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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Knowing how future climate damages might be distributed across time and space is an important research frontier and policy issue for climate scientists and economists alike. Projections of endogenous climate damages in macroeconomic models [Fernández-Villaverde et al., 2024] typically rely on reduced-form relationships between climate change and the macro-economy, which are generally based on *annual* climatic statistics—e.g. mean annual temperatures. Furthermore, models are generally aggregated for that climate variable to be *global*—mean annual global temperatures. In these integrated climate-economy models, carbon emissions are a by-product of regional economic activities. A reduced-form climate module captures endogenously how these carbon emissions turn into global annual mean temperature anomalies, from which regional annual mean temperature anomalies can be statistically down-scaled through a simple linear and time-invariant factor, a process also called 'pattern scaling'. Lastly, the regional physical impacts are interacted with dose-response functions estimated on global data to measure the economic impacts of endogenous climate change. These macroeconomic models are either global [Nordhaus, 1994, Barrage and Nordhaus, 2024, Cai and Lontzek, 2019, Traeger, 2023], regional [Nordhaus and Yang, 1996] or gridded, as in spatial integrated assessment modelling (IAM), e.g. Krusell and Smith Jr [2022], Cruz and Rossi-Hansberg [2024] and Desmet and Rossi-Hansberg [2024].

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

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

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

We further probe the consequences of this spatio-temporal aggregation of climate projections on quantifying the uncertainty surrounding any best-guess estimate of future climate damages. Uncertainties abound [Rising et al., 2022, Moore et al., 2024, Waidelich et al., 2024]. The quantifiable variance of future projections of climate impacts is affected by scenario uncertainty (differences in Shared Socioeconomic Pathways,SSPs), model uncertainty (differences in Earth System Models'—ESMs'—responses to the SSPs), internal variability (spatio-temporally, due to the chaotic nature of the climate and due to regional differences that may be hidden by regional aggregation), choices made in post-processing or bias-correcting ESM output (including how finely to apply projected changes in climate distributions from ESMs), regression uncertainty from the dose-response functions, and differences between observational data products used to fit the dose-response function and act as a baseline to which future ESM output is compared. 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 [Waidelich 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 [2024], 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 importance of accounting for both intra-annual variability and regional heterogeneity when assessing idiosyncratic climate damages. Our core intuition is akin to a Jensen's inequality argument: if intra-annual damages are convex in temperature, then annual averages may be misleading (i.e., temporal heterogeneity matters). A next step beyond our current approach would be to develop a framework that preserves both the idiosyncratic and common components of climate shocks in estimation and aggregation, while also moving beyond annual means and the global scale to fully capture the spatial and temporal heterogeneity of climate impacts from past weather shocks [Lemoine, 2018].

All this yields two main conclusions. First, switching from annual global mean temperature to the regional annual distribution of daily mean temperatures affects the magnitude of the estimates of economic damages: in 2050, using damage patterns interacted with the shift in the whole shape of the distribution of daily temperatures yields climate damage at the global scale that are around 25% larger than the damage obtained under the assumption of a shape-preserving shift in annual mean daily temperature. Standard aggregation leads to an underestimation of future climate damages. We test this result across a range of SSPs, from the least (SSP1-2.6) to the most carbon-intensive (SSP5-8.5), finding a range of of 21-28%. Second, we show that the distributional effect is far from clear-cut. Uncertainty in the change in the shape of the temperature distributions has wildly different effects across regions. In particular, we show that the omitted damages are not primarily driven by tail effects. Extreme events alone do not explain the intra-annual pattern of damages; rather, the entire distribution of temperatures plays a critical role. This effect holds consistently across different temperature 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°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°C mean-preserving shift in the temperature distribution (blue), and (iii) a +2°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°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 higher damages under the shape-preserving shift, whereas areas in orange (for Europe) and dark red (for North America) indicate higher damages under the shape-changing scenario. The remainder of the paper quantifies the magnitude of these omitted damages for different concentration pathways.

