

ESTIMATING THE ECONOMIC IMPACT OF TEMPERATURE VOLATILITY

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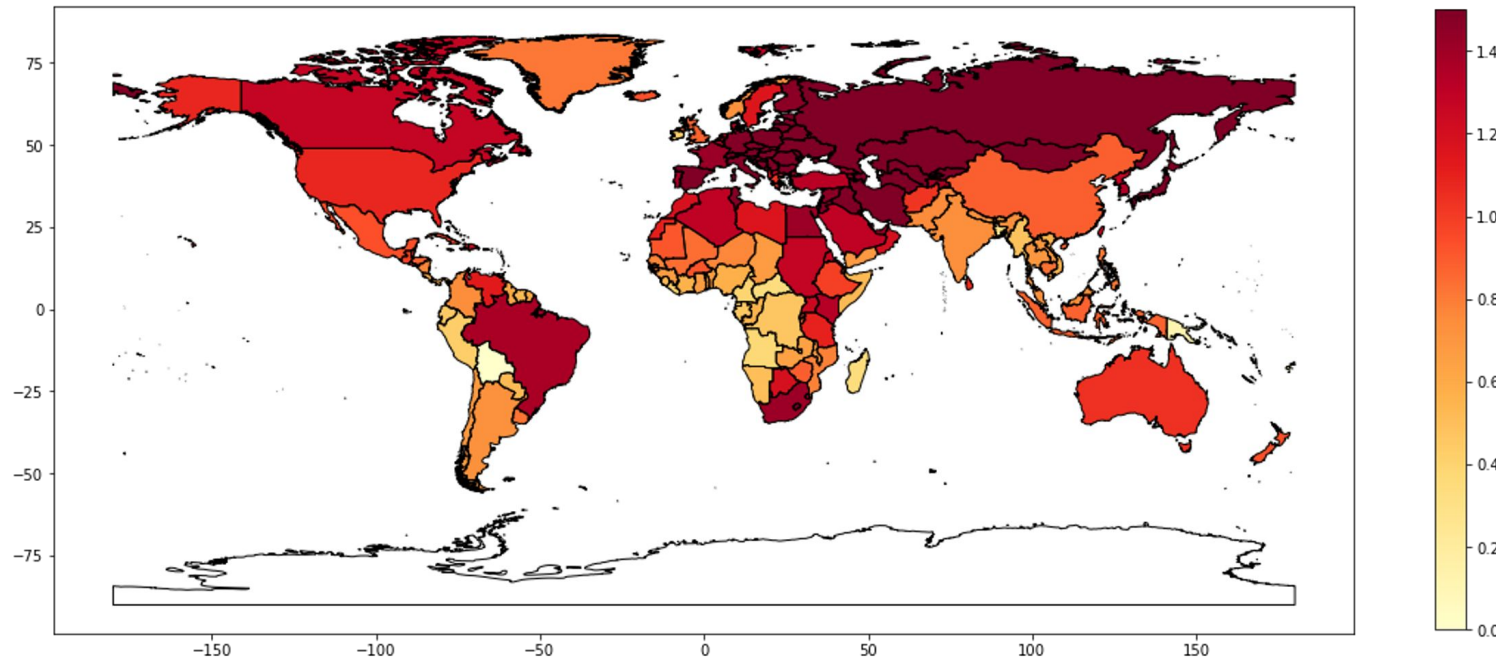
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The planet is warming...

Average annual temperature anomaly (°C), 2010-2020 vs 1901-1960

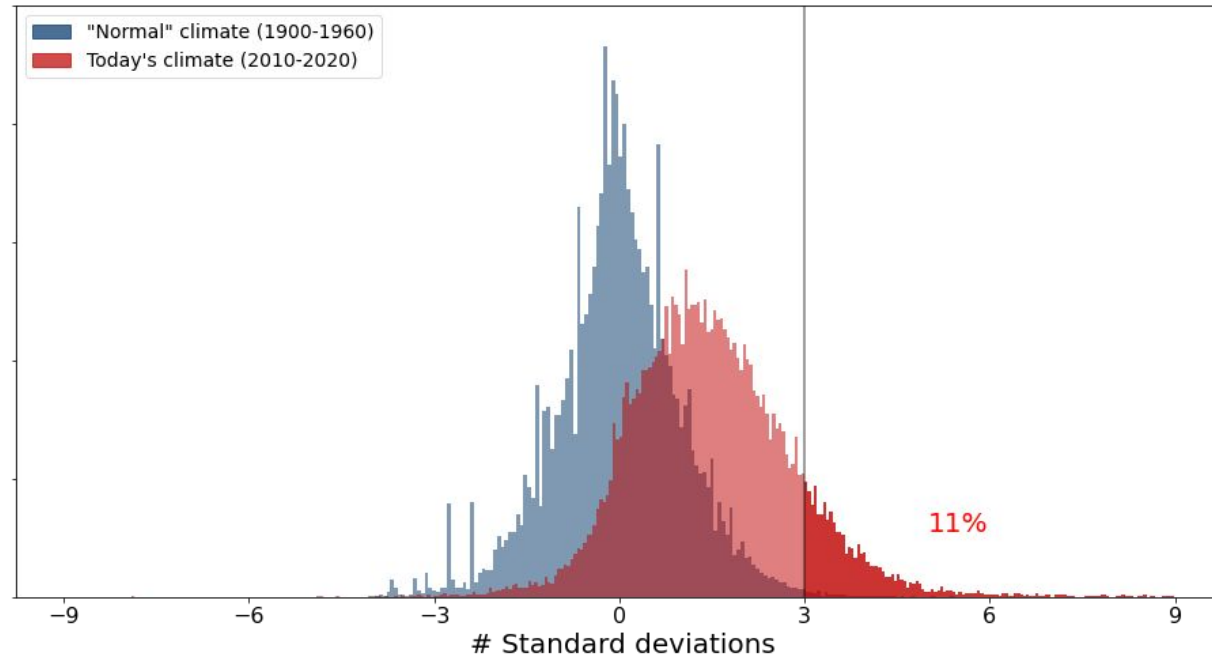


Source: Oxford Economics / UEA

$$\text{Annual anomaly: } \textit{Warming}_{c,y} = (TMP_{c,y} - \overline{TMP}_{c,1900-1960})$$

...and the temperature distribution is changing too

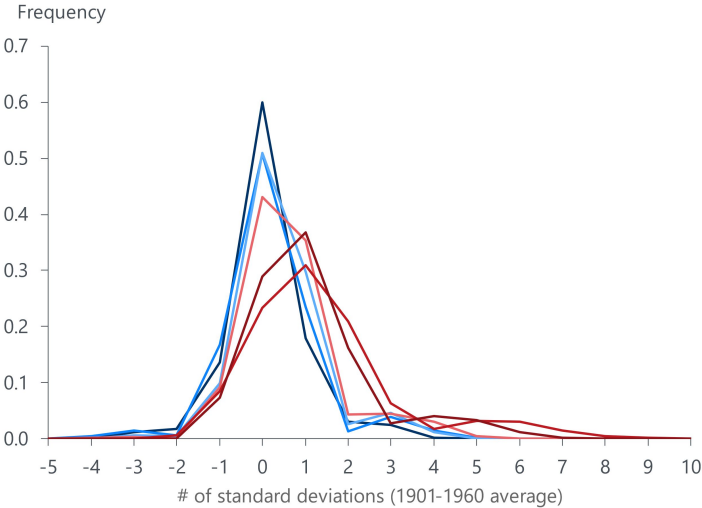
Changing distribution of global temperature anomalies



