mean temperatures may not be adequately captured by changes in annual mean temperature, which preserve the overall shape of seasonal warming patterns. On Figure 1 below, we illustrate this concern for two scenarios, each involving a $+2^{\circ}\text{C}$ increase in annual mean temperature. These scenarios are motivated by two stylized empirical regularities observed over recent decades. First, cold extremes across North America have warmed substantially faster than the winter mean temperature since 1980 [Blackport and Fyfe, 2024]. Second, the hottest summer days in North-West Europe have warmed roughly twice as fast as mean summer days since 1960 [Patterson, 2023]. In the illustrative figures below, North-West Europe is shown on the left panel and North America on the right. The top panel plots damage functions against the frequency of days in each temperature bin. For exposition, we use an inverted bell-shaped damage function, where marginal damages rise at both lower and higher temperature levels. The middle panel shows the histogram of daily temperatures for three cases: (i) the historical climate (green), (ii) a $+2^{\circ}\text{C}$ mean-preserving shift in the temperature distribution (blue), and (iii) a $+2^{\circ}\text{C}$ mean increase with a change in shape, characterized by a heavier hot tail (orange, left panel) or a reduced cold tail (dark red, right panel). The red dotted line represents the difference in frequency (days per temperature bin) between the shape-changing and shape-preserving $+2^{\circ}\text{C}$ scenarios, where the latter assumes a constant intra-annual temperature distribution. The difference between these two distributions highlights omitted days, i.e. specific temperature exposures that are not captured when impacts are assessed solely using changes in annual mean temperature. The bottom panel quantifies the resulting differences in aggregate damages by integrating observed intra-annual temperature distributions with the non-linear damage functions shown above. Areas in blue indicate

174 higher damages under the shape-preserving shift, whereas areas in orange (for
 175 Europe) and dark red (for North America) indicate higher damages under the
 176 shape-changing scenario. The remainder of the paper quantifies the magnitude
 of these omitted damages for different concentration pathways.

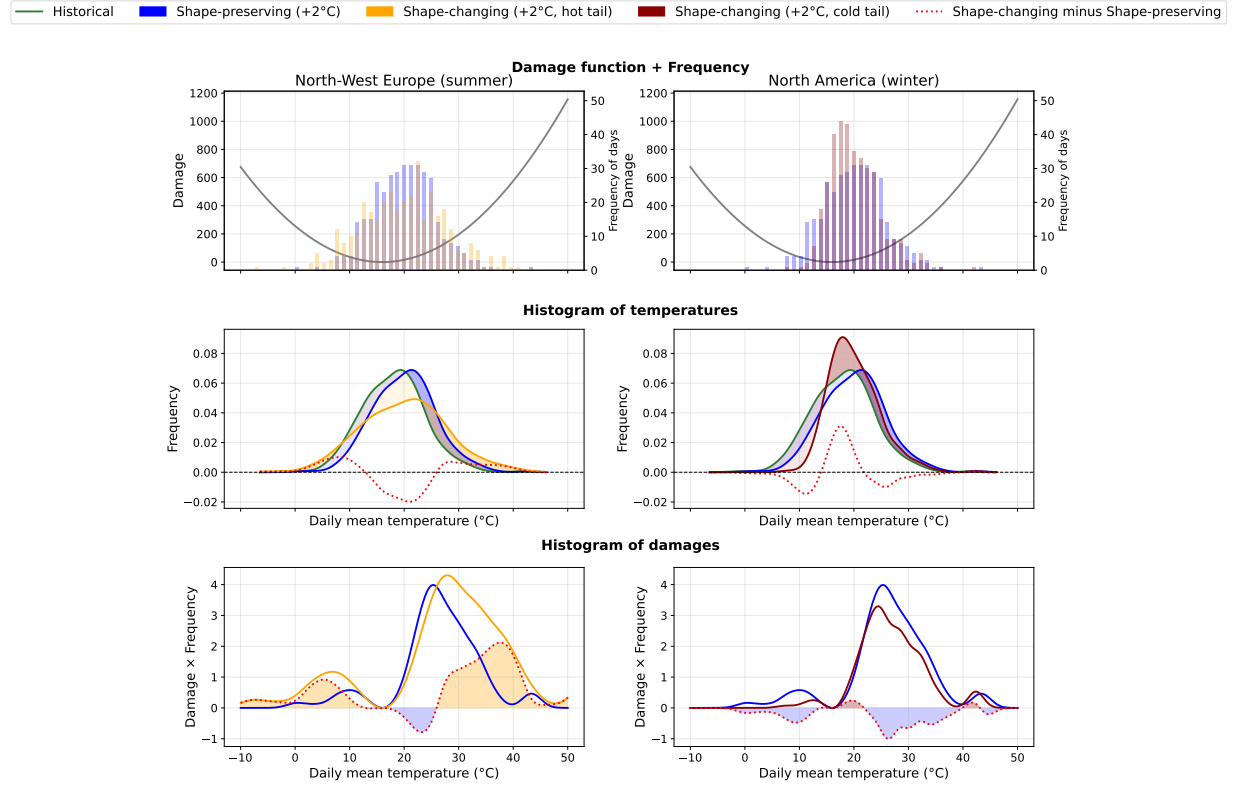


Figure 1. : Illustrative **Top** Damage function for different daily mean temperatures plotted against the distribution of temperatures. **Middle** Histogram of temperatures for historical, shape-preserving and shape-changing 2°C annual mean temperature increases, **Bottom** Histogram of damages for historical, shape-preserving and shape-changing 2°C annual mean temperature increases. **Left** For a 2°C mean increase in temperature with an increase in hotter days tail, **Right** For a 2°C mean increase in temperature with a decrease in cold days tail.

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178 After this stylized illustration, we now turn to climate data for quantification.