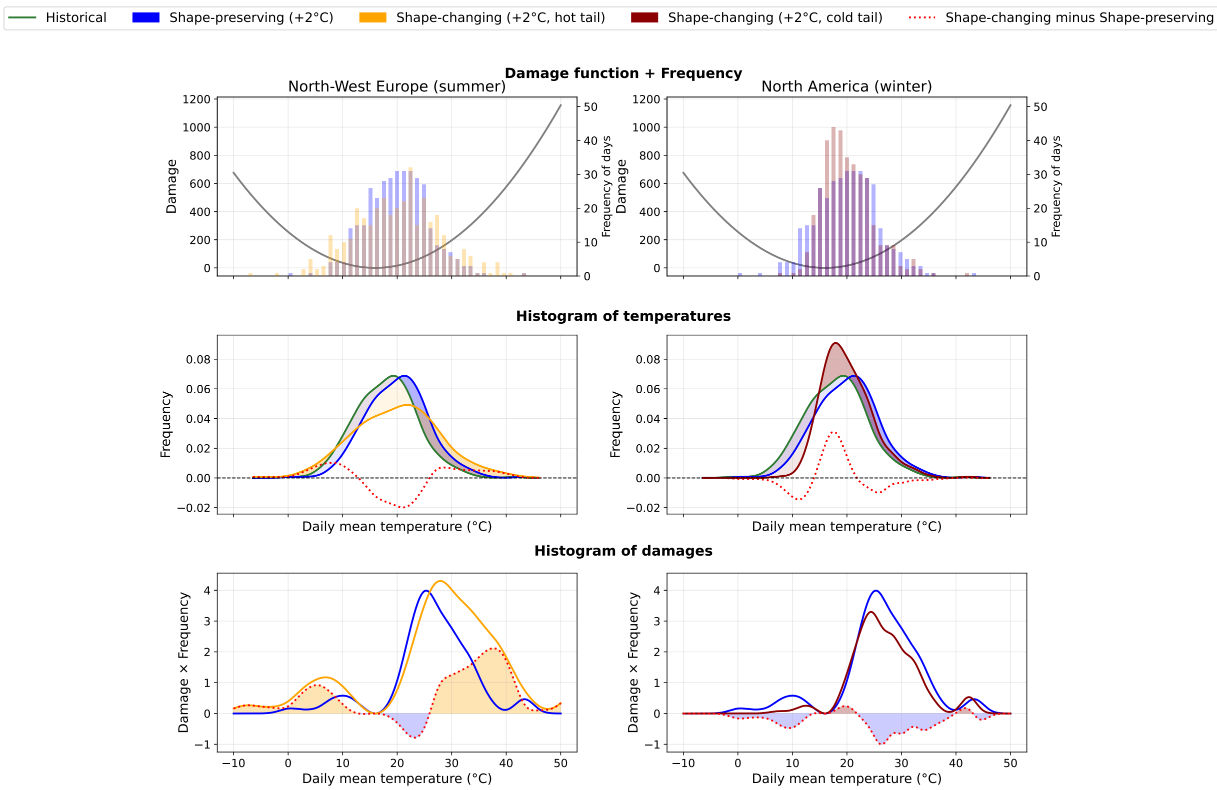

Figure 1. : Illustrative **Top** Damage function for different daily mean temperatures plotted against the distribution of temperatures. **Middle** Histogram of temperatures for historical, shape-preserving and shape-changing 2°C annual mean temperature increases, **Bottom** Histogram of damages for 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.

After this stylized illustration, we now turn to climate data for quantification. We compare the distribution of daily mean temperatures in actual climate projections 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 CO_2 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 example[1]. 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

[1]On the one hand, adding more years around 2050 would enable us to capture more of the internal variability which characterizes 2050 climate [Schwarzwald 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.

in annual temperature in 'projection' climate in this specific ESM. This yields a ESM-specific shape-preserving mean-shifted climate. This landscape samples scenario uncertainty, inter-model uncertainty, and regional differences in mean changes. Synthetic climates are constructed at a high level of precision[2] (0.01°C).

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

B. *Econometric estimates of climate damages*

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

[2]Because 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:

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

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

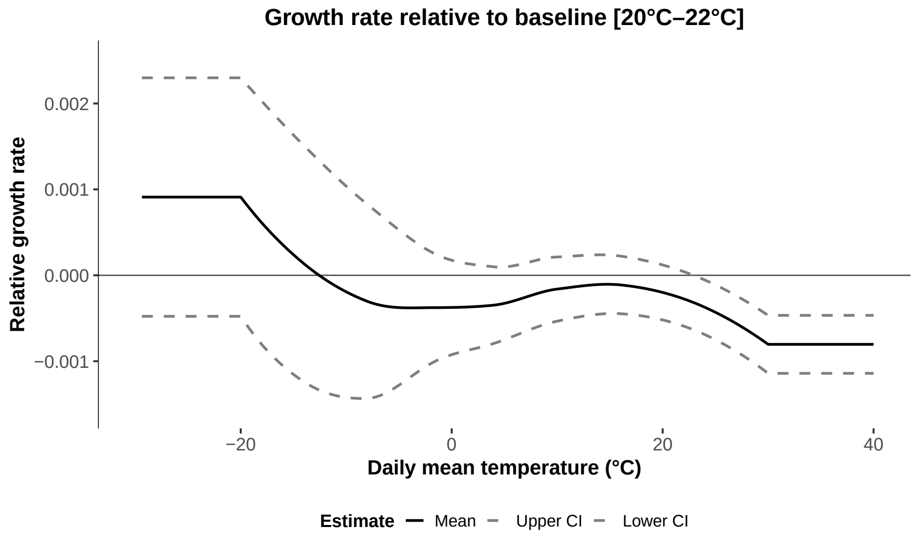

Figure 2. : Change in growth rate from one day in this bin relative to one additional day in [20°C : 22°C].