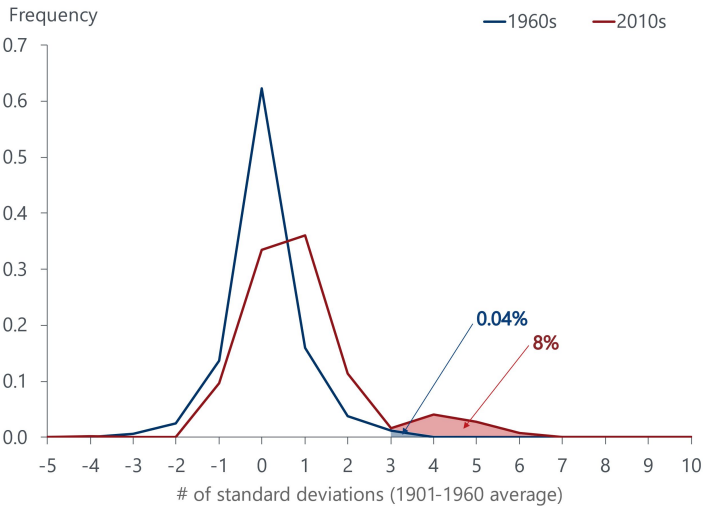
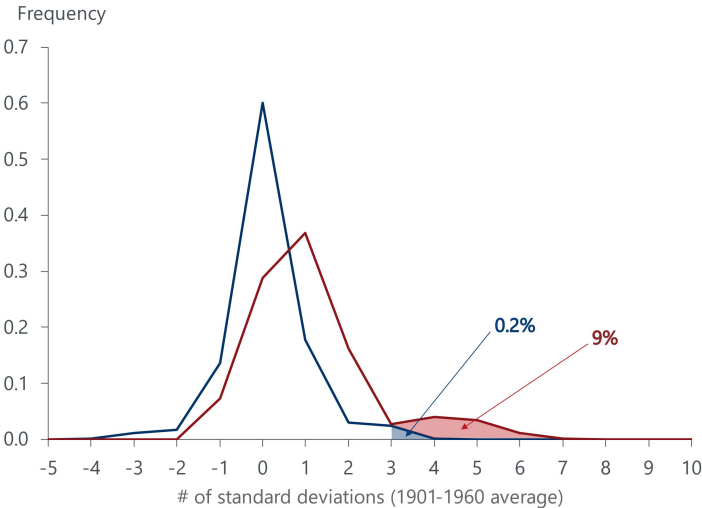
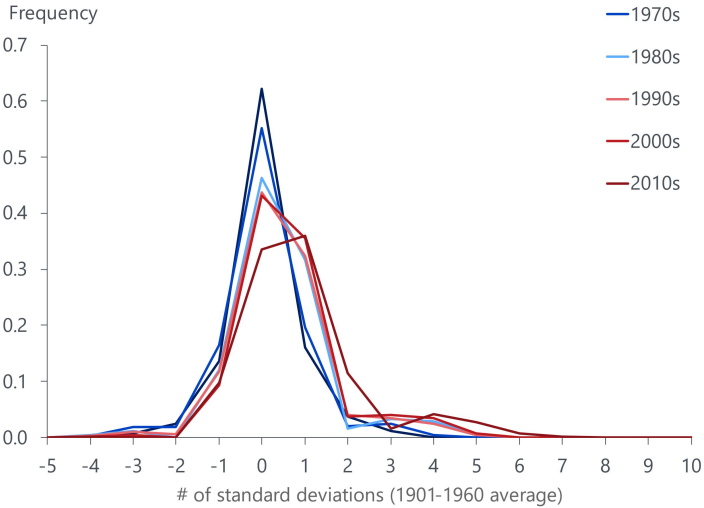
Source: Oxford Economics / UEA. Distribution of global temperature anomalies expressed in terms of country-specific historical standard deviations.

The trends are global

India: Mean temperature anomaly distribution



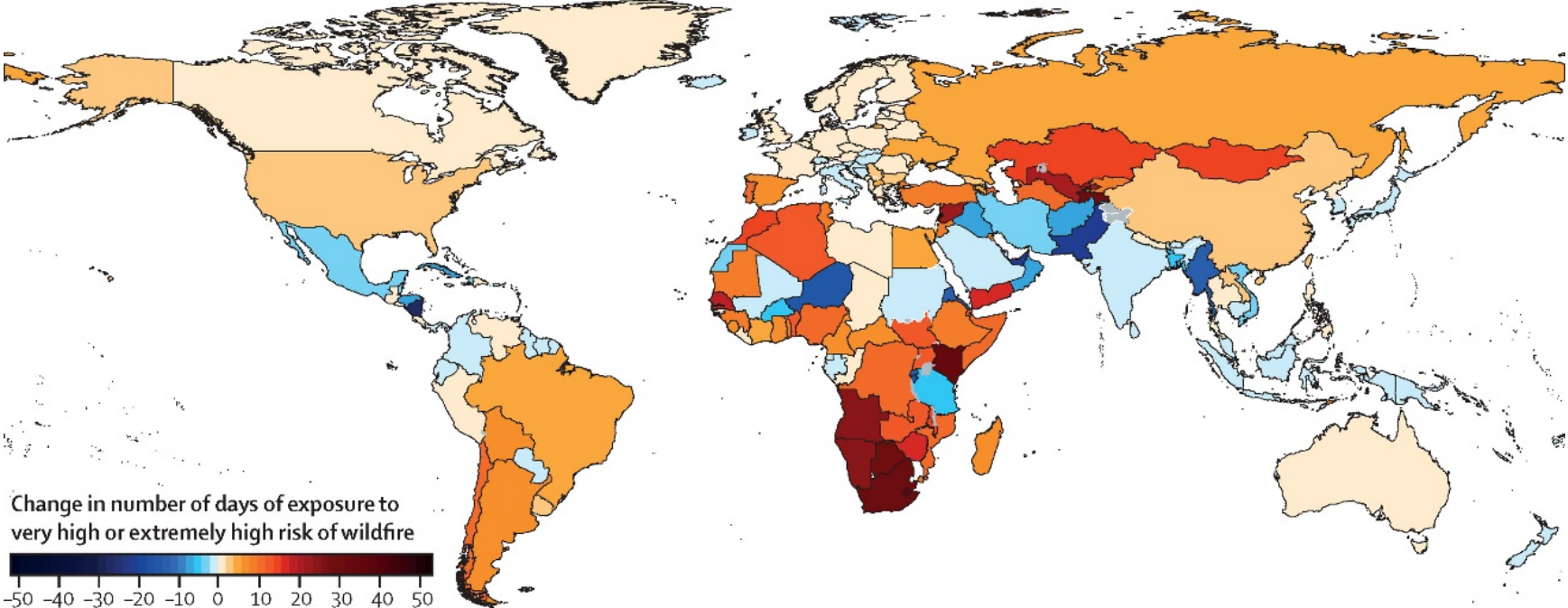
Canada: Mean temperature anomaly distribution



Source: Oxford Economics / UEA. Temperature anomaly distributions expressed in terms of country-specific historical standard deviations.

Contributing to droughts, wildfires, damage to infrastructures...

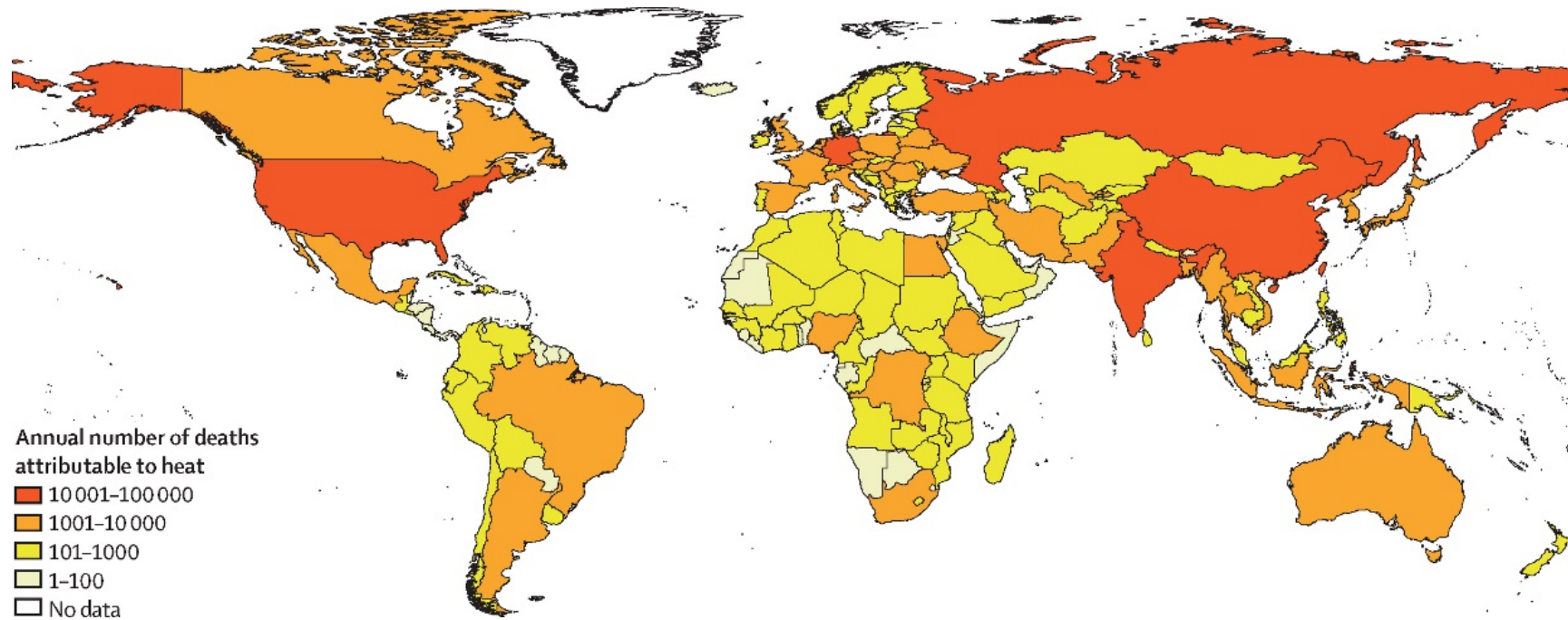
Population-weighted wildfire exposure, 2016-2019 vs 2001-2004



