

Assessing the impact of climate change and rising temperature on life insurance portfolios

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- 1 Motivation and relevant literature
- 2 Contribution
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- **Climate-driven mortality risks** have emerged as a growing concern in recent years.
- **Challenges** of quantifying and pricing climate-driven mortality risks:
 - How to separately capture heat-related and cold-related temperature effects.
 - How to capture the regional heterogeneity of climate risks within a unified model.
 - How to price the climate-related mortality risks.
- Recent literature with a focus in actuarial science: Robben et al. (2025), Robben et al. (2026), Robben and Barigou (2025), Guibert et al. (2026), Min et al. (2026), Arandjelović and Shevchenko (2026), Bégin et al. (2026), So et al. (2026).

- A new **temperature-related mortality model**: Integrating **Hermite splines** with a **DLNM** to separately capture the heat and cold temperature effects.
- **Pooled estimation**: **Sharing information** across age groups and regions to improve estimation and forecasting.
- **δ -loadings**: Capturing **age-group- and region-specific temperature effects** on mortality rates.
- **Pricing climate-related mortality risks**: Evaluate **whole life insurance portfolios** across climate scenarios.

- **Mortality data:**

- **Data frequency:** [Weekly](#) death counts and annual population data.
- **Time period:** 2000–2019.
- **Age group:** 65–69, 70–74, 75–79, 80–84, and 85+.
- **Location:** 15 selected NUTS-2 regions in mainland Spain.

- **Temperature data:**

- **Data frequency:** [Daily](#) mean temperature data.
- **Time period:** 2000–2019.
- **Location:** Regional temperature is calculated as the mean across all grid points within each NUTS-2 boundary.

- Basic notation:

- Individual age x : $x \in \mathcal{X} = \{x_{\min}, \dots, x_{\max}\}$.
- Age group $\mathcal{G}$: $\mathcal{A} = \{\mathcal{G}_1, \dots, \mathcal{G}_G\}$, such that $\bigcup_{\mathcal{G} \in \mathcal{A}} \mathcal{G} = \mathcal{X}$.
- Week t : $t \in \mathcal{T} = \{1, \dots, T_{\max}\}$.
- Region r : $r \in \mathcal{R} = \{r_1, \dots, r_R\}$.

- The weekly death count random variable at age x in region r , $D_r(x, t)$ is assumed to follow a **Poisson distribution**:

$$D_r(x, t) \sim \text{Poi}(E_r(x, t) \mu_r(x, t)). \quad (1)$$

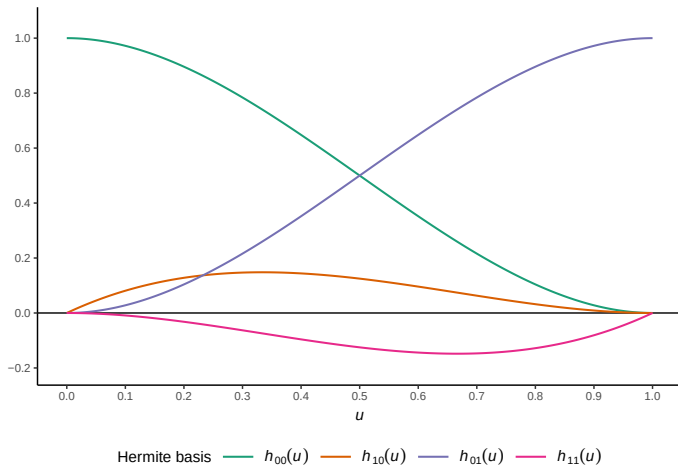
- The exposure to risk $E_r(x, t)$ is assumed to be **evenly distributed across ages within each age group** denoted as $E_r(x, t) = \frac{E_r(\mathcal{G}, t)}{\text{card}(\mathcal{G})}$. Then

$$D_r(\mathcal{G}, t) = \sum_{x \in \mathcal{G}} D_r(x, t) \sim \text{Poi}\left(E_r(x, t) \sum_{x \in \mathcal{G}} \mu_r(x, t)\right). \quad (2)$$

- The **weekly mortality hazard** for age x :

$$\mu_r(x, t) = \frac{\mathbb{E}[D_r(x, t)]}{E_r(x, t)}. \quad (3)$$

Figure 1: Cubic Hermite basis functions on the unit interval



- Hermite (1878) splines include four basis functions (Kreyszig, 1999) for $u \in [0, 1]$.