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

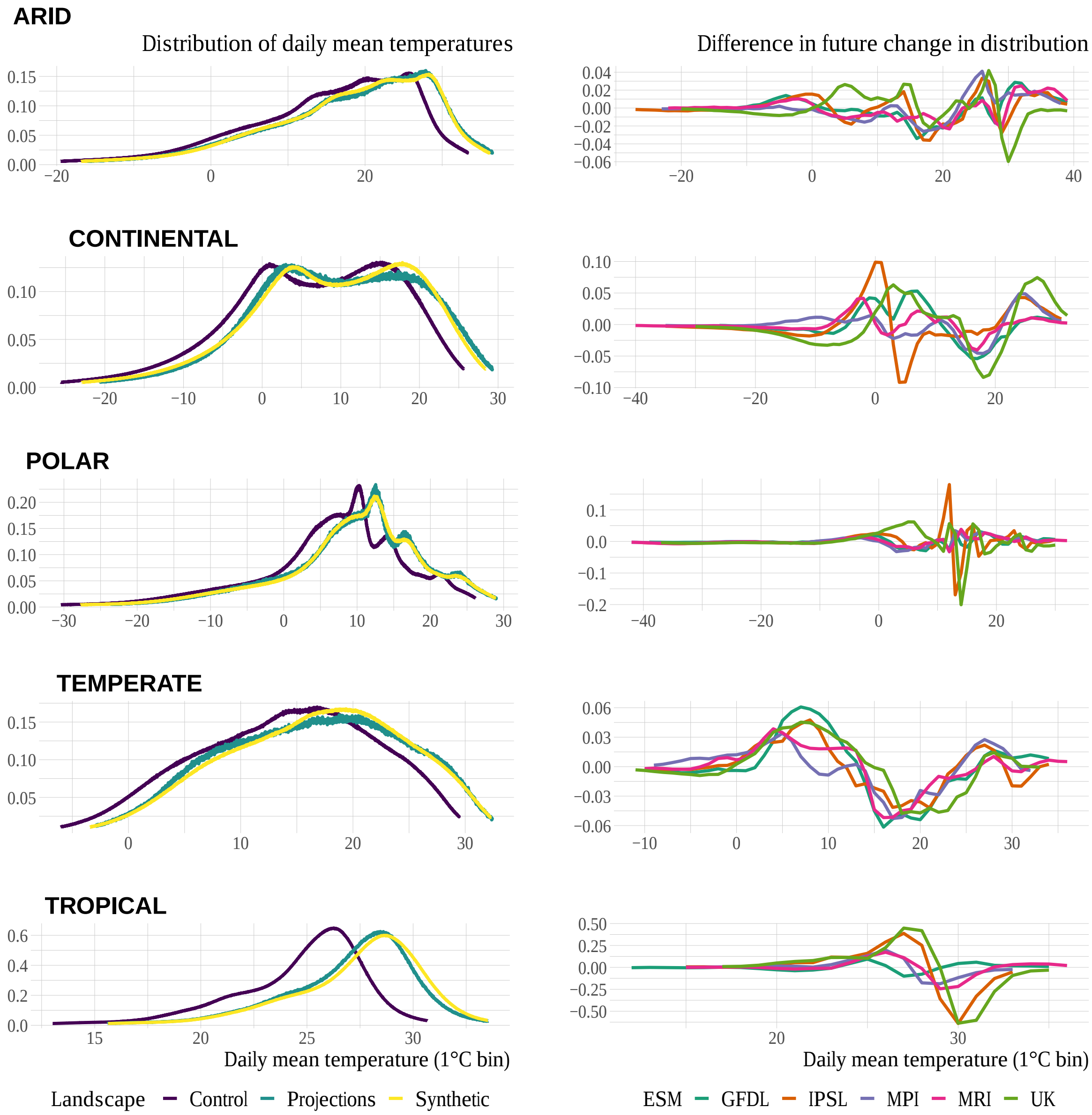

Figure 3. : **Left** Distribution of daily mean temperatures for four climate landscapes. **Right** Distribution of climate shift, i.e. difference in distribution of daily mean temperatures under projection vs. a synthetic climate. Data are for all DOSE regions, SSP5-8.5, 2050. Data is winsorized 1%,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

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

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 $\Omega^{glob,C}_{ymd} = \sum_b \gamma_b t^C_{bymd}$. 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.

