Supplementary Appendix for

Anomalous temperature and seasonality of injury mortality in the USA

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Statistical methods

We modelled the number of deaths in each year as following a Poisson distribution:

$$deaths_{state-time} \sim Poisson(death\ rate_{state-time} \,.\, population_{state-time})$$

with log-transformed death rates modelled as a sum of components that depend on location (state) of death, month of year, overall time (in months) and temperature anomaly:

$$\begin{aligned}\log(deaths_{state-time}) = \\ \alpha_0 + \beta_0 \cdot time + \\ \alpha_{state} + \beta_{state} \cdot time + \\ \alpha_{month} + \beta_{month} \cdot time + \\ \zeta_{state-month} + \\ \nu_{time} + \\ \gamma_{month} \cdot Anomaly_{state-time} + \\ \varepsilon_{state-time}\end{aligned}$$

The model contained terms that represent the national level and trend in mortality, with α_0 as the common intercept and β_0 the common time slope. Death rates also vary by month, which may be partly related to temperature and partly due to other monthly factors; monthly variations tend to be smooth across adjacent months.[1] Therefore, we allowed each month of the year to systematically have a different mortality level and trend, with α_{month} the month-specific intercept and β_{month} the month-specific time slope. We used a random walk for the month terms to smooth the coefficients, widely used to characterize smoothly varying associations.[2] The random walk had a cyclic structure, so that December was adjacent to January.

We also included state random intercepts and slopes for death rates, with α_{state} as the state-specific intercept and β_{state} the state-specific time slope. These terms measure deviations of each state from national values, and allow variation in level and trend in mortality by state. In addition, death rates in neighboring states may be more similar than in those further away, modelled using a Conditional Autoregressive (CAR) spatial model.[3] This allows mortality levels and trends of states to be estimated based on their own data as well as using those of their neighbors. The extent to which information is shared between neighboring states depends on the uncertainty of death rates in a state and the empirical similarity of death rates in neighboring states. We also included state-month interactions for intercepts and slopes ($\zeta_{state-month}$), to allow variation in mortality levels and trends in a particular state for different months and vice-versa. Non-linear change over time was captured by a first-order national random walk, ν_{time}.[2]

Finally, we included a term that relates log-transformed death rate to the above-defined state-month temperature anomaly, $\gamma_{month} \cdot Anomaly_{state-time}$. The coefficients of γ_{month} represent the logarithm of the monthly death rate ratio per 1°C increase in anomaly. There was a separate coefficient for each month which means that an anomaly of the same magnitude could have different associations with injury mortality in different months. As with the month-specific intercepts and trends, we used a cyclic random walk to smooth the coefficient of the temperature anomaly across months. An over-dispersion term ($\varepsilon_{state-time}$) captured the variation unaccounted for by other terms in the model, modelled as $N(0,\sigma_{\epsilon}^{2})$. We fitted the models using integrated nested Laplace approximation (INLA), using the R-INLA software, which offers orders of computational efficiency improvement in Bayesian inference compared to traditional MCMC.[4] The uncertainty in our results were obtained from 5000 draws from the posterior marginal of each month's excess relative risk. The reported 95% credible intervals, quoted in brackets where appropriate, are the 2.5th to 97.5th percentiles of the sampled values.

We conducted sensitivity analyses to assess how much our results might depend on the temperature metric used to generate anomalous temperature. First, instead of building our monthly temperature anomalies based on daily mean temperatures, we used daily maxima and minima. These measures were strongly correlated to those generated from daily means (Table S2), and therefore we did not run models using these alternatives.

Together with temperature anomaly based on daily mean temperatures, we also included a second measure of anomaly in the model. The additional measures were related to more extreme anomalous situations:

- temperature anomaly calculated based on 90^{th} percentile (°C) of daily mean temperatures within a month, compared to 30-year (long-term) norm of 90^{th} percentile for each state and month
- number of days in a month above the long-term 90^{th} percentile of norm temperature for each state and month (adjusted for length of month)
- number of 3+ day episodes above the long-term 90^{th} percentile of norm temperature for each state and month (adjusted for length of month)

The correlations among these variables and anomaly based on mean were between 0.60 and 0.89 (Table S3). The estimated rate ratios of temperature anomaly based on daily means (i.e., the anomaly measure used in the main analysis) were robust to the addition of alternative measures of anomaly, while the coefficients of the additional measures were generally not significant and with large credible intervals. Therefore, we did not include the alternative additional measures of extreme anomalous temperature in the main analysis.

Figure S1. Percent change in death rates in year in which each month was +1°C compared with 1980-2009 norm temperatures by type of injury, sex and age group.