179 We compare the distribution of daily mean temperatures in actual climate pro-

jections to a counter-factual synthetic projection where the shape of the distribution remains the same while the mean annual temperature increases, a standard assumption in the literature. We build different climate landscapes, where ‘climate’ is defined as the underlying distribution, from which a specific regional temperature distribution over a year is drawn [Waidelich et al., 2024]. We use CMIP6 bias-corrected and downscaled data at a resolution of 60 arc-minutes from five earth system models (ESM) stored in ISIMIP Protocol 3B [Frieler et al., 2023]: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MPI-ESM2-0, UKESM1-0-LL. ISIMIP subset of climate models and de-biasing techniques were designed to assess impacts of climate change and to span the larger ensemble of CMIP models [Warszawski et al., 2014]. Thus, our illustrative study underestimates inter-model uncertainty among the over 100 CMIP6 models. Data is available for three shared socioeconomic pathways (SSP 1-2.6, 3-7.0, 5-8.5). We construct three different climate landscapes for each SSP. The first is the climate landscape without climate change, the ‘control’ climate: it is the mean distribution of ‘picontrol’ time series experiments run over 2006 to 2100 with pre-industrial CO₂ concentration. The second is the landscape from actual climate projections which consists of bias-corrected, downscaled output from five ESMs forced with future emissions from three different SSPs, the ‘projection’ climate: we use the average of the 10-year distribution around a date to approximately capture the underlying distribution from which the specific weather realization from a specific year is drawn, i.e. 2045-2055 in our example¹. This landscape samples scenario uncertainty, inter-model uncertainty, and regionally specific changes in the shape of daily mean temperature distributions. The third climate landscape is a ‘synthetic’ landscape, where we add for each temperature observed in the ‘control’ climate of each of the five ESM the mean of the change

¹On the one hand, adding more years around 2050 would enable us to capture more of the internal variability which characterizes 2050 climate [Schwarzwalder and Lenssen, 2022], for instance more El Niño cycles. On the other hand, it would come with a costly assumption of perfect symmetry around 2050 in climate change dynamics. By capturing less internal variability, we probably under-count the impact of including regional information.

206 in annual temperature in ‘projection’ climate in this specific ESM. This yields
 207 a ESM-specific shape-preserving mean-shifted climate. This landscape samples
 208 scenario uncertainty, inter-model uncertainty, and regional differences in mean
 209 changes. Synthetic climates are constructed at a high level of precision² (0.01°C).

210 Rather than aggregating this data at the global scale, we construct regional
 211 climate landscapes. Indeed, using a global dataset means that locations in which
 212 a given temperature is relatively cold and places in which the same temperature
 213 is relatively warm fall within the same bin of temperature, which distorts the
 214 picture of regional climate shifts, and biases the estimates used to convert these
 215 climate shifts into economic damage. We aggregate at the level of five major
 216 Köppen regions [Beck et al., 2023]: arid, continental, polar, temperate and trop-
 217 ical. It is reasonable to think that these climate classifications are both good
 218 ensembles in terms of warming patterns but also in terms of damage patterns
 219 to capture differences between relatively homogeneous regions. If the differences
 220 between damage patterns differ for many other reasons (e.g. cultural and polit-
 221 ical), we capture some of the regional heterogeneity due to climatic conditions.
 222 When building these climate landscapes, we keep only locations for which we have
 223 economic data to estimate dose-response functions below and treat each of these
 224 economic region within each climatic Köppen region as a single unit.

225 *B. Econometric estimates of climate damages*

226 The next step to compute damages that might be omitted from the spatial and
 227 temporal aggregation of climate projections is then to combine the omitted shift
 228 depicted in Figure 2 with non-linear dose-response functions of GDP to binned
 229 daily mean temperatures. For the empirical analysis we combine Wenz et al.
 230 [2023]’s Database Of Sub-national Economic Output (DOSE v2) with Hersbach
 231 et al. [2020]’s climate reanalysis (ERA5). We process the climate reanalysis by

²Because we shift distributions using granular data, this process is computationally intensive. Since damages are estimated from binned data, the binning procedure can slightly alter the distribution when shifting the data. As a rule of thumb, we ensure ex post that the annual mean temperature of the synthetic climate closely matches that of the projected climate, with a tolerance on the order of 10^{-2} .

first calculating degree-days at the grid-cell level and then aggregating to DOSE regions. We use the combined data to estimate dose-response functions of GDP growth to daily mean temperatures. We estimate the model:

$$(1) \quad g_{it} = \alpha_i + P_{it}\beta + \sum_{b=1}^B n_{bit}\gamma_b + \mu_t + \epsilon_{it}$$

with the growth rate of GDP per capita PPP in USD in administrative unit i in year t as g_{it} , with the number of days with daily mean temperature in the bin indexed b as n_{bit} , and with total annual precipitation P_{it} . Note that here, P_{it} is indeed only a control, focused on annual totals, rather than daily ones [Kotz et al., 2022]. The model also includes region fixed effects α_i and year fixed effects μ_t . Errors ϵ_{it} are clustered at the level of countries to account for spatial and temporal autocorrelation. Our main parameters of interest are the coefficients of temperature bins γ_b which represent the non-linear association between daily temperature levels and economic growth. The 2°C temperature bins are winsorized at level 99% for econometric estimation to limit the influence of rare events for which we do not have sufficient observations. Furthermore, we follow Cruz and Rossi-Hansberg [2024] and smooth the behavior of the point estimates across temperature bins on the whole temperature distribution in 2050 with degree-two polynomials, assuming that temperature effect on growth changes remains constant above and below our upper and lower bins used for the estimation. We also weigh each point estimate by the inverse of their standard errors to provide a greater weight to the more accurate estimates.

C. Descriptive statistics

Figure 3 gives summary statistics for the warming and damage patterns of each region in 2050 for SSP5-8.5. Graphs on the left plot the distribution of mean daily temperatures for all climate landscapes, taking the average of all five earth system models. The distributions have different shapes, both in terms

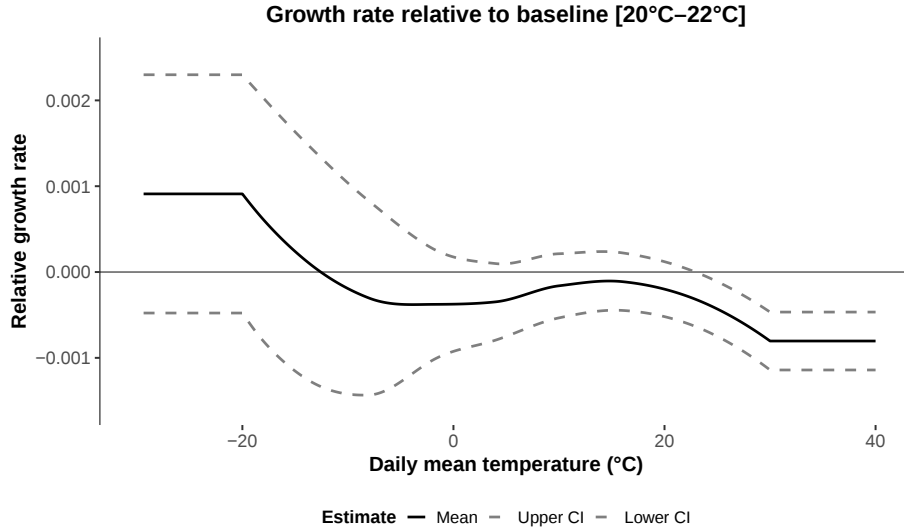


Figure 2. : Change in growth rate from one day in this bin relative to one additional day in $[20^{\circ}\text{C} : 22^{\circ}\text{C}]$.