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

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

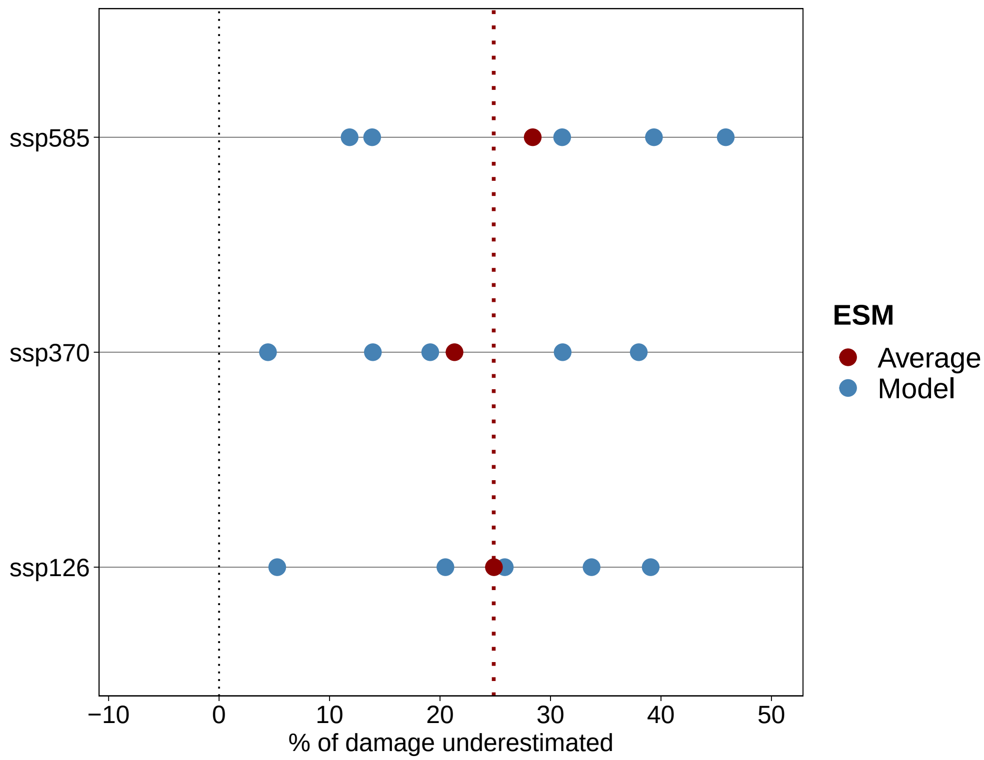

Figure 4. : Global DD for each ESM and the average over ESM.

Overall, this shift in the aggregate profile of climate impacts should motivate stronger mitigation and adaptation efforts, as intra-annual changes in the temperature distribution lead to greater overall damages. But what are the distributional 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 $DD^i_{share} = \left(DD^i \cdot s_i \cdot w_i\right) / \sum_\omega \left(DD^\omega \cdot s_\omega \cdot w_\omega\right)$.

SSP	Arid (12% of GDP)	Continental (27% of GDP)	Polar (1% of GDP)	Temperate (53% of GDP)	Tropical (8% of GDP)
1-2.6	2.71 [2.414]	57.16 [2.251]	2633.76 [0.018]	29.39 [2.372]	0.55 [9.126]
3-7.0	7.01 [2.307]	47.35 [2.849]	587.08 [0.09]	13.12 [2.722]	25.35 [5.905]
5-8.5	4.29 [2.24]	54.92 [3.005]	532.57 [0.112]	16.43 [2.797]	75.28 [4.654]

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: $DD^{share}_{i,b} = \left(DD^b \cdot w_b\right) / \left(DD^i \cdot s_i \cdot w_i\right)$. 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