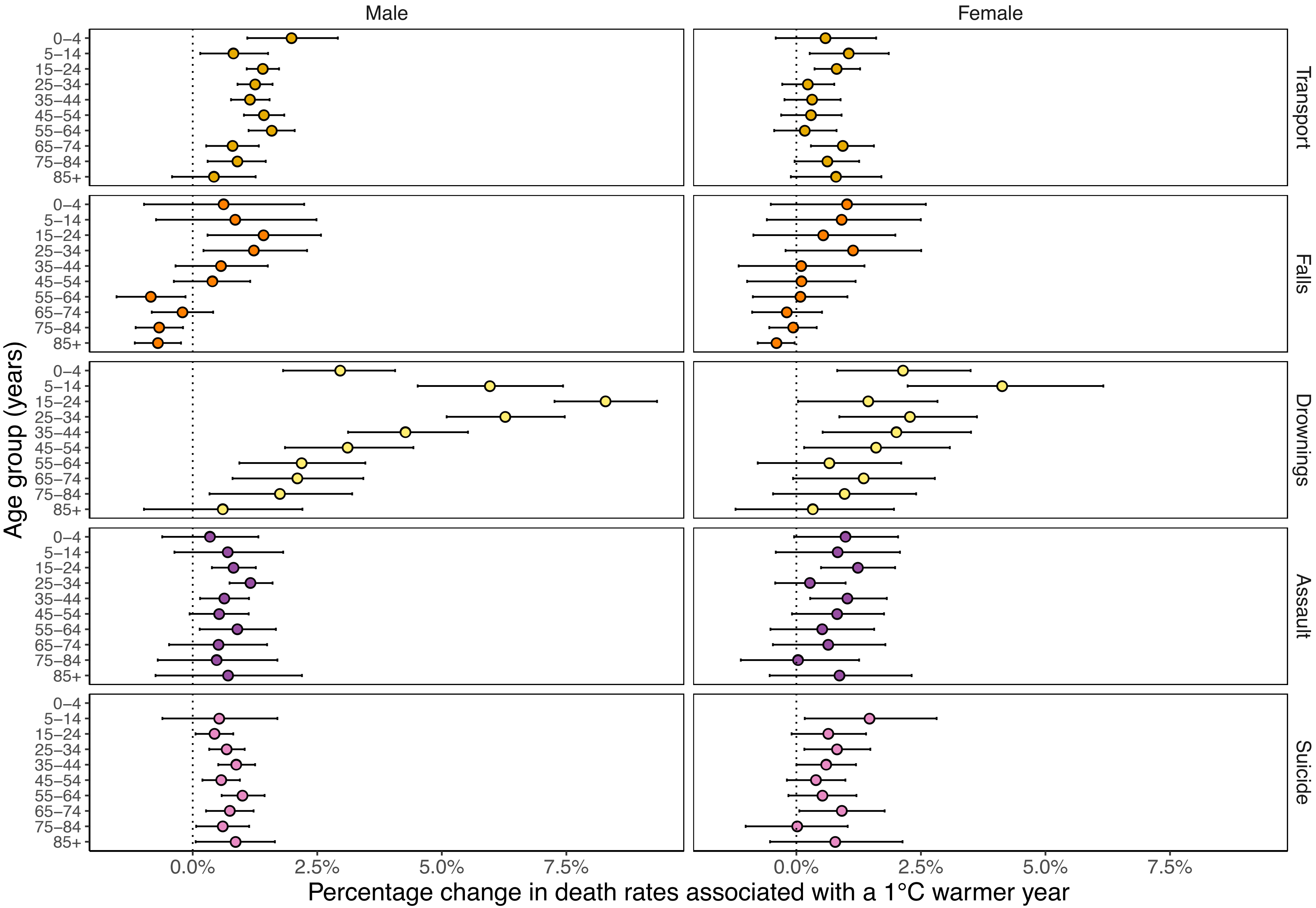
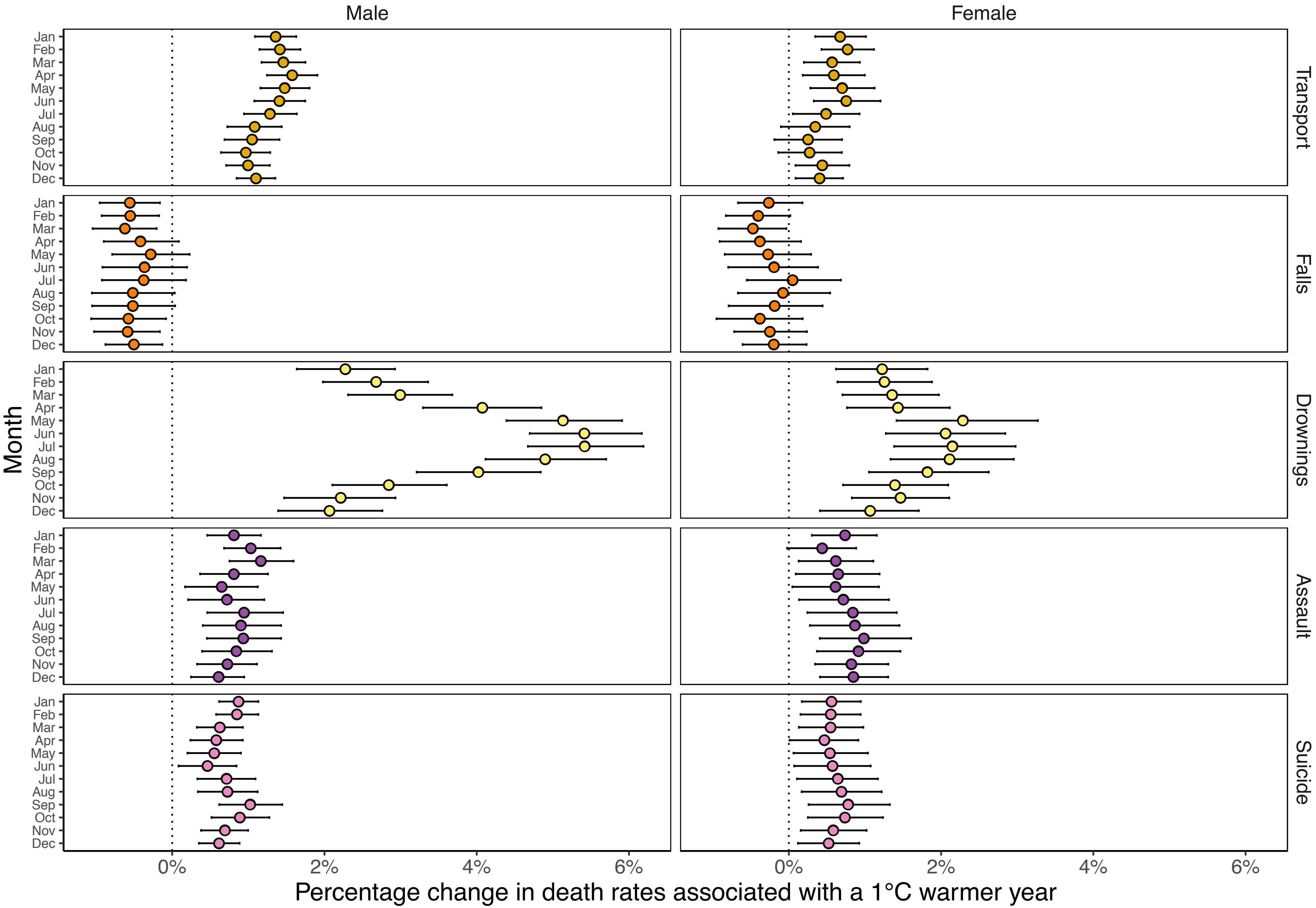