Source: *The Lancet Countdown on health and climate change, 2020*

...and even taking lives

Annual heat-related mortality in population over 65 years, 2014-2018



Source: *The Lancet Countdown on health and climate change, 2020*

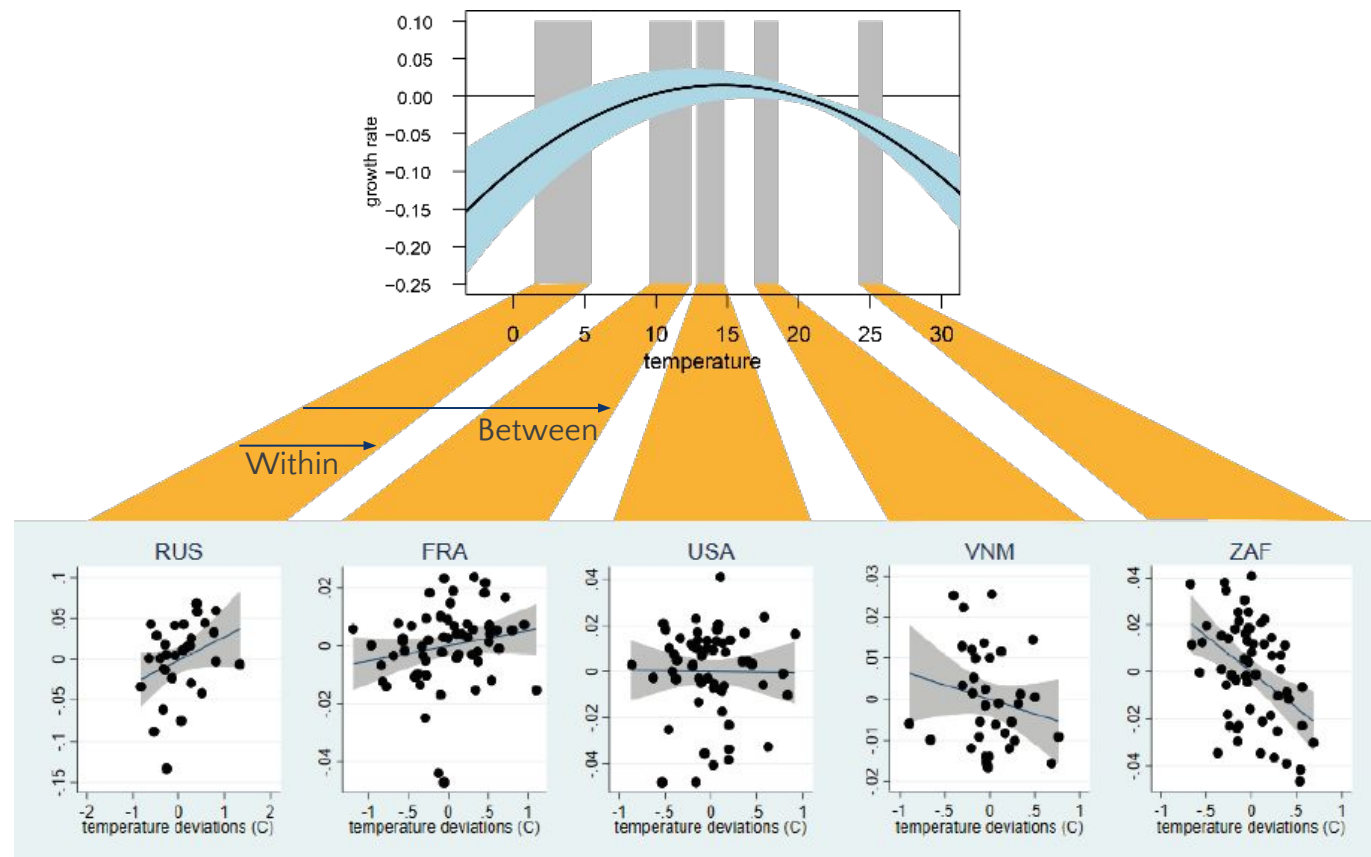


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Quantifying impacts

Quadratics in average temperatures exploit statistical variation over both countries and time...

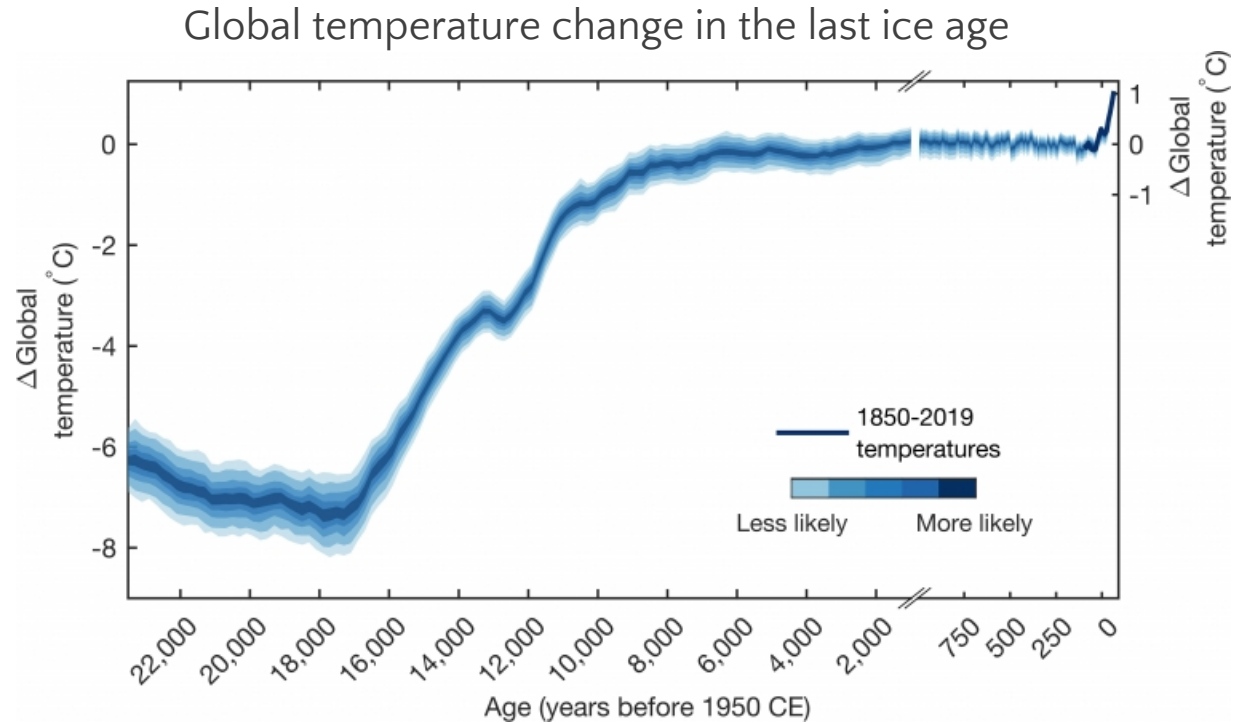
Construction of the temperature damage curve