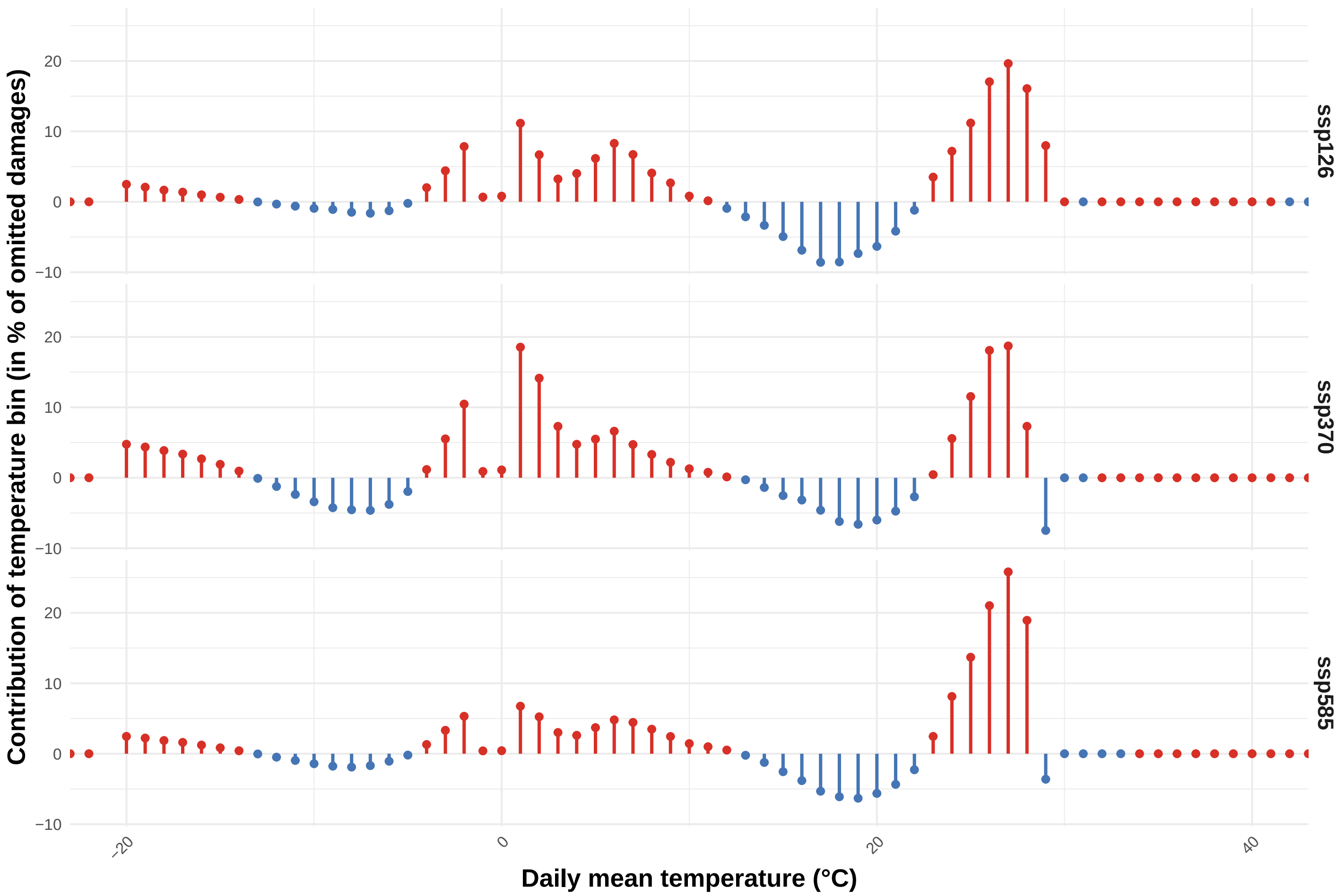

Figure 5. : Temperature levels contribution (in %) to global under-estimated damages between projections and synthetic climate for each SSP (rows). In red (blue), the bin represent a positive (negative) share of the overall underestimation. We limit the x-axis to [-20:40], average the effects over 1°C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

between synthetic and projection climates in Figure 5 are indeed located along the whole distribution rather than concentrated in extreme temperature levels. Thus, changes across the entire shape of the intra-annual temperature distribution are important. The observed changes in distributional shape exhibit consistent patterns across all SSPs. This should encourage caution in relying on thresholds or 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 [Rudik et al., 2022].

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

Our analysis also comes with limitations. In particular, our estimation of regional damage functions is based on the idea that differences in the economic damage caused by weather—and therefore by climate change—is intimately linked to climatic zones. However, there are many factors that go well beyond geographical determinism that we do not explore here. Furthermore, Earth System Models are imperfect, and some may not be able to capture well the shape (or changes in the shape) of the temperature distribution [Kornhuber et al., 2023]. When it comes to estimating the future damage of climate change, other approaches use annual temperature [Bilal and Känzig, 2024] and, thus, avoid the problem of time-fixed effects, which erase a large portion of climate impacts. The question of aggregation is less of an issue in this case, as these approaches consider annual temperature to be a sufficient statistic for estimating impacts. Nevertheless, the question of the relevance of past natural variability as a proxy for global annual climate change based on complex processes and rising carbon concentration remains, and is left for further research.

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

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

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Appendix A. Building climate landscapes

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

Appendix B. Köppen regions

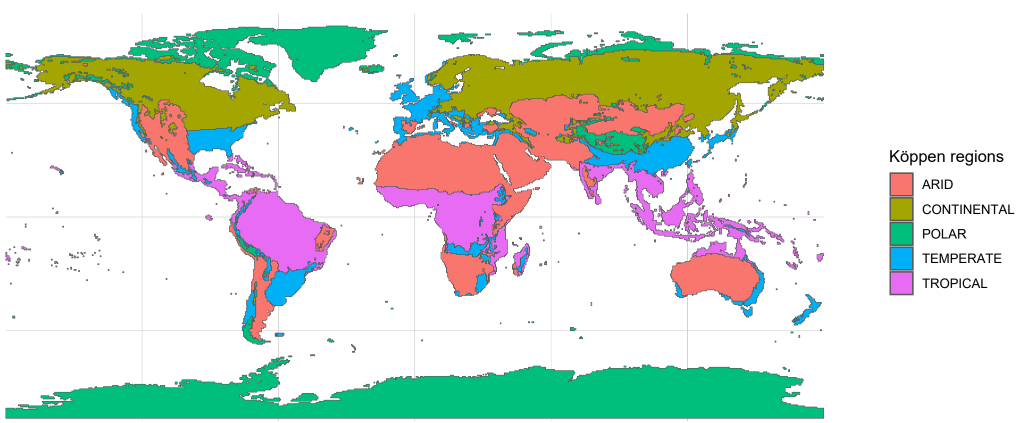

Figure 6. : Köppen climatic zones

[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.

