TECHNICAL RESEARCH BRIEF

A Cross-Dose-Response Function: Mortality-Temperature Relationship with Temperature Quantile

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1 Summary

Estimating the welfare impacts of climate change requires reconciling rich meteorological data with available socioeconomic indicators. Popular models, such as saturated panels and distributed lag nonlinear models (DLNMs), often force researchers to choose between temporal aggregation bias and omitted variable bias. This research introduces a methodological advancement to estimate the non-linear relationship between temperature shocks and economic outcomes using a **Cross-Dose-Response Function (CDRF)** model with temperature quantiles.

The model maps high-frequency meteorological data to low-frequency socioeconomic indicators while circumventing the access barriers associated with restricted daily data. It not only resolves the attenuation from temporal aggregation that inherent in traditional panel models but also explicitly controls for the heterogeneity of adaptive capacity across time, demography, and income.

Core Value Proposition:

- **Methodological Novelty:** Application of the Riesz-Representation Theorem to map hourly weather distributions to monthly mortality rates. The CDRF model resolves the omitted variable bias often found in high-frequency models by directly incorporating covariates.
- **Estimation Stability:** Expands data support by replacing Min-Max normalization with temperature quantiles, mitigating the "sensitive tail" problem inherent in flexible Fourier Functional (FFF) form semi-parametric estimation.
- **Computational Rigor:** Utilization of a high-performance computing (Python/GPU) pipeline to process nearly 40 years of hourly meteorological data, generating a monthly panel across 403 U.S. counties (183,768 monthly observations).

2 The Methodological Challenge

Current climate econometrics faces a dichotomy in estimating damage functions:

1. **Saturated Panel Models (Annual/Monthly):** Rely on aggregated weather variables. While they control for unobserved heterogeneity, they often suffer from a weak causal link by losing the variation of high-frequency weather events.
2. **Distributed Lag Non-linear Models (Daily):** Require daily outcome data (e.g., daily death counts). This data is often restricted or confidential, limiting reproducibility and scope. Further-

more, these models often require complex second-stage procedures to control for unobserved heterogeneity.

The Solution: The CDRF framework allows for the use of **publicly available monthly data** while retaining the information from **hourly temperature distributions**.

3 Technical Innovation: Quantile-Based Semi-Parametric Estimation

Unlike standard approaches that use absolute temperature (Min-Max normalization) for FFF form, this research introduces **Temperature Quantiles (τ)** as the temperature shock.

Why Quantiles?

- **Conceptual Alignment:** A 10°C (50°F) reading represents a mild event in Chicago (49^{th} percentile) but an extreme shock in Miami (2^{nd} percentile). Quantiles internalize local acclimatization.
- **Estimation Stability:** Raw temperature distributions often cluster in the center, leaving tails sparse (the "sensitive tail" problem). Quantile transformation ensures uniform data support across the domain $[0, 1]$, significantly improving the robustness of the FFF estimator throughout the domain.