257 of their dispersion and their mean. The shifts in the average temperature are
 258 also of different magnitude, which is consistent with the observation of spatially
 259 heterogeneous global warming. Shifts in shapes are also diverse, and not just
 260 because of the initial shape of each distribution as we show on the graphs on
 261 the left. These graphs describe the difference between the ‘synthetic’ and the
 262 ‘projection’ landscapes for different earth system models: for each temperature
 263 level, it gives the difference in frequency between two distributions. The first
 264 distribution is constructed by adding to each daily temperature for each climate
 265 model the mean of the annual anomaly observed in that model, thus obtaining
 266 a shape-preserving shift in mean, which is the assumption generally made in the
 267 literature. The second distribution is taken from climate model projections of
 268 daily mean temperatures. These difference can have opposite signs and various
 269 magnitude depending on the model considered.

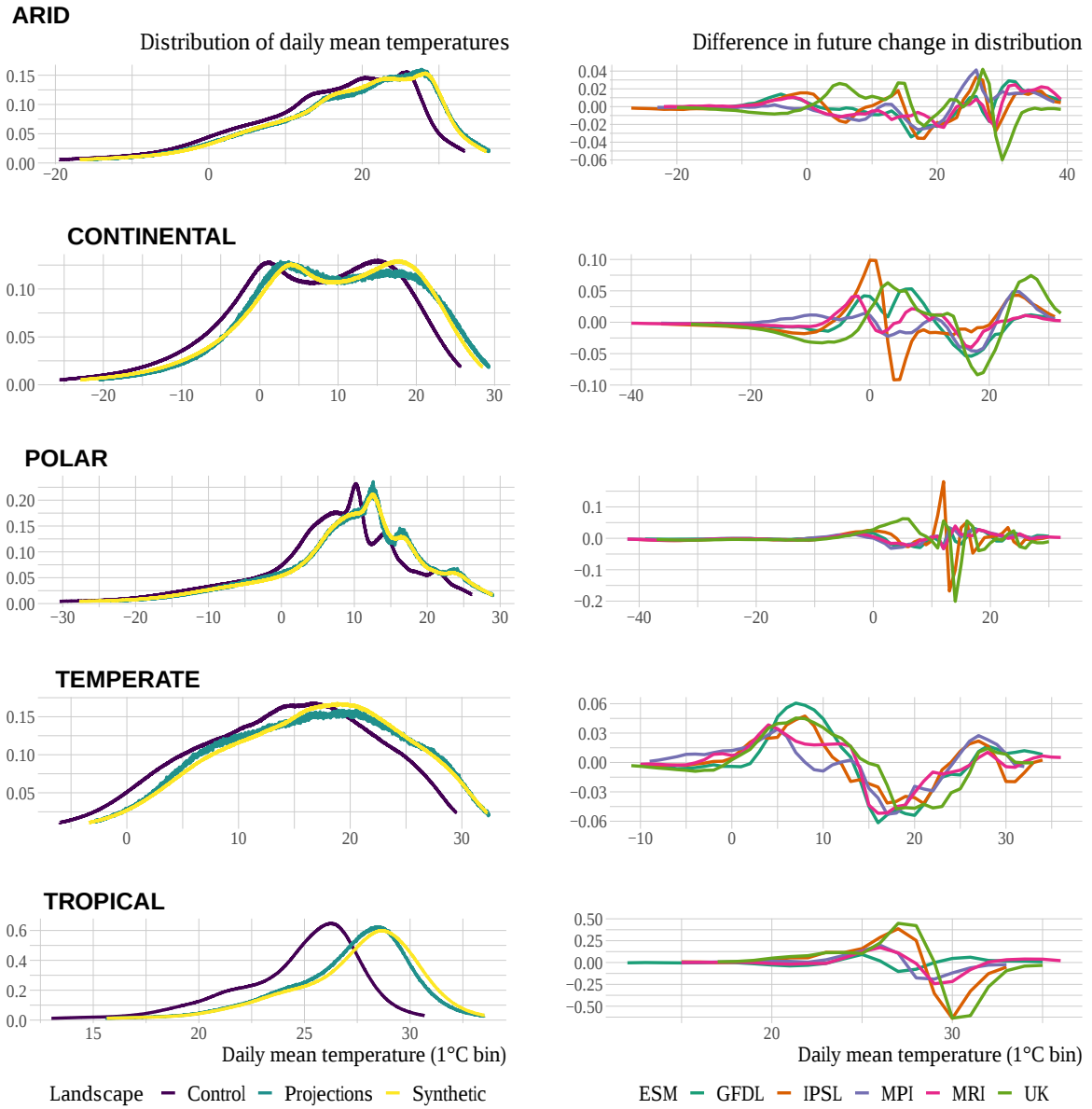


Figure 3. : **Left** Distribution of daily mean temperatures for four climate landscapes. **Right** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic climate. Data are for all DOSE regions, SSP5-8.5, 2050. Data is winsorized 1%, x and y-axis differ.

II. Quantification

A. Missing shape-related growth effect of climate change

We express the GDP growth effect of daily temperatures in climate projections as a share of this effect in synthetic climate, i.e. in a setting where we assume that the shape of the distribution of daily temperatures remains the same when the mean increases. Indeed, we want to measure how much the change in the shape of the distribution of daily mean temperatures matter for the estimation of economic damages. To have a measure that approaches standard climate damages, growth effects in warming climates are expressed with respect to growth effects in control climate. Growth effect at each bin b is γ_b . We apply a double difference procedure to find the change in growth effect between synthetic climate and projections. The share of the climate growth effect underestimated by the aggregation of climate data under synthetic climate in a given area writes:

$$(2) \quad DD^\omega = 100 * \frac{\Omega^{\omega, synthetic} - \Omega^{\omega, projections}}{|\Omega^{\omega, synthetic} - \Omega^{\omega, control}|}$$

where, for a given SSP and earth system model in year 2050 in our climate landscape C (control, projections, synthetic) for a given dose-response function ω in sub-administrative region DOSE d in Köppen-Geiger climate zone k , damage is $\Omega_{ymd}^{glob, C} = \sum_b \gamma_b t_{bymd}^C$. This estimate reflects the percentage increase (or decrease) in damages that results from omitting the shape change, relative to the standard damage estimates based on a shape-preserving synthetic shift in the mean. We take the absolute value in the denominator because it is possible that welfare could increase under climate change scenarios. Using the absolute deviation ensures that, regardless of whether climate change implies welfare gains or losses, a positive normalized difference consistently indicates that we underestimate damages (or overestimate the benefits) of climate change in the projected scenario.