Male
Female
Transport
Falls
Drownings
Assault
Suicide
0–4
5–14
15–24
25–34
35–44
45–54
55–64
65–74
75–84
85+
Age group (years)
0.0%
2.5%
5.0%
7.5%
Percentage change in death rates associated with a 1°C warmer year

Figure S2. Percent change in death rates in year in which each month was +1°C compared with 1980-2009 norm temperatures by type of injury, sex and month.



Male
Female
Transport
Falls
Drownings
Assault
Suicide
Month
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
0%
2%
4%
6%
Percentage change in death rates associated with a 1°C warmer year

Table S1. Injury groups used in the analysis with ICD-9 and ICD-10 codes.

Injury type	ICD-9	ICD-10
All injuries	E800-E999	V0-Y89
Unintentional	E800-E949, E980-E989	V0-V99, W0-99, X0-X59, Y10-Y34, Y40-Y89
Transport	E800-E807, E810-E838, E840-E849	V0-V99
Falls	E880-E888	W0-W19
Drowning	E910-E910	W65-W74
Intentional	E950-E979.9, E990-E999	X60-X99, Y0-Y9, Y35-Y39
Suicide	E950-E959	X60-X84
Assault	E960-E979, E990-E999	X85-X99, Y0-Y9, Y35-Y39

Table S2. Correlation coefficients between monthly anomalies generated from daily mean temperature and daily maximum and minimum temperatures. Each correlation coefficient was calculated in each state for each month for 1980-2016, then averaged over all states for each month.

Month	Mean daily temperature and maximum daily temperature	Mean daily temperature and minimum daily temperature
January	0.98	0.98
February	0.98	0.98
March	0.97	0.97
April	0.97	0.96
May	0.96	0.94
June	0.95	0.92
July	0.97	0.94
August	0.96	0.93
September	0.93	0.91
October	0.91	0.93
November	0.96	0.97
December	0.97	0.98

Table S3. Correlation coefficients between anomaly of mean daily temperature and measures of extreme anomalous temperature described in Methods. Each correlation coefficient was calculated in each state for each month for 1980-2016, then averaged over all states for each month.

Temperature variables	Anomaly of mean (main analysis)	Anomaly of 90th percentile	Number of days above long-term 90th percentile	Number of 3+ day episodes above long-term 90th percentile
Anomaly of mean (main analysis)		0.79	0.75	0.6
Anomaly of 90th percentile	0.79		0.89	0.77
Number of days above long-term 90th percentile	0.75	0.89		0.86
Number of 3+ day episodes above long-term 90th percentile	0.6	0.77	0.86	

References

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