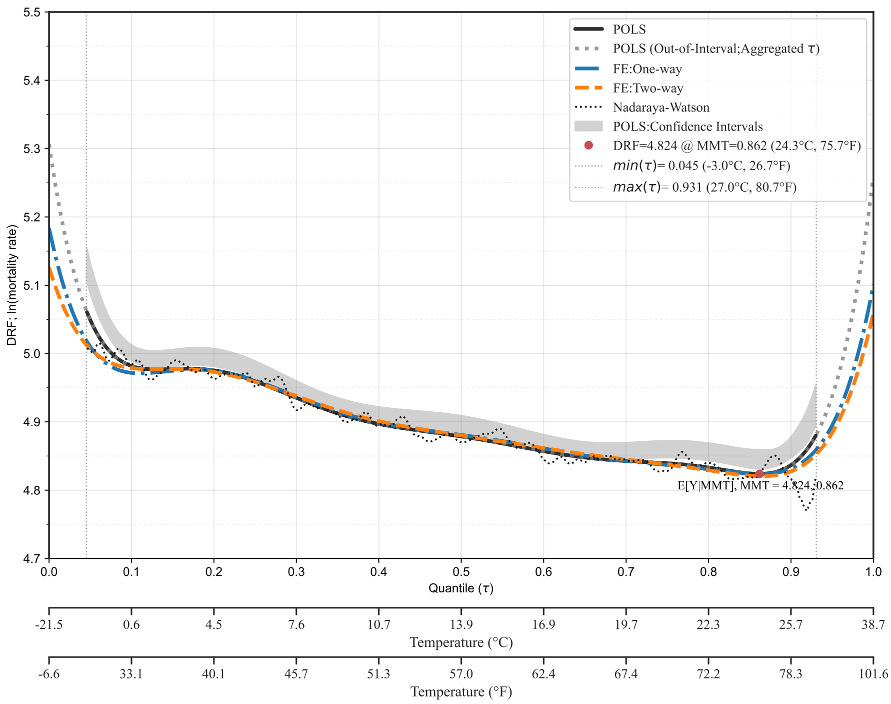


Figure 1: *Validation of Methodological Consistency: The Dose-Response Function (DRF) estimated via Pooled OLS with temperature quantiles (Black line) captures the U-shaped mortality risk. Crucially, the estimate is robust at extreme tails and economically indistinguishable from Fixed Effect (FE) models, demonstrating that the quantile metric effectively internalizes location-specific climate heterogeneity.*

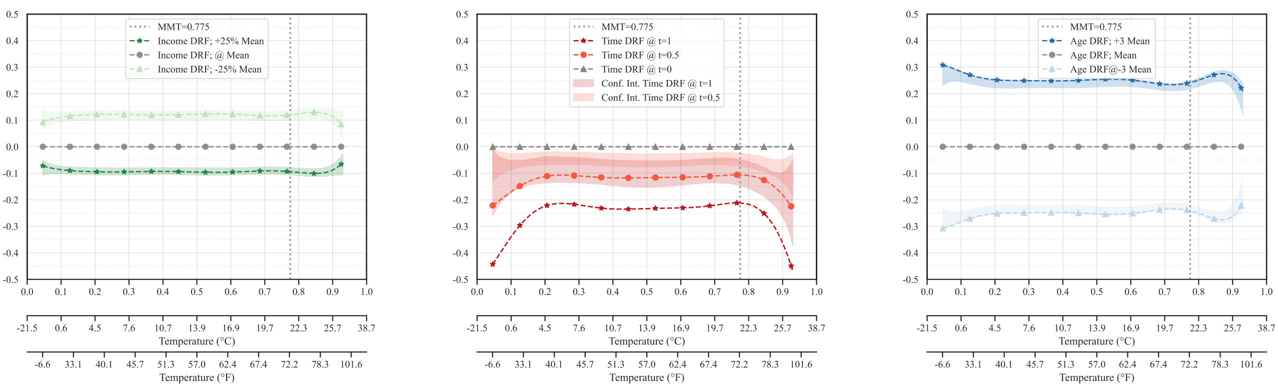
Validation Result

The model was tested against fixed-effect specifications. The pooled OLS with quantile inputs yielded results economically indistinguishable from FE models, proving that the quantile metric effectively captures location-specific climate heterogeneity.

4 Key Empirical Findings (U.S. Data 1982-2019)

Using a balanced monthly panel of 403 U.S. counties for 38 years, the estimated CDRF from a Pooled OLS estimation reveals:

- **Income as a Shield:** A 25% increase in county-level income reduces mortality risk by approximately 10% across the temperature interval.
- **Limits of Autonomous Adaptation:** The linear time trend (a proxy for technological progress) showed no statistically significant reduction in mortality risk. This finding challenges the optimistic assumption that “time heals all.”
- **Demographic Vulnerability:** A county where the mean population age is 3 years older than the average carries a 25% higher mortality rate.
- **Granular Heterogeneity Analysis:** The CDRF model precisely predicts heterogeneous mortality responses in neighboring counties (e.g., Tampa Bay) exposed to identical weather shocks, solely based on socioeconomic divergence.