Following [Richards \(2020\)](#) and [Richards et al. \(2020\)](#), we propose **multi-population Hermite baseline mortality model**:

$$\begin{aligned}
 \mathcal{H}_r(x, t) = \log(\mu_r(x, t)) = & \underbrace{\alpha_r h_{00}(u) + m_{0,r} h_{10}(u) + \gamma_r h_{01}(u) + m_{1,r} h_{11}(u)}_{\text{Region-specific Hermite term}} \\
 & + \underbrace{(\phi_r h_{00}(u) + \kappa_r h_{01}(u)) \frac{t}{52}}_{\text{Region-specific trend}} \\
 & + \underbrace{\sum_{j=1}^2 \rho_{1,j} \sin\left(\frac{2\pi jt}{52}\right) + \sum_{k=1}^2 \rho_{2,k} \cos\left(\frac{2\pi kt}{52}\right)}_{\text{Common seasonal pattern}}, \quad (4)
 \end{aligned}$$

- $u = (x - x_{\min}) / (x_{\max} - x_{\min})$ for age $x \in [x_{\min}, x_{\max}]$.
- α_r , $m_{0,r}$, γ_r , and $m_{1,r}$: Region-specific coefficients for Hermite basis functions.
- ϕ_r and κ_r : Region-specific trend coefficients.
- $\rho_{1,j}$ and $\rho_{2,k}$: Common seasonality coefficients.
- The baseline model is selected based on AIC and BIC.

We consider a **quasi-Poisson regression DLNM with a logarithmic link function**:

$$\log(\mu(t)) = \beta_0 + \sum_{\ell=0}^L f(y(t-\ell), \ell; \varsigma) \boldsymbol{\eta} + \mathbf{z}_t^\top \boldsymbol{\beta}. \quad (5)$$

- $y(t-\ell)$: Temperature at lag from 0 to maximum lag L .
- $\mathbf{z}_t$: Confounders (e.g., the time **trend** and **seasonality**) with coefficients $\boldsymbol{\beta}$.
- $f(y(t-\ell), \ell; \varsigma)$: **two-dimensional exposure-lag function** defined as follows:

$$f(y(t-\ell), \ell; \varsigma) = \left(\mathbf{s}_y(y(t-\ell); \varsigma_y) \otimes \mathbf{s}_l(\ell; \varsigma_\ell) \right)^\top. \quad (6)$$

- $\varsigma = [\varsigma_y \quad \varsigma_\ell]$: The degrees of freedom for the basis functions $\mathbf{s}_y$ and $\mathbf{s}_l$.
- $\mathbf{s}_y(y_{t-\ell}; \varsigma_y)$ and $\mathbf{s}_l(\ell; \varsigma_\ell)$: Exposure-response basis and lag-response basis function.
- For simplicity, we define $\mathbf{C}(t)$ as $\mathbf{C}(t) = \sum_{\ell=0}^L f(y(t-\ell), \ell; \varsigma)$, with coefficients $\boldsymbol{\eta}$.

We propose the temperature-augmented Hermite mortality model as follows:

$$\log(\mu_r(x, t)) = \mathcal{H}_r(x, t) + \delta_r^H(\mathcal{G}) \bar{\mathbf{C}}_r^H(t) \boldsymbol{\eta}^H + \delta_r^C(\mathcal{G}) \bar{\mathbf{C}}_r^C(t) \boldsymbol{\eta}^C. \quad (7)$$

- $\mathcal{H}_r(x, t)$: Hermite baseline mortality model.
- $\delta_r^H(\mathcal{G})$ and $\delta_r^C(\mathcal{G})$: The **age-region-specific** loadings for **heat and cold effects**.
- $\bar{\mathbf{C}}_r^H(t)$ and $\bar{\mathbf{C}}_r^C(t)$: The **adjusted heat-related and cold-related cross-basis matrices** with their coefficient $\boldsymbol{\eta}^H$ and $\boldsymbol{\eta}^C$, computed in two steps:
 - The heat- and cold-adjusted temperature series $y_r^H(t)$ and $y_r^C(t)$:

$$y_r^H(t) = \max(y_r(t), y_{\text{ref}}^H), \text{ and } y_r^C(t) = \min(y_r(t), y_{\text{ref}}^C), \quad (8)$$