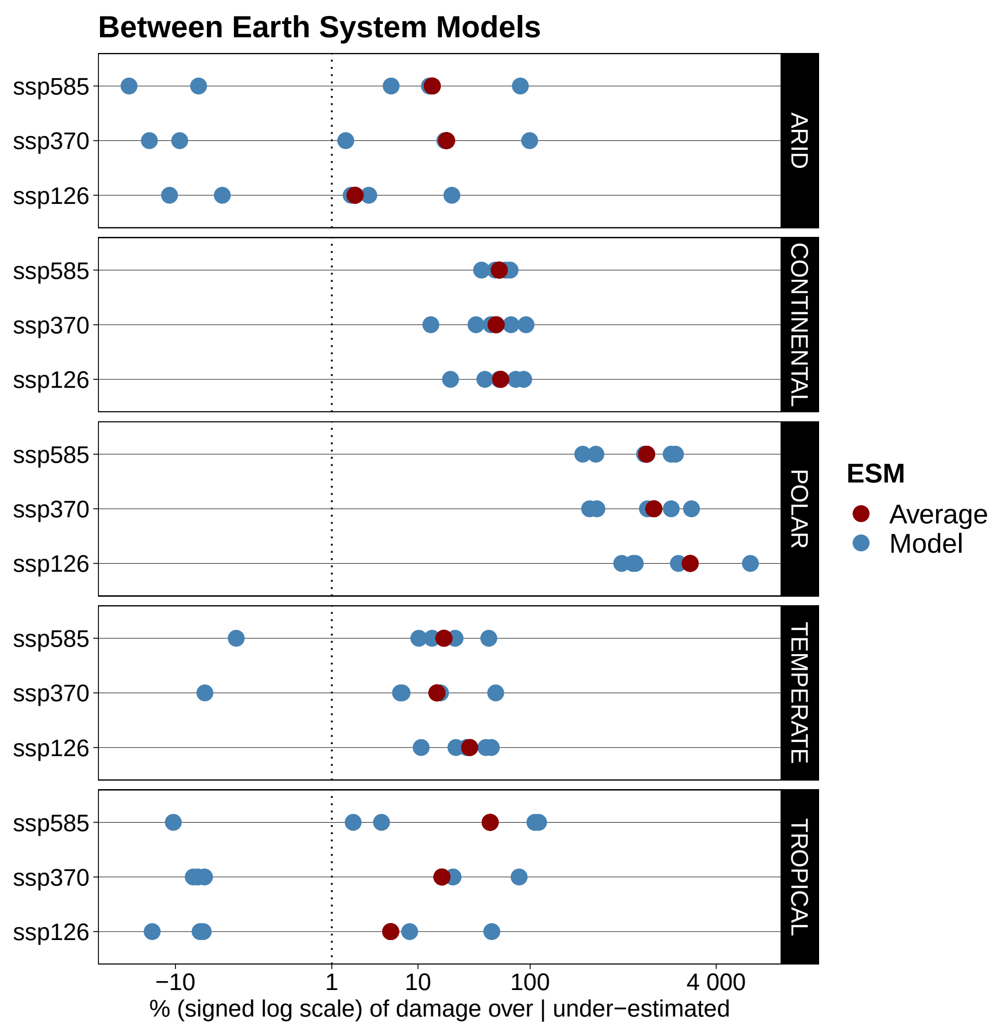

Figure 7. : Distribution of relative DD for each region and SSP, for different ESM and the average across ESM.