Source: Oxford Economics, adapted from Burke et al. 2015

$$\Delta \ln(\text{GDP}) = f(\text{Temperature}, \text{Temperature}^2)$$

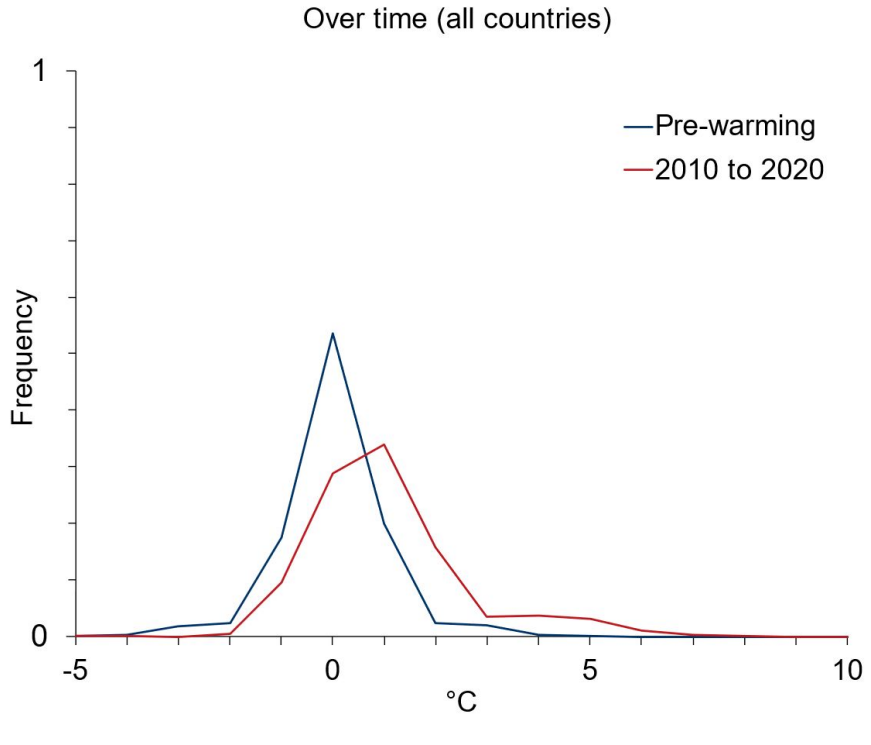
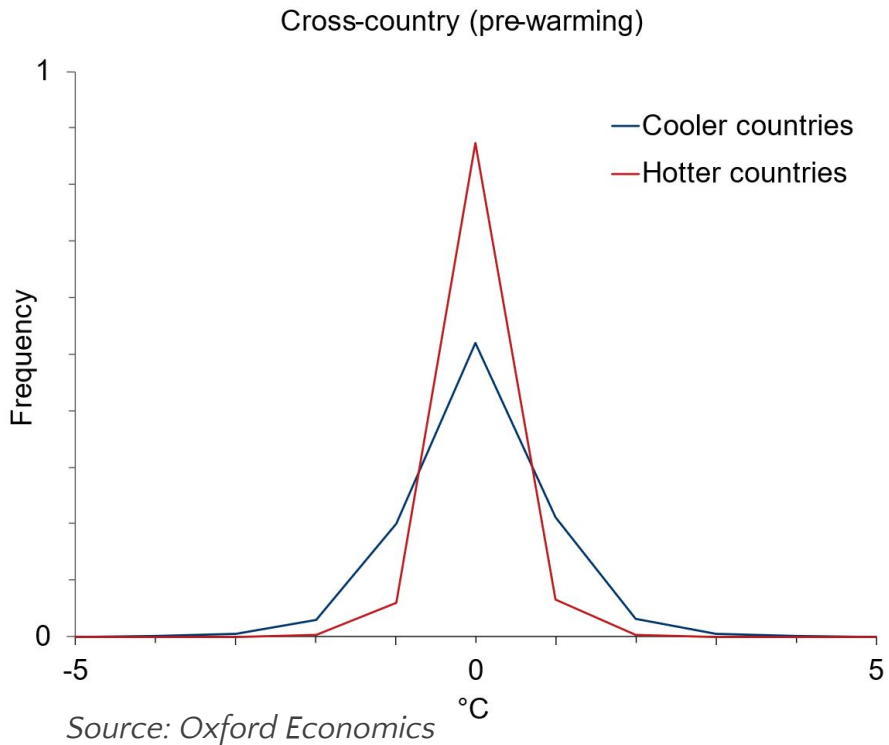
But average temperature levels had been stable for >10,000 years...



Source: Oxford Economics, University of Arizona. Global average surface temperature since the last ice age 24,000 years ago. Time is stretched for the past 1000 years to visualize recent changes.

...and cross-country and time-varying distributions show opposite trends

Cross-country versus over-time trends in average temperature anomaly distributions



Quantifying climate *change*

1. Re-define the damage function in terms of **warming**, i.e., temperature *anomalies* rather than average temperature *levels* · directly captures the impact of warming by constraining cross-country comparisons to differences in temperature anomalies rather than temperature levels.
2. Test whether including explicit measures of the temperature distribution such as **volatility and extremes** affect the damage assessment or improve statistical power.



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Regression analysis

Three core specifications for $\Delta \ln(\text{GDP})$



Augmented warming specifications aim to better isolate the impact of extreme temperature anomalies and more erratic temperatures on the economy.

Annual anomaly:

$$\text{Warming}_{c,y} = (TMP_{c,y} - \overline{TMP}_{c,pre-warming})$$

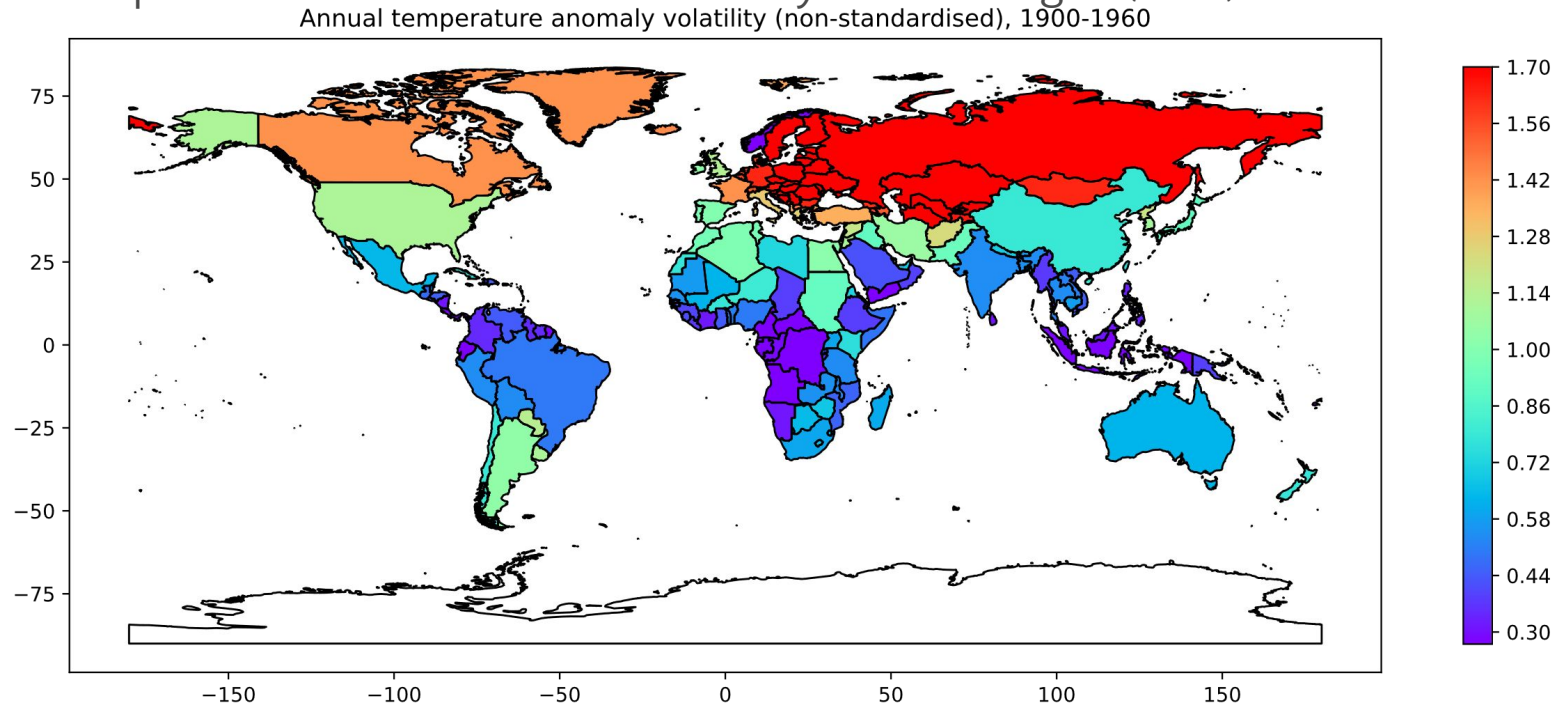
Monthly anomaly (used for volatility, skewness):

$$\text{Anomaly}_{c,m} = (TMP_{c,m} - \overline{TMP}_{c,m,pre-warming}) / \bar{\sigma}_{c,pre-warming}$$

For country c in year y , month m .

Data

- First difference of the natural logarithm of real annual GDP per capita from WDI (225 countries).
- Monthly geospatial temperature data from the University of East Anglia (UEA) over the 1901–2020 timespan.



Source: Oxford Economics / UEA

High frequency and granularity of the data allows us to capture aspects such as volatility over a year based on the monthly and coordinate-level observations, which we aggregate with population weighting and annualise.