B. Aggregate impacts

While we build regional climate landscapes that use the granularity given in climate datasets rather than too aggregated information to discuss climate policy, we seek for global indicators that can easily be applied to aggregate economic models. We compute for each DOSE region within each larger Köppen-Geiger zone the share of missing growth due to disaggregated warming and damage patterns. We use area-weighting to build DOSE-level estimates of missing growth from DOSE*Koppen estimates. For the sake of transparency and to avoid reassigning DOSE regions—on which the dose-response function was originally estimated—based on shifting Köppen-Geiger zones, we assume that DOSE regions retain their current Köppen-Geiger classification in 2050. While the distribution of Köppen-Geiger zones might change under a changing climate [Beck et al., 2023], such estimated shifts (13% transition at 1km resolution in the worst SSP5-8.5 by 2100) would introduce an additional layer of uncertainty into our estimates.

We then aggregate the DOSE-level growth effect to the global scale based on the share of each zone in global GDP in 2015, $s_\omega = GDP_\omega / \sum_j GDP_j$. As for Köppen-Geiger region, we do not add a layer of uncertainty related to future growth paths under different SSP. When aggregating across regions to assess the absolute effect in terms of growth, it is essential to account for the absolute change between the synthetic and historical climate. Using only the relative measure DD^ω fails to weight for the fact that different regions experience different magnitudes of climate impact. Our final weighted variable of interest therefore captures the share of aggregate damages that are omitted due to the structure of the global aggregation procedure.

$$(3) \quad DD_{global} = \frac{\sum_\omega (DD^\omega \cdot s_\omega \cdot w_\omega)}{\sum_\omega s_\omega \cdot w_\omega}$$

where the weighting w_ω is: $w_\omega = |\Omega^{\omega, synthetic} - \Omega^{\omega, control}|$. On Figure 4, we plot our estimate of the share of missing growth effects for each ESM and the mean

320 across ESM. The assumption made in the literature of a shape-preserving shift
 321 in mean annual global temperature interacted with global damage patterns thus
 322 yields biased estimates of future economic damages of climate change. This bias is
 323 an underestimation of future damages: accounting for the shift in regional shape
 324 would increase the actual damage by on average 25% (21-28% depending on the
 325 SSP, 4-46% depending on the ESM and the SSP) in 2050. The shift in shape
 matters also for less carbon-intensive pathways.

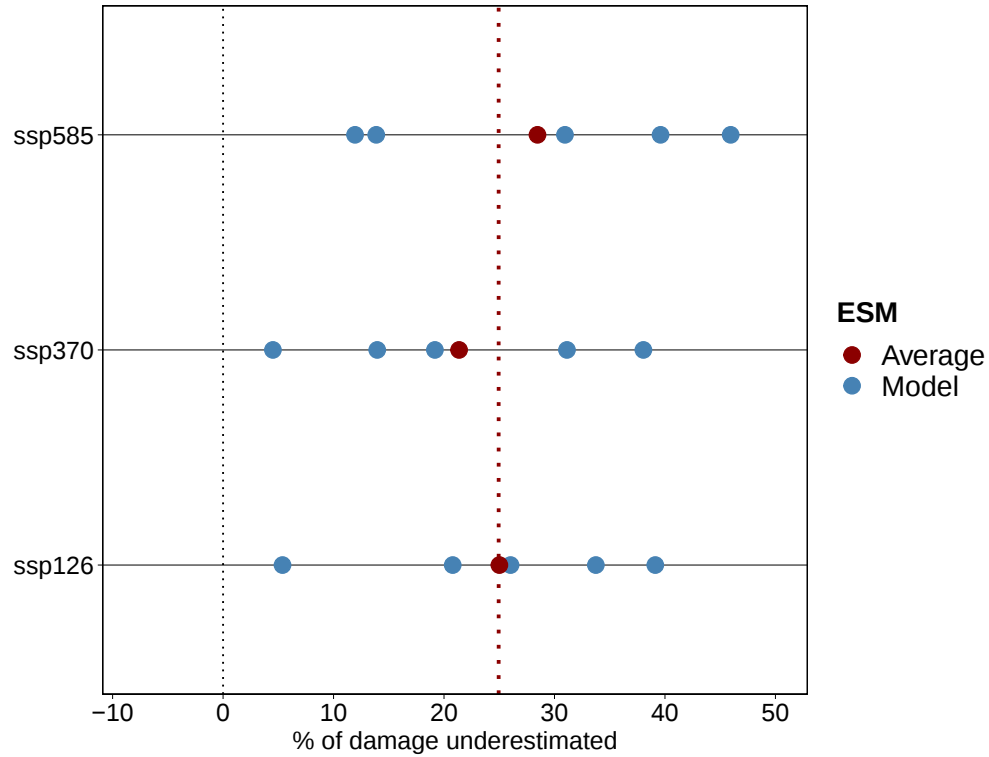


Figure 4. : Global DD for each ESM and the average over ESM.

326
 327 Overall, this shift in the aggregate profile of climate impacts should motivate
 328 stronger mitigation and adaptation efforts, as intra-annual changes in the temper-
 329 ature distribution lead to greater overall damages. But what are the distributional
 330 effects of these omitted intra-annual shifts in warming patterns?

C. Distributional impacts

Thus far, we have focused on the aggregate impact of the omitted shift in the regional shape of daily temperature distributions. We now turn to the distribution of damages. The table below reports, for each Köppen-Geiger region, its share of global GDP in 2015, the absolute damage in synthetic climate in comparison with control climate and the percentage of damages that are underestimated across different SSPs. Several key conclusions can be drawn. Ignoring the intra-annual distribution of temperatures in all regions means underestimating damages. This underestimation can be substantial—for instance, in polar regions—but its overall impact is limited due to either the low absolute change in damages between control and synthetic climate within those areas or the small share of these regions in global GDP. The share of each region is

$$DD_{share}^i = (DD^i \cdot s_i \cdot w_i) / \sum_{\omega} (DD^{\omega} \cdot s_{\omega} \cdot w_{\omega}).$$

SSP	Arid (12% of GDP)	Continental (27% of GDP)	Polar (1% of GDP)	Temperate (53% of GDP)	Tropical (8% of GDP)
1-2.6	2.91 [2.406]	57.07 [2.253]	2387.78 [0.02]	29.45 [2.369]	0.8 [9.066]
3-7.0	7.24 [2.297]	47.28 [2.851]	569.77 [0.092]	13.1 [2.718]	26.12 [5.823]
5-8.5	4.34 [2.229]	54.88 [3.007]	528.73 [0.113]	16.47 [2.793]	77.22 [4.568]

Table 1—: DD (in %) and [absolute synthetic damage] for different SSP in each Köppen-Geiger zones (with their share in 2015 GDP).