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

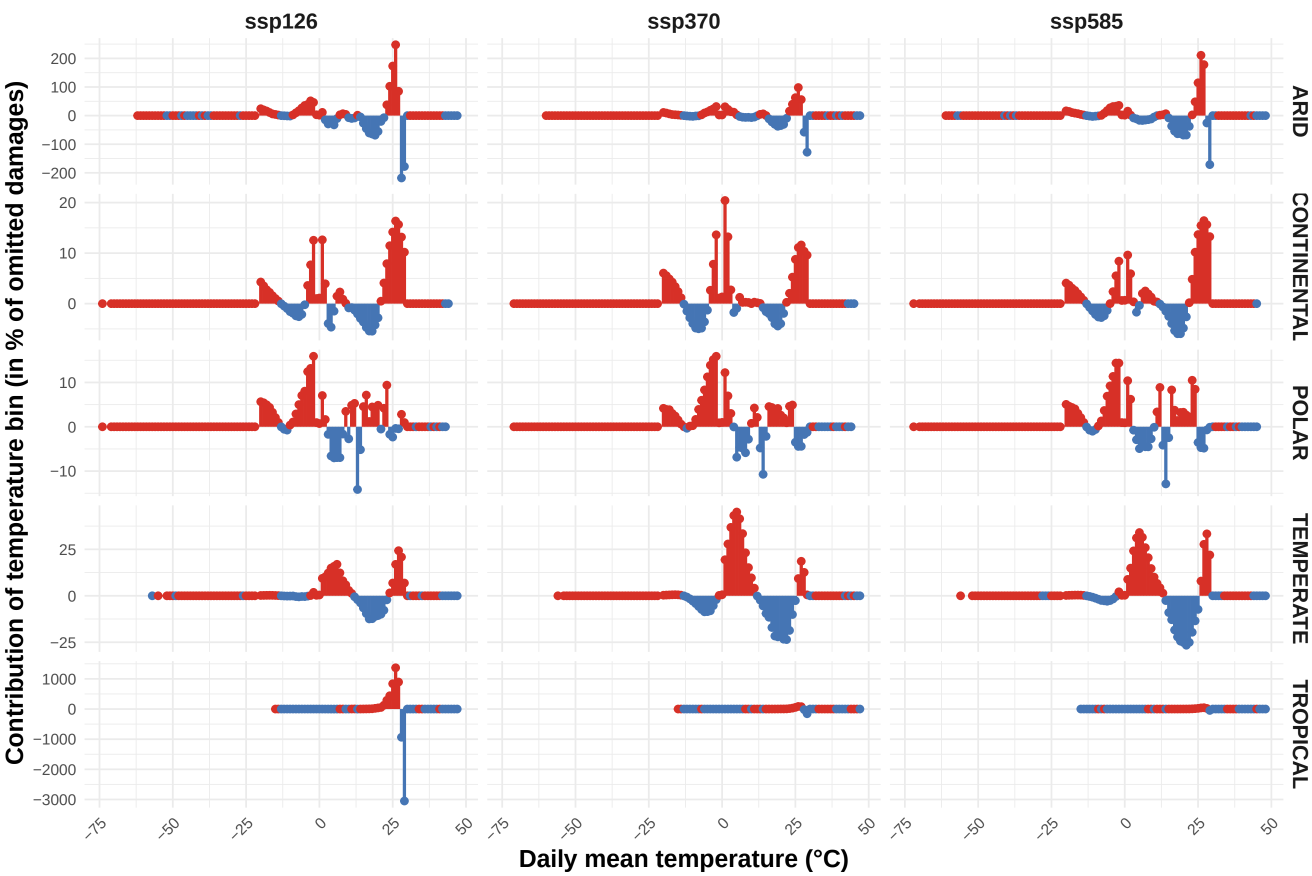

Figure 8. : Decomposition for each Koppen-Geiger zone. Temperature levels contribution (in %) to over/under estimated damages between projections and synthetic-model climate. The bins are plotted for each Köppen-Geiger zone (columns) and each SSP (rows). In red (blue), the bin represent a positive (negative)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

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

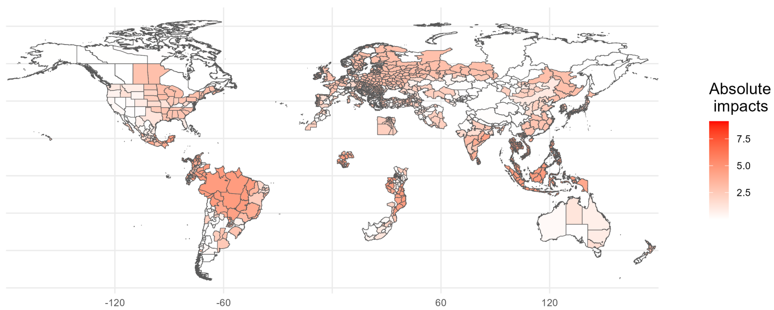

Figure 9. : Absolute damages (%), 2050, SSP5-8.5.

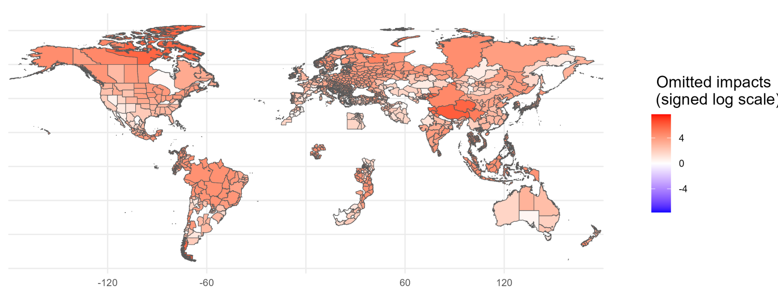

Figure 10. : Omitted damages (%), 2050, SSP5-8.5.