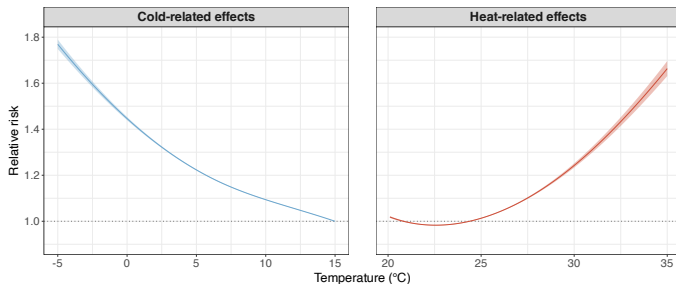
where y_{ref}^H and y_{ref}^C denote the **reference temperatures for heat and cold**, respectively.

- The heat- and cold-related cross-basis matrices:

$$\bar{\mathbf{C}}_r^H(t) = \mathbf{C}_r^H(t) - \mathbf{C}_{\text{ref}}^H, \text{ and } \bar{\mathbf{C}}_r^C(t) = \mathbf{C}_r^C(t) - \mathbf{C}_{\text{ref}}^C. \quad (9)$$

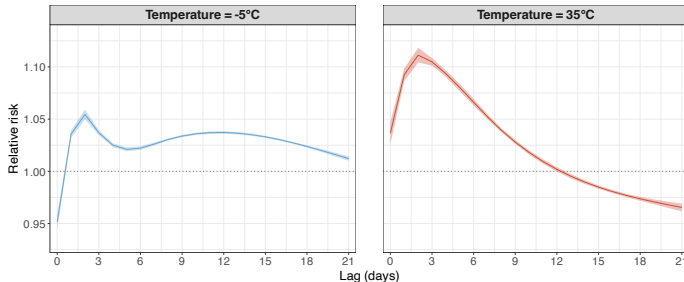
- This model is estimated by two-stage approach.

Figure 2: Overall cumulative effects of temperature on mortality rates.



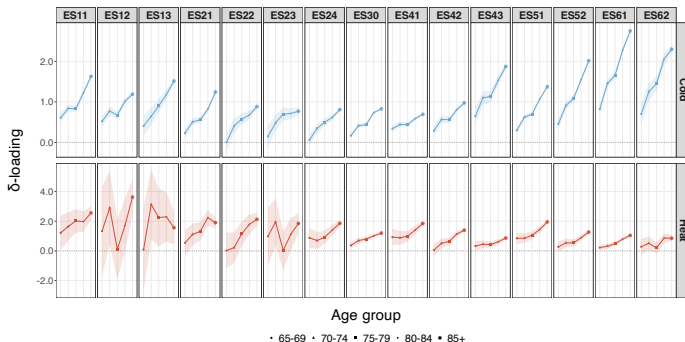
- The reference temperature for heat and cold: $y_{\text{ref}}^{\text{C}} = 15^{\circ}\text{C}$ and $y_{\text{ref}}^{\text{H}} = 20^{\circ}\text{C}$.
- **Temperature effects are negligible** between 15°C and 20°C ($\text{RR} = 1$).
- **U-shaped curve**: Elevated mortality risks under extreme cold and heat conditions.

Figure 3: Lagged effects for cold- and heat-related mortality risks.



- **Persistent adverse effects of cold exposure:** Rise to the peak in 2–3 days and remains above 1 throughout the remainder of 21-day period.
- **Immediate and acute effects of heat exposure:** Rise rapidly to the peak and decline rapidly after 12 days (**harvesting effects**).

Figure 4: Estimated age-group-region-specific δ -loadings for cold and heat effects.