When we decompose by temperature levels to identify whether hot or cold days are responsible for the omitted damages in the shape, we find that the picture depends on the Köppen-Geiger zone considered but remains stable across SSPs. The share of each bin b as a share of region i damage is: $DD_{i,b}^{share} = (DD^b \cdot w_b) / (DD^i \cdot s_i \cdot w_i)$. In the figure below, we plot—for each SSP— how each temperature level contributes to the overall aggregate damage. In red (blue), the bin contributes positively (negatively) to the overall underestimation of damages. These results are obtained interacting the climate shifts from Figure 2 with the damage function from Figure 3.

While one might expect tail effects to be driving our results, it turns out that it is not only extreme events that matter for welfare. Most of the omitted shift

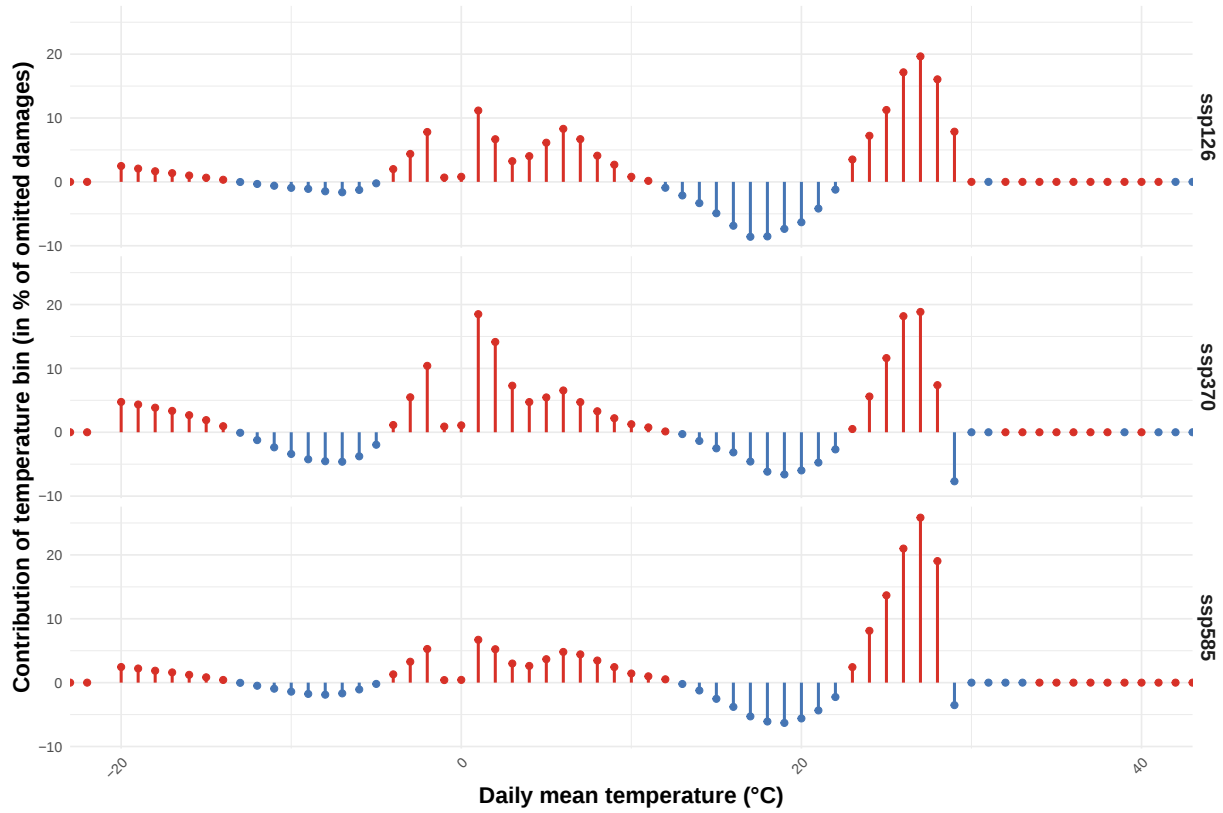


Figure 5. : Temperature levels contribution (in %) to global under-estimated damages between projections and synthetic climate for each SSP (rows). In red (blue), the bin represent a positive (negative) share of the overall underestimation. We limit the x-axis to $[-20:40]$, average the effects over 1°C bins and scale the effect so that the total sums to 100%.

355 between synthetic and projection climates in Figure 5 are indeed located along
 356 the whole distribution rather than concentrated in extreme temperature levels.
 357 Thus, changes across the entire shape of the intra-annual temperature distribution
 358 are important. The observed changes in distributional shape exhibit consistent
 359 patterns across all SSPs. This should encourage caution in relying on thresholds or
 360 arbitrary moments of the temperature distribution for projecting future damages.

III. Conclusion

Linear relationships are isomorphic to aggregation and other mathematical transformation. Climate-society relationships, meanwhile, are famously nonlinear. Disaggregating spatial and temporal climate responses matters. Indeed, switching from global annual mean temperatures to regional distributions of daily mean temperatures affects the magnitude of economic damages from climate change, since the shape of the intra-annual temperature distribution is neither fixed across space or time. Spatio-temporal disaggregation, thus, reveals how uncertainty between climate models on the entire shape of the distribution of future weather realizations cascades down to regional damage estimates. Accounting for daily temperatures rather than annual averages increases the estimation of economic damages, a finding consistent with previous studies with daily temperatures [Rudik et al., 2022] or seasonality [Estrada et al., 2025].

In 2050, under all SSPs, using non-linear intra-annual damage patterns interacted with the shift in the entire shape of the distribution of daily temperatures yields climate damages at the global scale that are on average 25% (21-28%, depending on the SSP) larger than the damage obtained under the assumption of shape-preserving shift in annual mean daily temperature. The shape uncertainty about shifts in daily temperature distributions should therefore be taken into consideration for decision-making. We show that the omitted damages are not primarily driven by tail effects, but are distributed across the full range of daily mean temperatures. Extreme events alone do not account for the intra-annual damage pattern; instead, the entire temperature distribution plays a critical role.

To our knowledge, we provide the first comparison between various approaches to spatial and temporal aggregation regarding impacts of changes in mean surface temperatures on economic activity and quantify how much these often-overlooked aggregation procedures matter empirically. We believe that this procedure can be reasonably translated vertically and horizontally. Vertically, this framework can be applied to other economic damages stemming, for instance, from changes in the

390 shape of the annual distribution of daily maximum temperatures. Horizontally,
391 the framework could be used to infer results in regions for which we do not have
392 socioeconomic data to estimate damage functions. Here we have kept the DOSE
393 regions for the sake of consistency. But using Köppen-Geiger climatic zones, i.e.
394 widely available physical data, to build ensembles and generalize the results over
395 these ensembles could be a useful detour at first, alongside a necessary deepening
396 in the availability of socioeconomic data, particularly in Africa.