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

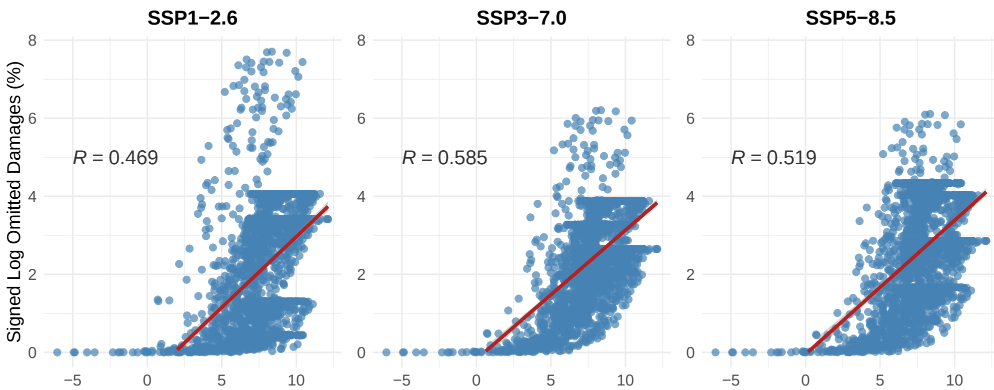

Figure 11. : Regional DD, year 2050.

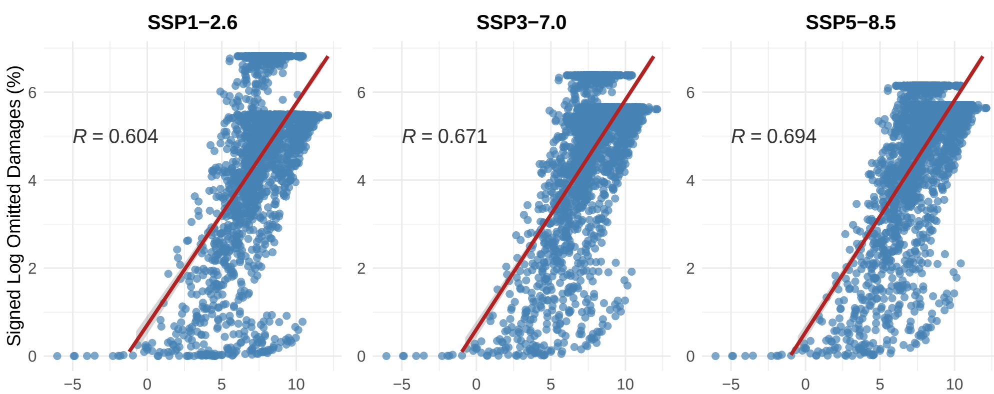

Figure 12. : Absolute difference in damage, 2050.

Appendix D. Results from econometric specification

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

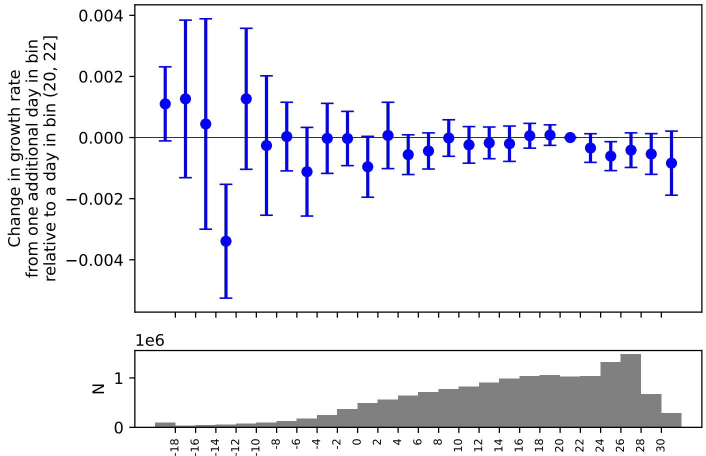

Figure 13. : Dose-response function.

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.

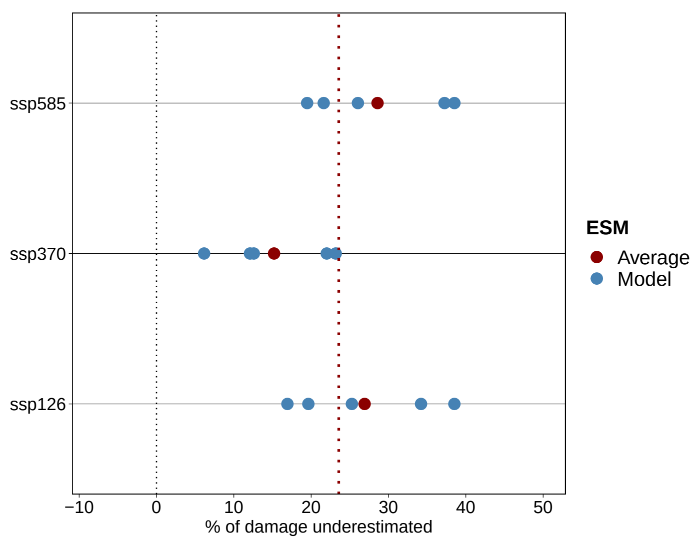

Figure 14. : Alternative regression with GDP levels rather. Global DD estimates.

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