- Age effects: Higher δ -loadings for older age groups.
- Regional adaption:
 - Warmer regions (e.g., ES52, ES61, and ES62) in southern Spain: **More resilient to extreme heat than to extreme cold.**
 - Cooler regions (e.g., ES11, ES12, ES13, ES21, and ES22) in northern Spain: Greater resilience to cold effects than to heat effects.

- Three SSP scenarios $\mathcal{S} = \{\text{SSP2-4.5}, \text{SSP3-7.0}, \text{SSP5-8.5}\}$.
- Quantify **scenario uncertainty** by generating multiple stochastic trajectories by [Avanzi et al. \(2026\)](#) approach.
- Generate multiple stochastic trajectories from 15 CMIP6 climate models by **quantile mapping approach**:

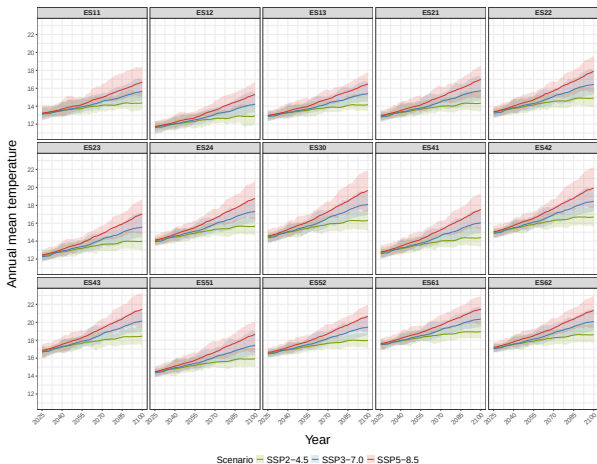
$$y_{r,q} = \nu_{0,r}^{(m)} + \nu_{1,r}^{(m)} \hat{y}_{r,q}^{(m)}. \quad (10)$$

- $y_{r,q}$ and $\hat{y}_{r,q}^{(m)}$: The q th quantiles of the observed historical data and the backcasts from CMIP6 climate model m .
- $\hat{\nu}_{0,r}^{(m)}$ and $\hat{\nu}_{1,r}^{(m)}$: Bias-corrected coefficients.
- Bias-corrected backcasts: $\hat{y}_r^{(m),*}(t) = \hat{\nu}_{0,r}^{(m)} + \hat{\nu}_{1,r}^{(m)} \hat{y}_r^{(m)}(t)$.
- Assume residuals: $z_r^{(m)}(t) = y_r(t) - \hat{y}_r^{(m),*}(t) \sim \mathcal{N}\left(0, \left(\sigma_r^{(m)}\right)^2\right)$.
- Bias-corrected future temperature projections:

$$\tilde{y}_r^{(m)}(t) = \hat{y}_r^{(m),*}(t) + \tilde{z}_r^{(m)}(t). \quad (11)$$

Projection results: SSP scenario-based temperature projection

Figure 5: Projected annual mean daily temperature under different SSP scenarios.



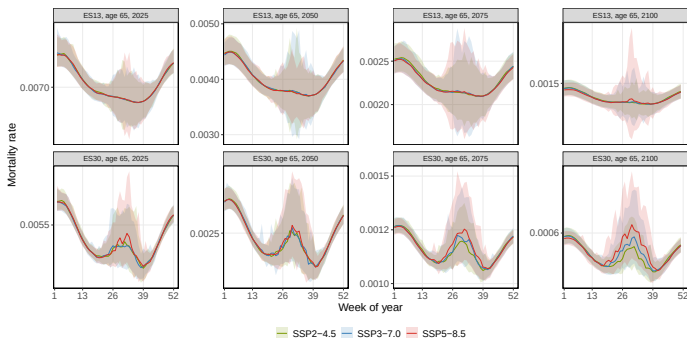
- Higher temperature and **greater uncertainty** under SSP5-8.5.
- Significant increase in temperature **after 2050**.