397 Our analysis also comes with limitations. In particular, our estimation of re-
398 gional damage functions is based on the idea that differences in the economic dam-
399 age caused by weather—and therefore by climate change—is intimately linked to
400 climatic zones. However, there are many factors that go well beyond geographical
401 determinism that we do not explore here. Furthermore, Earth System Models
402 are imperfect, and some may not be able to capture well the shape (or changes
403 in the shape) of the temperature distribution [Kornhuber et al., 2023]. When it
404 comes to estimating the future damage of climate change, other approaches use
405 annual temperature [Bilal and Känzig, forthcoming] and, thus, avoid the problem
406 of time-fixed effects, which erase a large portion of climate impacts. The question
407 of aggregation is less of an issue in this case, as these approaches consider an-
408 nual temperature to be a sufficient statistic for estimating impacts. Nevertheless,
409 the question of the relevance of past natural variability as a proxy for global an-
410 nual climate change based on complex processes and rising carbon concentration
411 remains, and is left for further research.

412 Another limitation lies in defining a rule of thumb that holds universally—across
413 different parts of the world (e.g., tropical vs. temperate regions) and under various
414 future climate scenarios (e.g., with more or less severe climate disruption)—for
415 how far one should go in disaggregating climate variables. Beyond daily mean
416 temperature, one could further investigate repeated events with potentially non-
417 linear impacts, interactions between temperature and precipitation to account for
418 wet-bulb effects, or distinguish between daytime and nighttime temperatures to

419 better capture the nature of heatwaves, among others.

420 Finally, while we studied variations of damage patterns in space and time, we
421 have left out the question of variation of damage patterns with societal adapta-
422 tion to climatic changes, what has been dubbed a ‘swinging climate’ [Mérel et al.,
423 2024]. How might a given daily temperature yield different damages in any par-
424 ticular region as it moves away from its normal climatic zone? That raises the
425 question of how adaptation might interact with the entire distribution of climatic
426 factors, a question similarly left for further research.

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435 Columbia University Research Grid.

Appendix A. Building climate landscapes

437 We scale the frequency of observations by the share of land area in each cell
 438 using GPW4 dataset. We compare changes in shapes of daily mean tempera-
 439 ture distributions T_{mr} in five Köppen regions r and climate model m , i.e. the
 440 distribution of all T_{mr} daily mean temperatures in region r and model m , in
 441 three different climates C . Climate C are: a control climate, ISIMIP projec-
 442 tions, the synthetic distribution. We bin the temperature distributions t at
 443 0.01°C : $f(\cdot)$ is a function that bin the distributions. Our final landscapes for
 444 each year are: (1) control climate, without climate change $T_{mr}^{control} = f(t_{mr}^{control})$,
 445 (2) ISIMIP projections $T_{mr}^{proj} = f(t_{mr}^{proj})$, (3) Synthetic with model average are
 446 built by adding the difference between binned projections and control climate,
 447 $T_{mr}^{synth.model} = f\left(t_{mr}^{control} + T_{mr}^{proj} - T_{mr}^{control}\right)$.

Appendix B. Köppen regions

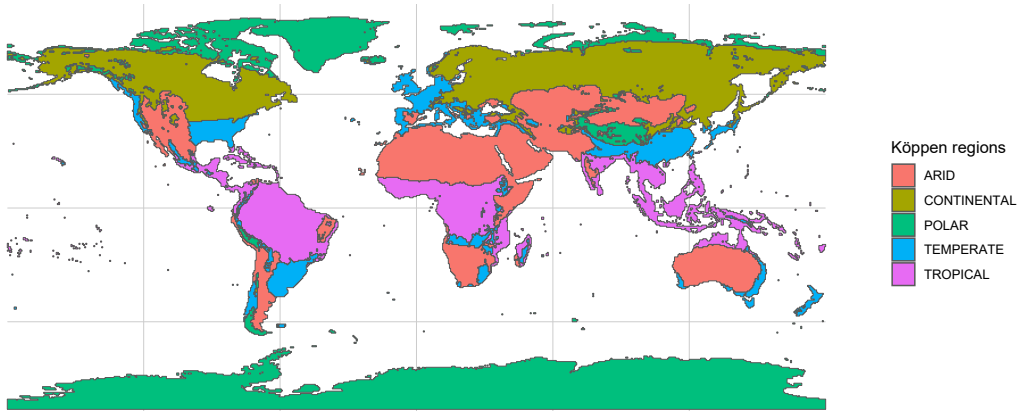


Figure 6. : Köppen climatic zones

[Beck et al., 2023]

Appendix C. More results on the distributional aspects

I plot the distribution of relative DD for each region and SSP for different ESM. The x-axis is signed log scale as the relative estimates can have large absolute values. Indeed, these relative changes in damage are not weighted by the absolute climate damage.