Results

Model	(1) $\lambda = \text{Temperature}$	(2) $\lambda = \text{Warming}$	(3) $\lambda = \text{Warming}$	(4) $\lambda = \text{Warming}$
λ	0.0396*** (0.0114)	0.0120 (-0.00862)	0.0505*** (0.0182)	0.0538*** (0.0178)
λ^2	-0.00134*** (0.000347)	-0.00848* (0.00461)	-0.0152** (0.00610)	-0.0155** (0.00608)
<i>Volatility</i>			-0.0204*** (0.00621)	-0.0204*** (0.00624)
<i>Skewness</i>			-0.0183*** (0.00726)	-0.0193*** (0.00721)
<i>Kurtosis</i>			-0.00434 (0.00355)	
<i>Constant</i>	-0.296 (0.234)	-0.193 (0.213)	-0.176 (0.211)	-0.181 (0.212)
<i>Observations</i>	9,080	9,055	9,055	9,055
R^2	0.331	0.330	0.332	0.332

Robust standard errors in parentheses. *** p<0.01, **p<0.05, * p<0.1

$$\Delta y_{i,t} = \alpha + \beta_0 W_{i,t} + \beta_1 W_{i,t}^2 + \beta_2 \mu(2)_{i,t} + \beta_3 \mu(3)_{i,t} + f_i + v_t + \theta_{i_1} t + \theta_{i_2} t^2 + \varepsilon_{3i,t}$$

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Damage forecasts

Forecasting volatility & skewness

$$\Delta Y_{c,y} = f(\text{Warming}_{c,y}, \text{Warming}_{c,y}^2, \text{Volatility}_{c,y}, \text{Skewness}_{c,y})$$

$$\text{Volatility}_{c,y} = \overline{\text{Volatility}}_{c, \text{pre-warming}} + \rho_{1,r} * \text{Warming}_{c,y}$$

Region	N. America	Latam	Caribbean	Europe	Africa	SE Asia	Rest of Asia	Oceania
<i>W</i>	0.266*** (0.0379)	0.956*** (0.0325)	1.397*** (0.0187)	0.196*** (0.0109)	0.771*** (0.0168)	1.046*** (0.0356)	0.394*** (0.0123)	1.231*** (0.0453)
<i>Obs.</i>	240	1,200	1,020	2,520	3,060	1,140	1,560	1,020
<i>R</i> ²	0.171	0.418	0.846	0.114	0.406	0.431	0.398	0.421

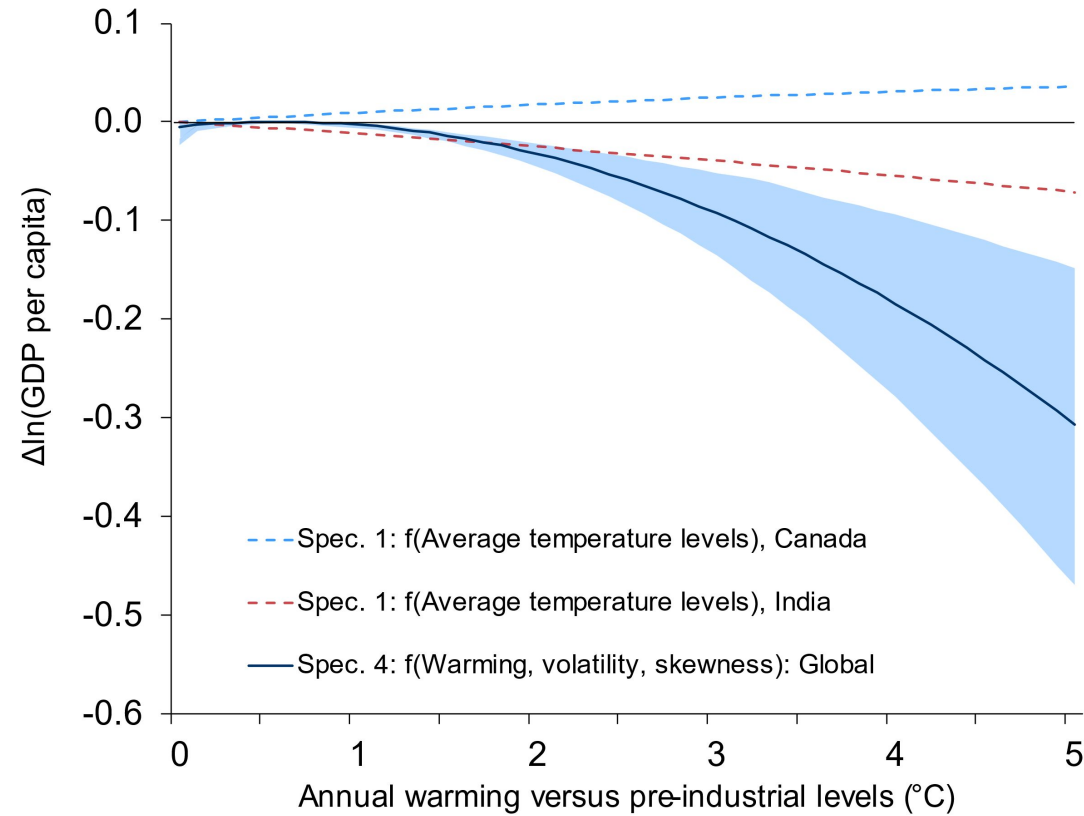
$$\text{Skewness}_{c,y} = \overline{\text{Skewness}}_{c, \text{pre-warming}} + \rho_{2,r} * \text{Warming}_{c,y}$$

Region	N. America	Latam	Caribbean	Europe	Africa	SE Asia	Rest of Asia	Oceania
<i>W</i>	1.293*** (0.0727)	1.853*** (0.0384)	1.257*** (0.0247)	1.040*** (0.0132)	1.523*** (0.0227)	1.900*** (0.0406)	1.055*** (0.0182)	1.952*** (0.0612)
<i>Obs.</i>	240	1,200	1,020	2,520	3,060	1,140	1,560	1,020
<i>R</i> ²	0.569	0.660	0.717	0.712	0.595	0.658	0.682	0.500

For country *c* in respective region *r*, and year *y*

□ Damage function : Global

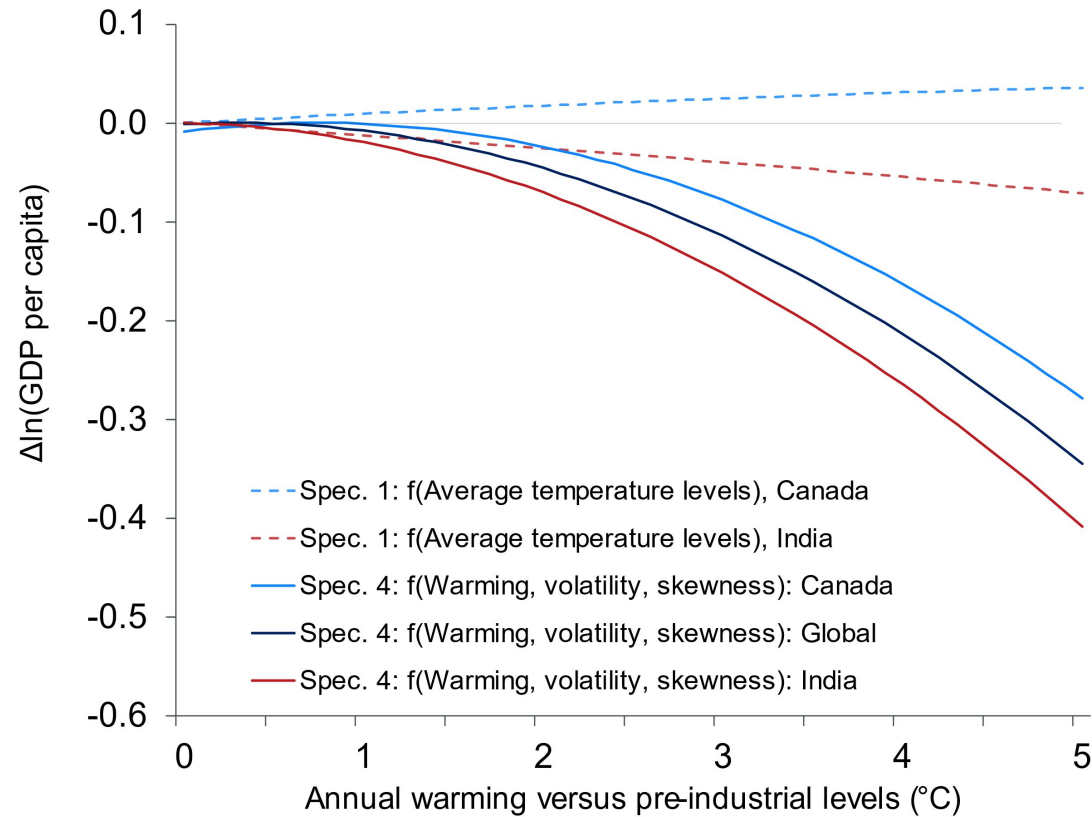
Contributions of Warming, Volatility and Skewness to GDP growth



Source: Oxford Economics. Shaded area represents regional heterogeneity.