- Account for **model uncertainty** by applying **parametric bootstrap** (Guibert et al., 2026; Min et al., 2026).
- Generate the bootstrapped parameter vector $\hat{\Theta}^{(b)} = [\hat{\theta}^{(b)} \quad \hat{\delta}^{(b)}]$ for the temperature-augmented Hermite mortality model from **multivariate normal distribution**:

$$\hat{\Theta}^{(b)} \sim \mathcal{MVN}(\hat{\mu}_{\Theta}, \hat{\Sigma}_{\Theta}), \quad b = 1, \dots, B, \quad (12)$$

- $\hat{\mu}_{\Theta}$: The maximum likelihood estimator.
- $\hat{\Sigma}_{\Theta}$: The asymptotic covariance matrix.
- To reduce computational complexity, each simulation draw for model uncertainty is **matched to one simulation draw** for scenario uncertainty in each CMIP6 climate model.

Figure 6: Mortality projections for age 85 in ES13 (Cantabria) and ES30 (Madrid).



- Mortality improvements: mortality rates fall over time.
- **Compensation effects:** Lower winter mortality rates due to **warmer winter conditions**.
- **Excess death effects:** **More heat waves** lead to higher mortality rates in summer.
- **Reshaping of seasonal mortality:** Winter compensations **cannot offset** excess summer deaths eventually, **shifting the mortality peak to summer**.

- An aggregate **whole life insurance portfolio** comprises a total of M policies, allocated across all selected regions by population weight m_r with $\sum_{r \in \mathcal{R}} w_r = 1$, and issued in 2025 and 2050 to individuals aged 65.
- Generate a total of $N = 15,000$ systematic paths with an equal number of paths generated from each of the 15 climate models under SSP scenario s .
- Set death benefit \$ 1 million, interest rate 5%, and the limiting age 110.

- The projected death probabilities for age x in week t and region r under scenario s :

$$q_r^{(s,n)}(x, t) = 1 - \exp\left(-\mu_r^{(s,n)}(x, t)\right), \quad (13)$$

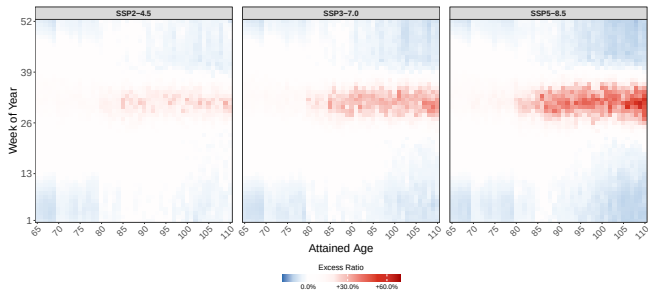
- The expected present value (EPV) of portfolio payoffs in region r in week t :

$$L_r^{(s,n)}(x, t) = (1 + \iota)^{-\frac{t}{52}} L \prod_{j=1}^{t-1} \left(1 - q_r^{(s,n)}(x, j)\right) q_r^{(s,n)}(x, t). \quad (14)$$

- L : Individual death benefits.
- ι : Constant interest rate.
- The **EPV of total payoffs** on the portfolio across all regions:

$$L^{(s,n)}(x) = \sum_{r \in \mathcal{R}} \sum_{t \in \mathcal{T}} L_r^{(s,n)}(x, t). \quad (15)$$

Figure 7: Weekly portfolio excess ratio relative to Hermite baseline model in issue year 2050.



- More summer heat waves $\Rightarrow$ More heat-related deaths $\Rightarrow$ Higher weekly portfolio payoffs in summer $\Rightarrow$ **Positive excess ratios (More pronounced under SSP5-8.5).**
- Warmer winter conditions $\Rightarrow$ Fewer cold-related deaths $\Rightarrow$ Lower weekly portfolio payoffs in winter $\Rightarrow$ **Negative excess ratios (Less pronounced under SSP5-8.5).**

- Prepose **multi-population temperature-augmented mortality model**.
- **Split the heat- and cold-related DLNM components** to separately capture temperature effects and **adjust age-group- and region-specific effects** by δ -loadings.
- Incorporate **SSP scenario** and **model uncertainty** in mortality projections.
- Examine the **pricing** of whole life insurance under three SSP scenarios.
- Future research:
 - Apply different baseline **stochastic mortality models**, such as Cairns-Blake-Dowd type models ([Cairns et al., 2006](#)).
 - Extend the proposed model to incorporate **socioeconomic variables**.
 - **Hedge** climate-related mortality risk based on insurers' perspective.

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