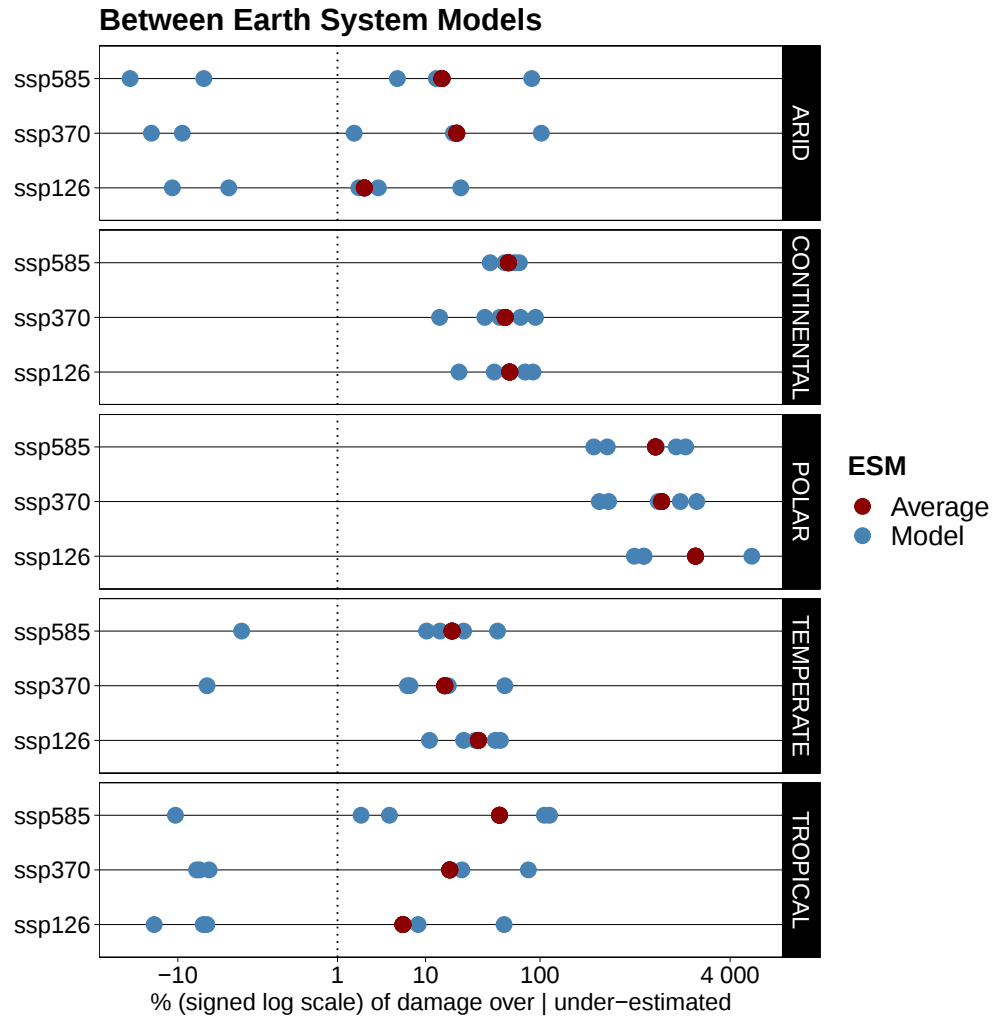


Figure 7. : Distribution of relative DD for each region and SSP, for different ESM and the average across ESM.

453 I plot the share of each 1°C temperature bin of damages in the under or over-
 454 estimation of damages in each SSP and Köppen-Geiger region . The intra-annual
 patterns (sign, not magnitude) are stable across SSP in each region.

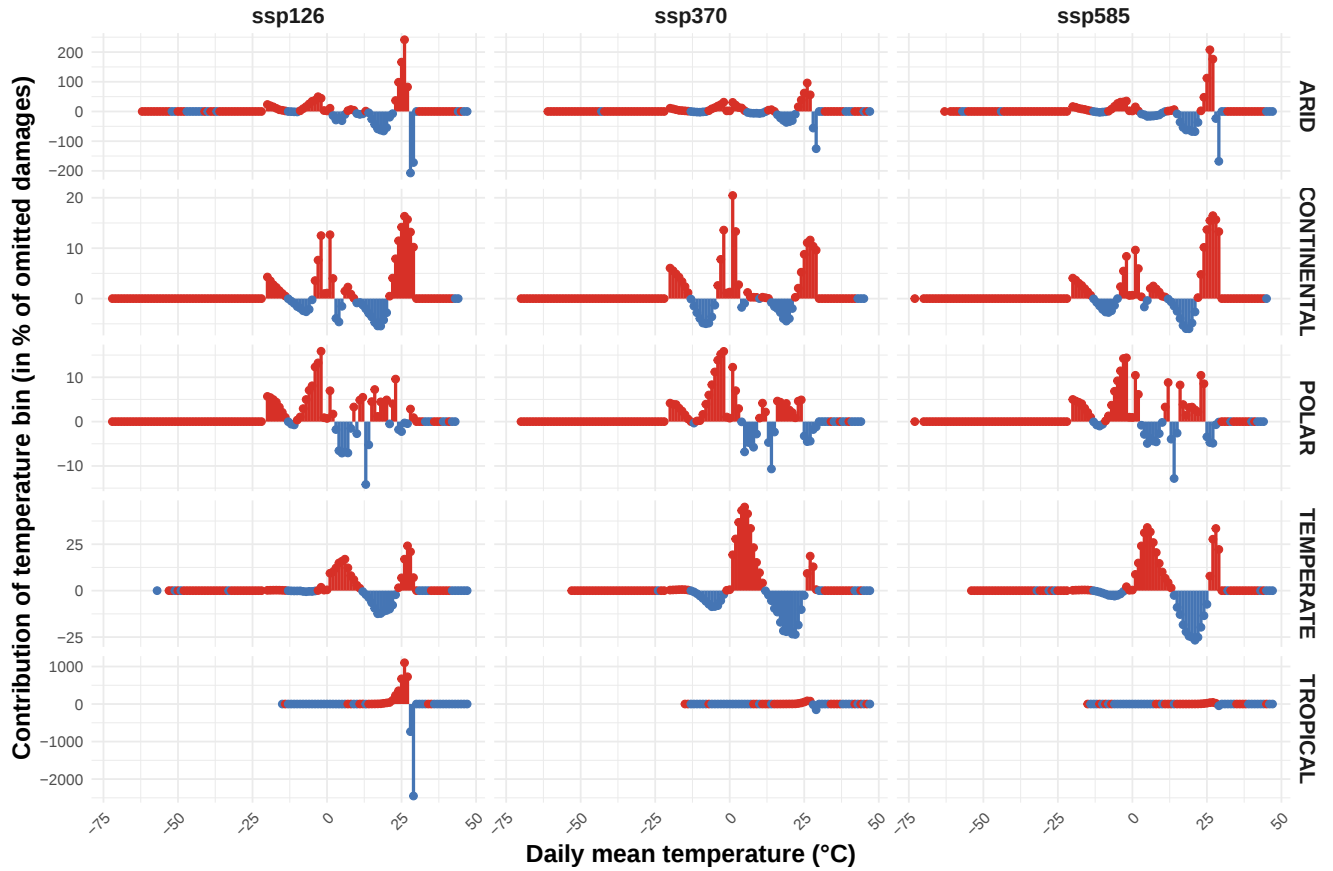


Figure 8. : Decomposition for each Koppen-Geiger zone. Temperature levels contribution (in %) to over/under estimated damages between projections and synthetic-model climate. The bins are plotted for each Köppen-Geiger zone (columns) and each SSP (rows). In red (blue), the bin represent a positive (negative) share of the overall effect.

455

456 We plot the distribution of absolute damages and omitted damages (DD) over
 457 the world for DOSE regions.

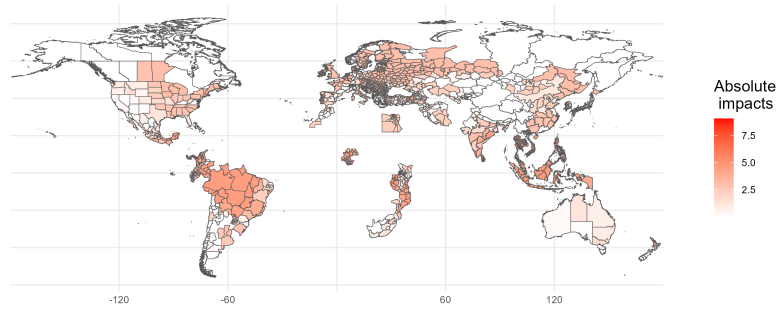


Figure 9. : Absolute damages (%), 2050, SSP5-8.5.