□ Damage function: Country-specific

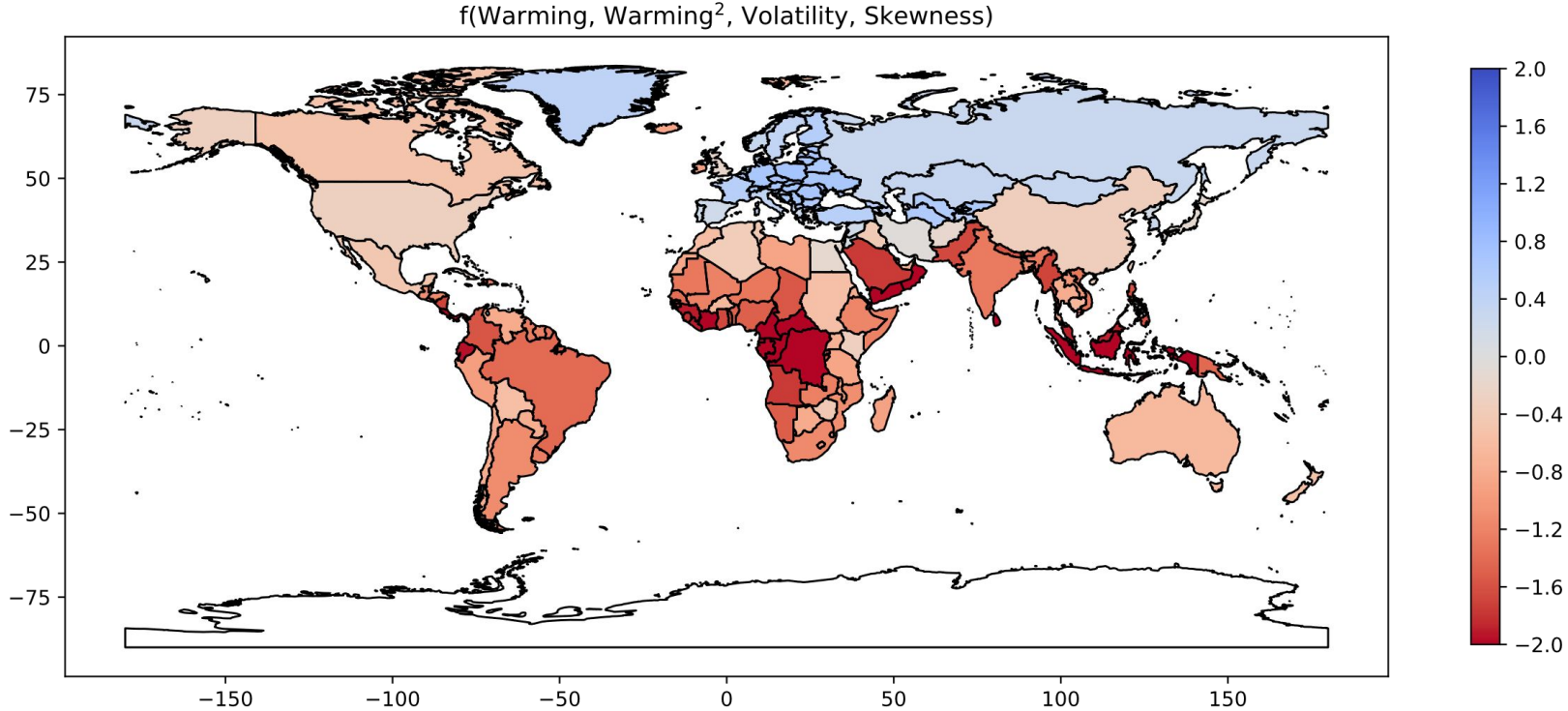
Contributions of Warming, Volatility and Skewness to GDP growth



Source: Oxford Economics

Historical damage trends

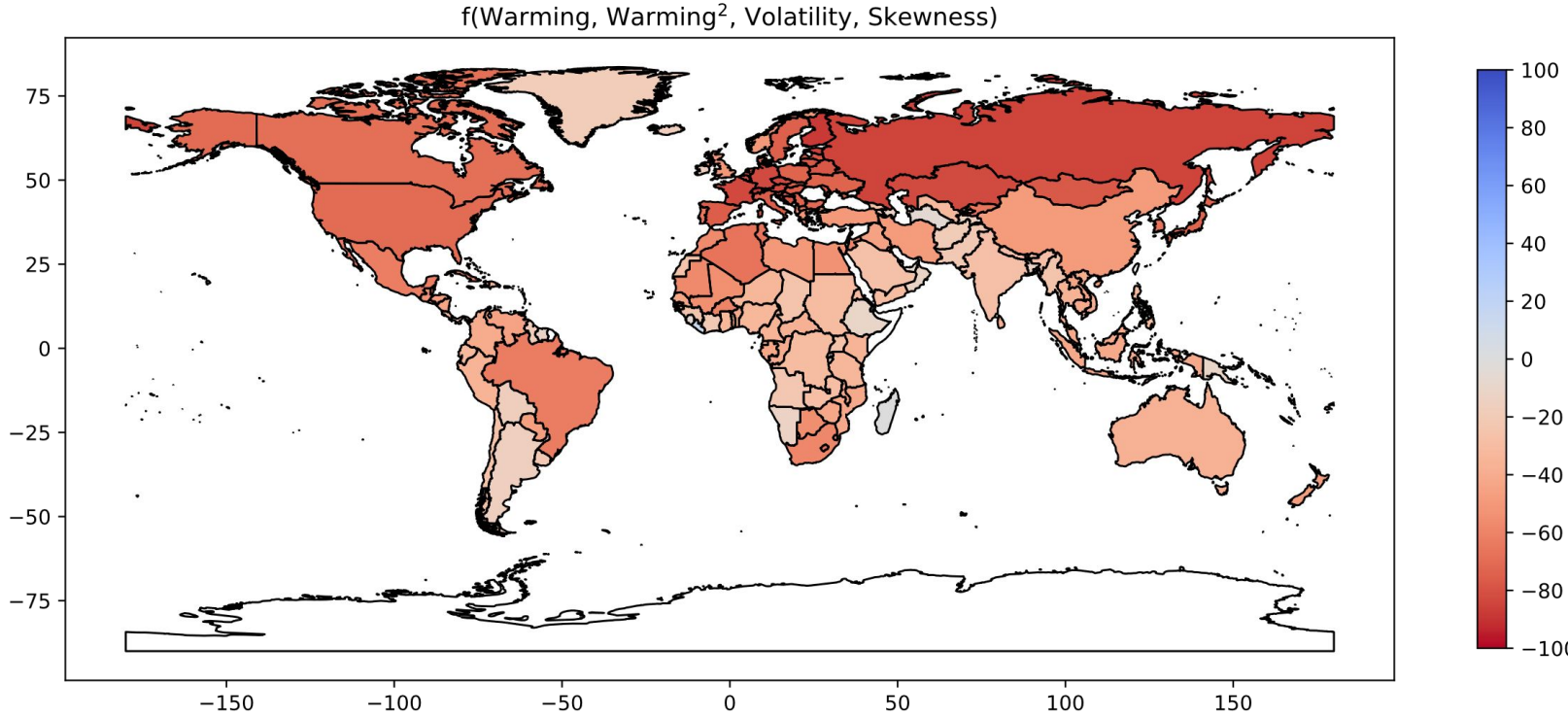
Average historical percentage-point impact of climate change on GDP growth, 1960-2019



Source: Oxford Economics

Possible future damage trends

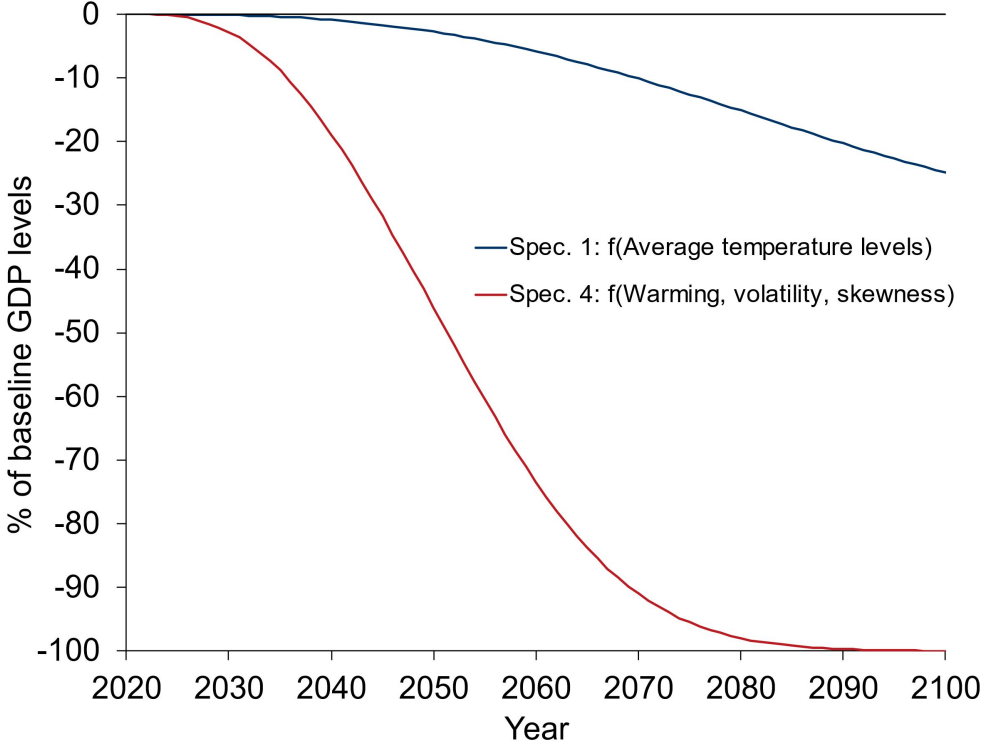
Percentage change in GDP levels by 2050 under a high-emissions scenario (RCP 7.0), vs. flat temperature counterfactual



Source: Oxford Economics

Climate catastrophe?