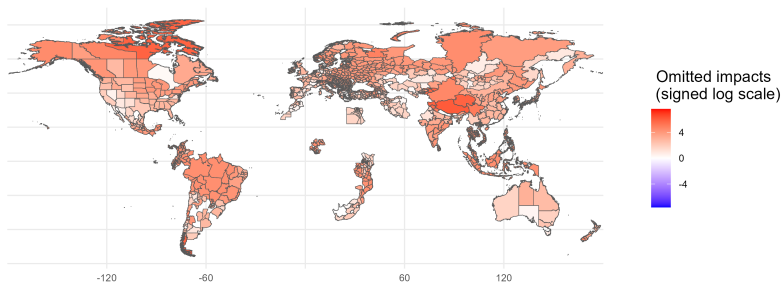


Figure 10. : Omitted damages (%), 2050, SSP5-8.5.

458 There is a low positive correlation of omitted damages (regional DD) with
 459 income, even if the data are scattered. We do the same for the absolute change
 in damage.

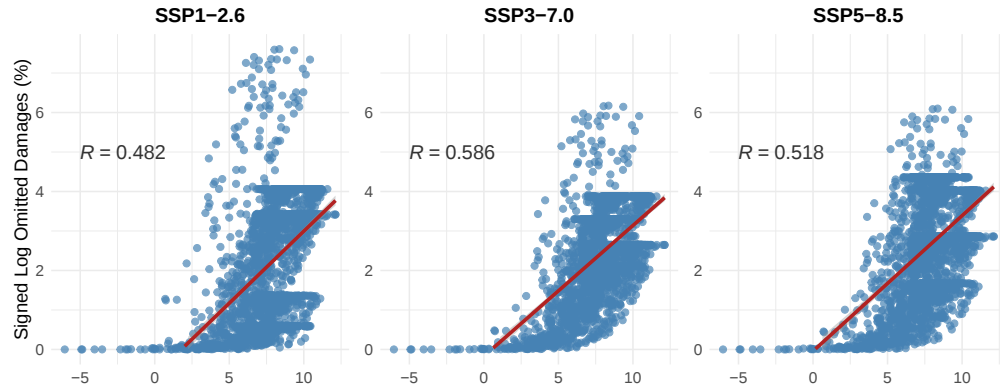


Figure 11. : Regional DD, year 2050.

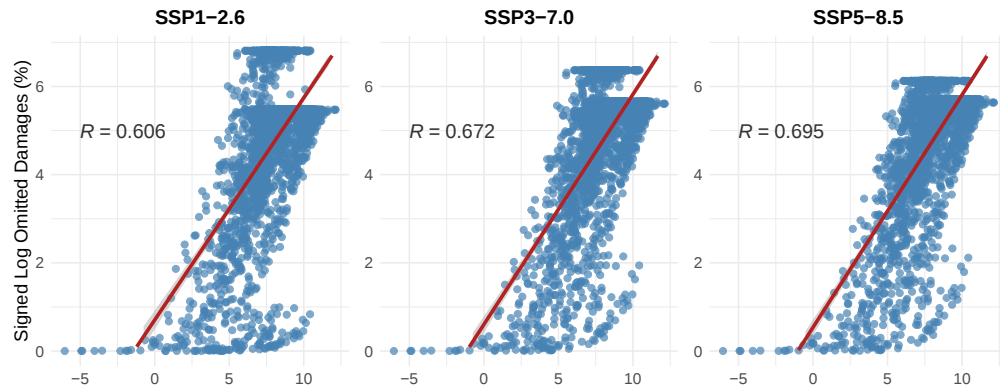


Figure 12. : Absolute difference in damage, 2050.

460

461 **Appendix D. Results from econometric specification**

462 These are the regression results for our benchmark dose-response function.

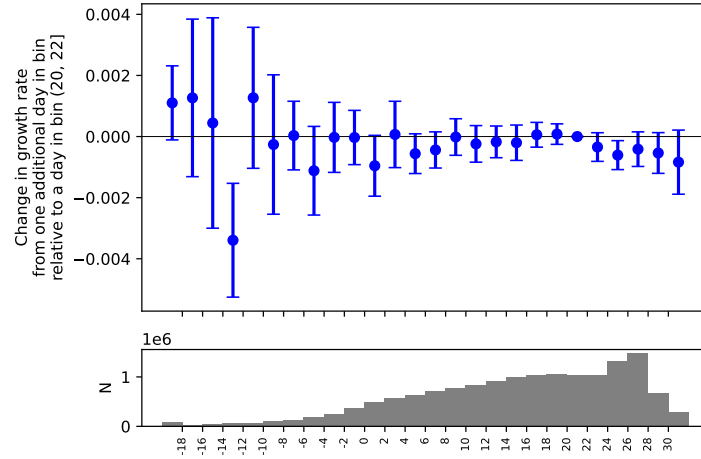


Figure 13. : Dose-response function.

Appendix E. Results with alternative dose-response functions

We estimate dose-response functions with the same specification except that g_{it} is not GDP growth but level. Global DD remains robust.

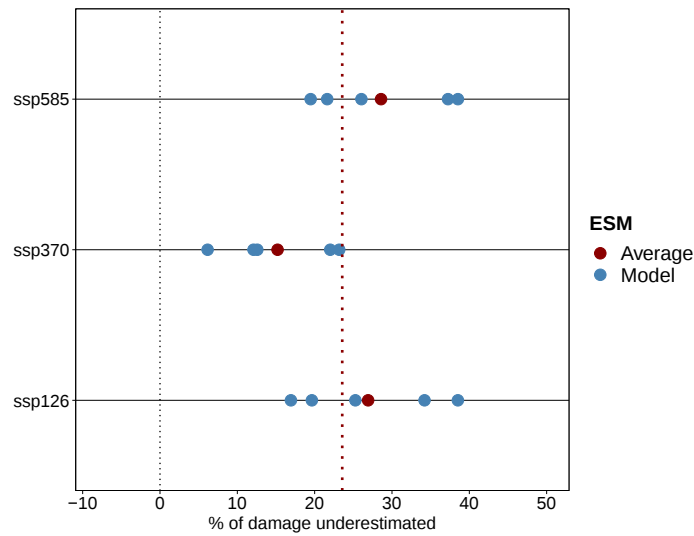


Figure 14. : Alternative regression with GDP levels rather. Global DD estimates.

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