Global GDP impacts under a high-emissions scenario (RCP 7.0), vs. flat temperature counterfactual



Source: Oxford Economics

-5°C of warming is an extinction-level event (Song, Kemp, Tian et al. 2021).

Robustness

Robustness

Results are robust to:

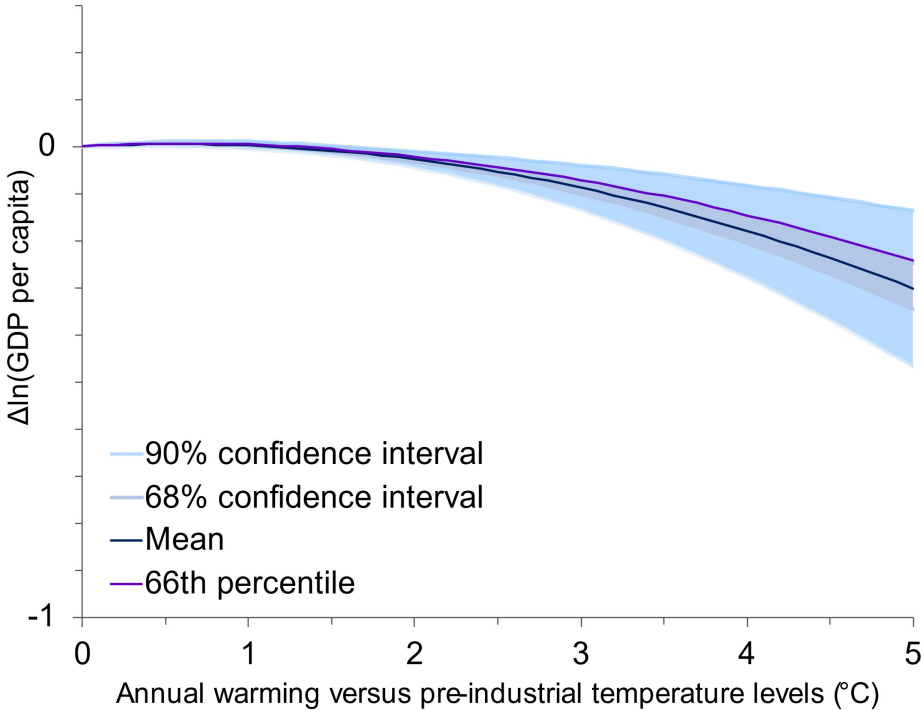
- **Different functions forms** (e.g. quadratics and higher order polynomials, interaction effects)
- **Inclusion of other weather regressors** (e.g. precipitation)
- **Different data aggregation methods** (i.e. calculating moments at country or coordinate level first)

Collinearity

Linear correlation matrix of regressors

<i>Warming</i>	1			
<i>Warming²</i>	0.78	1		
<i>Volatility</i>	0.41	0.36	1	
<i>Skewness</i>	0.70	0.29	0.22	1
	<i>Warming</i>	<i>Warming²</i>	<i>Volatility</i>	<i>Skewness</i>

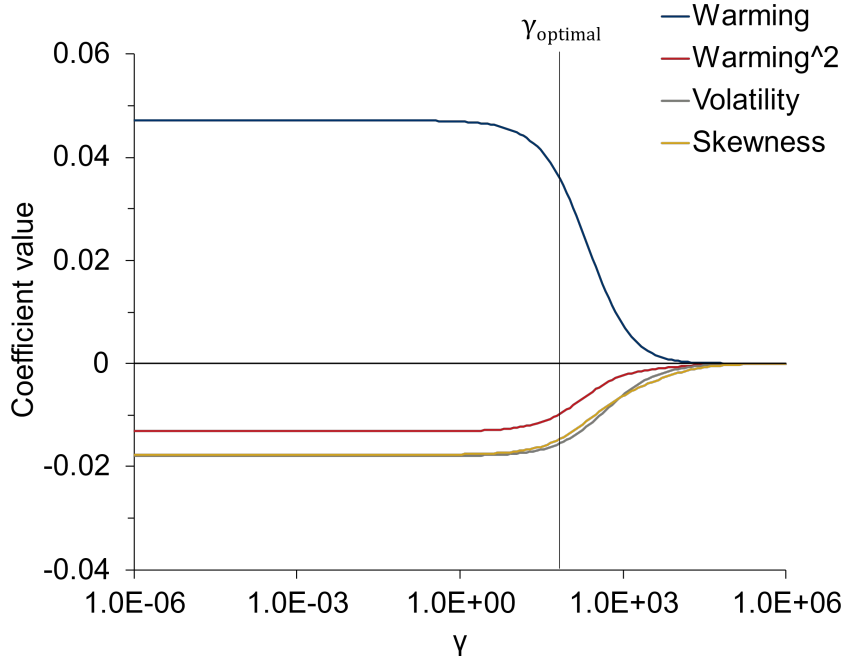
Confidence intervals using bootstrapped residuals of the dependent variable



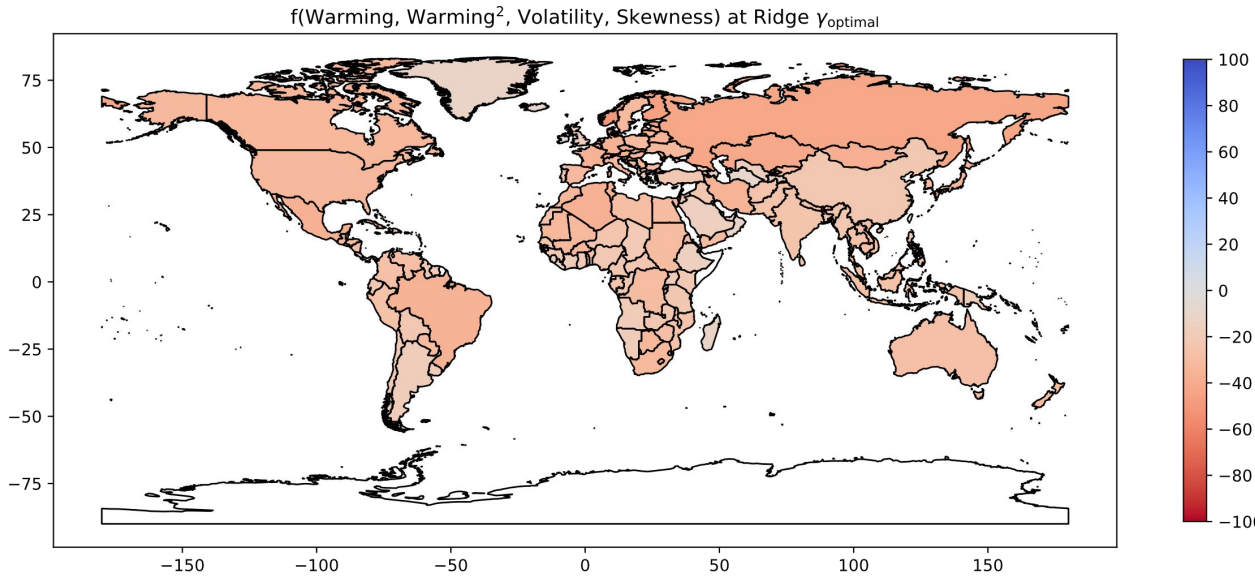
Source: Oxford Economics

Collinearity

Ridge regression coefficients as a function of regularisation, γ



Percentage change in GDP levels by 2050 under a high-emissions scenario (RCP 7.0), vs. flat temperature counterfactual



Source: Oxford Economics. Based on the following optimisation problem applied to two cross-validation samples:

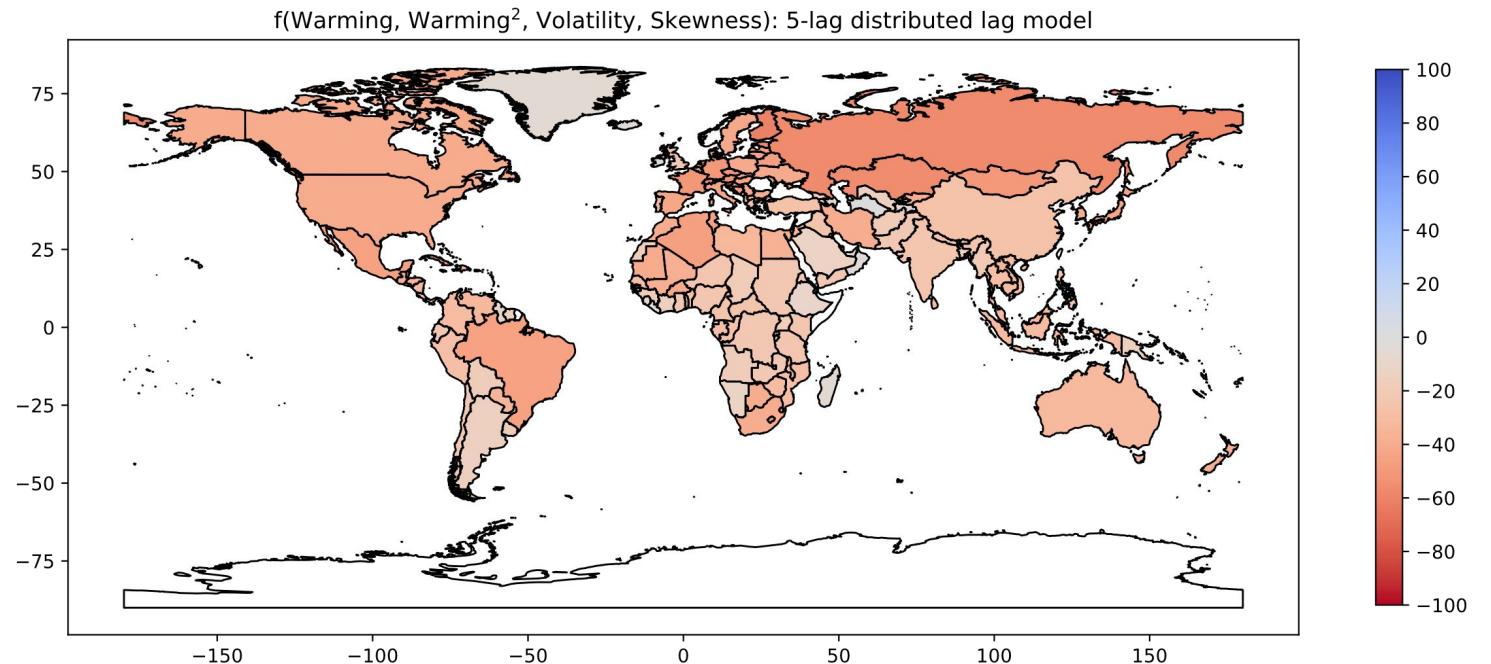
$$\min[\sum_{i,t} (\Delta Y_{it} - \alpha - \beta_0 \lambda_{i,t} - \beta_1 \lambda_{i,t}^2 - \beta_2 \mu(2)_{i,t} - \beta_3 \mu(3)_{i,t} - f_i - v_t - \theta_{i1} t - \theta_{i2} t^2)^2 + \gamma \sum_{k=0}^3 \beta_k^2], \gamma \in \text{logspace}[-6,6]$$

Dynamics

Marginal effects

W	Lags = 0	Lags = 5
0.5°C	-0.0068 (0.0048)	-0.0026 (0.0123)
1°C	-0.0223 (0.0074)	-0.0147 (0.0135)
1.5°C	-0.0379 (0.0125)	-0.0268 (0.0201)
2°C	-0.0534 (0.0183)	-0.0389 (0.0299)
2.5°C	-0.0689 (0.0261)	-0.0509 (0.0403)
3°C	-0.0844 (0.0333)	-0.0630 (0.0494)

Percentage change in GDP levels by 2050 under a high-emissions scenario (RCP 7.0), vs. flat temperature counterfactual



Because we are estimating a non-linear model, we calculate marginal effects for both the contemporaneous and lagged response functions at each point of the warming support and add up these marginal effects over time. That is, in the 5-lag model and ignoring controls, $\Delta y_{i,t} = \beta_0 W_{i,t} + \beta_1 W_{i,t}^2 + \beta_2 \mu(2)_{i,t} + \beta_3 \mu(3)_{i,t} + \dots + \beta_{16} W_{i,t-5} + \beta_{17} W_{i,t-5}^2 + \beta_{18} \mu(2)_{i,t-5} + \beta_{19} \mu(3)_{i,t-5}$, the marginal effect on growth at some warming W^* is then $\hat{\beta}_0 + 2\hat{\beta}_1 W^* + \hat{\beta}_2 \hat{\rho}_2 + \hat{\beta}_3 \hat{\rho}_3 + \dots + \hat{\beta}_{16} + 2\hat{\beta}_{17} W^* + \hat{\beta}_{18} \hat{\rho}_2 + \hat{\beta}_{19} \hat{\rho}_3$. The result from this procedure is an estimate for the cumulative effect on income from one degree of warming, as a function of a country's initial warming.



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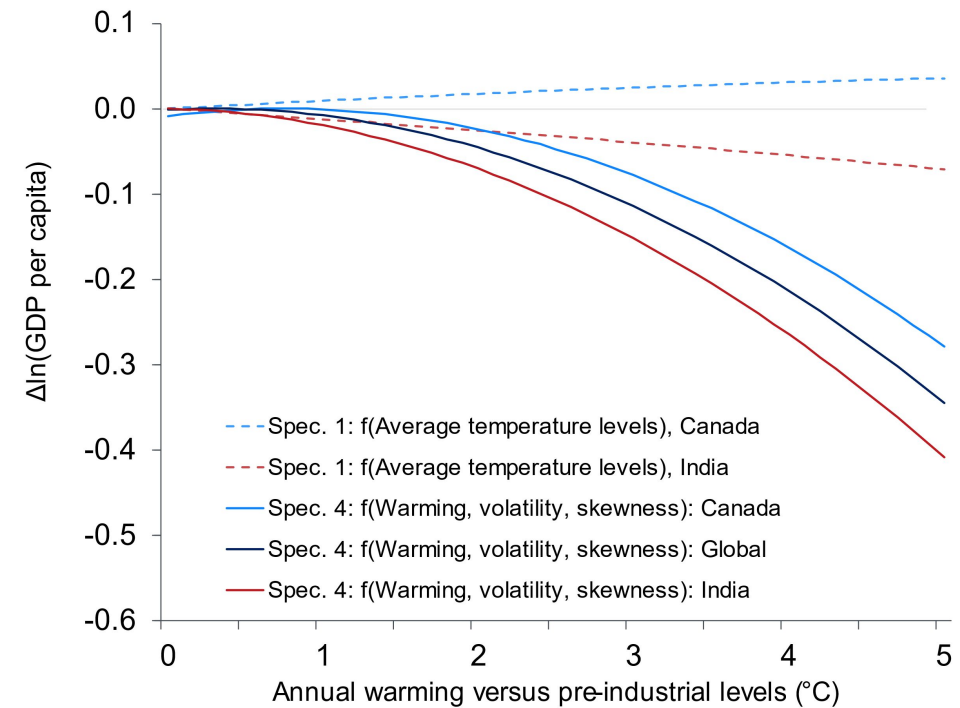
Conclusion

Key findings

Temperature anomalies are economically important and statistically significant.

1. Warming past historical norms has the potential to cause negative, non-linear impacts on GDP growth.
2. Accounting for volatility and tail composition of the temperature anomaly distribution suggests that the marginal effects of warming are even larger.
3. Cooler northern hemisphere economies are less vulnerable, but more exposed, therefore experiencing greater long-run damages.

Partial contributions of Warming, Volatility and Skewness



Source: Oxford Economics



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Questions?

Appendix

Standardisation

These monthly anomalies are then standardised, defined in terms of historical, pre-warming standard deviations to control for differences in volatility already noted across cooler and hotter geographies. This gives us the standardised anomaly, sa .

$$anomaly_{c,m} = (TMP_{c,m} - \overline{TMP}_{c,m,pre-warming})$$

↓

$$sa_{c,m} = (TMP_{c,m} - \overline{TMP}_{c,m,pre-warming}) / \bar{\sigma}_{c,pre-warming}$$

Where

$$\bar{\sigma}_{c,pre-warming} = \sqrt{\frac{\sum_{1901}^{1960} (TMP_{c,m} - \overline{TMP}_{c,m,1901-1960})^2}{60 * 12}}$$

Like de-meaning the temperature levels, this final adjustment allows us to focus on changes attributed to warming alone, rather than from comparing average levels across hotter and cooler countries. While our warming term demeans temperatures under the assumption that countries are already adapted to their historical average temperatures, our distribution metrics focus on the standardised anomaly under the assumption that all countries are already adapted to their historical temperature volatility. Therefore, the distribution metrics in specification (3) measure changes in temperature anomaly distributions that can attributed to warming *alone*.

Distribution metrics

Once we have defined the standardised anomaly sa , the distribution metrics themselves are easily calculated using typical formulae for volatility, skewness, and kurtosis, i.e.:

$$sa_{c,m} = (TMP_{c,m} - \overline{TMP}_{c,m,pre-warming}) / \bar{\sigma}_{c,pre-warming}$$

Then annual volatility $\mu(2)$, skewness $\mu(3)$, and kurtosis $\mu(4)$ are calculated as follows:

$$\mu(2)_{c,y} = \sqrt{\frac{\sum_1^{12} sa_{c,m}^2}{12}}$$

And,

$$\mu(k)_{c,y} = \frac{\sum_1^{12} sa_{c,m}^k}{12 * (\sqrt{\mu(2)_{c,y}})^k}$$

For $k \in [3, 4]$.

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