(a) Income as a Shield

(b) Limits of Autonomous Adaptation

(c) Demographic Vulnerability

Figure 2: *Estimated Cross-Dose Response Functions (CDRF). The CDRF is estimated via Pooled OLS using a FFF form specification on log mortality rate, temperature quantile, linear time trend, income, and age. The subfigures display the temperature-dependent partial effects of each covariate on the mortality rate. In other words, the CDRF model decomposes the DRF function in Figure 1 by covariates. (a)* ***Income:*** *A +25% income deviation (darker green) significantly reduces mortality risk across the domain. (b)* ***Time:*** *The linear time trend shows potential large risk reduction at extremes, particularly, but estimates lack statistical significance. (c)* ***Age:*** *An older population profile significantly amplifies risk.*

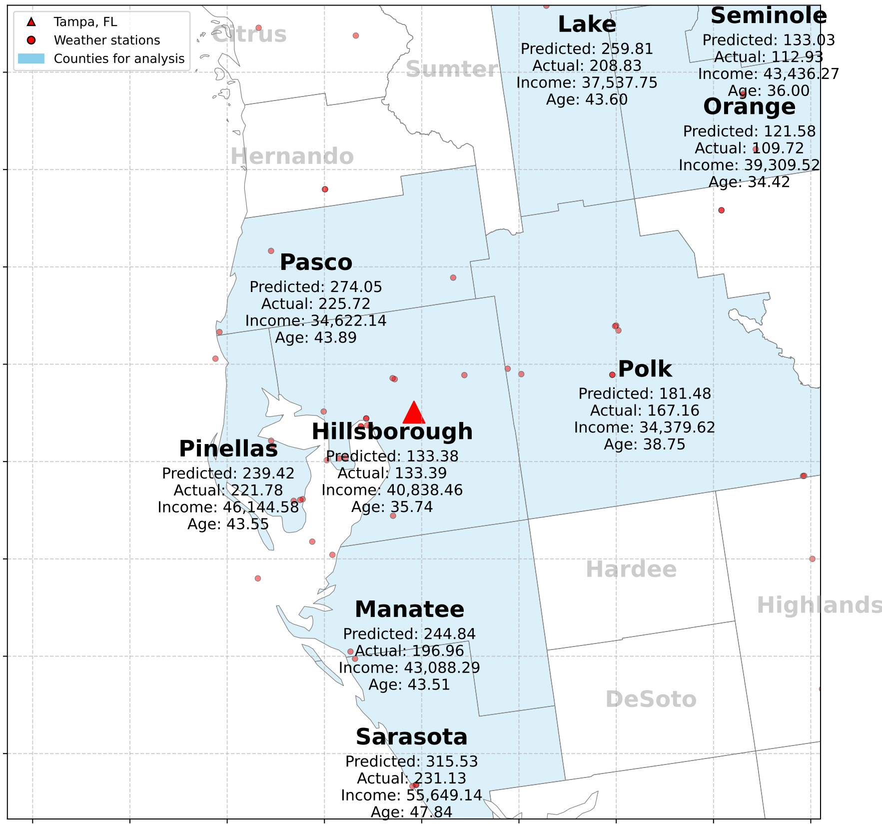


Figure 3: *Granular Heterogeneity Analysis (Tampa Bay Area): The CDRF model isolates heterogeneous mortality responses in neighboring counties exposed to the same weather. For example, it predicts a significantly higher mortality rate in Pinellas compared to Hillsborough due to an older population, despite identical climate exposure. Conversely, for Polk County, it predicts elevated mortality driven by lower income.*

These findings suggest that adaptation is not an automatic dividend of time; it is a function of economic capacity, underscoring a critical dimension of climate inequality.

5 Technical Capabilities & Scalability

By removing the strict data requirements associated with conventional estimation methods, the CDRF model demonstrates immediate applicability. The CDRF framework is modular and domain-agnostic. While currently applied to the mortality-temperature domain, its origin[1] lies in the Cross-Temperature Response Function (CTRF) framework within energy economics. The model offers significant potential in areas where conventional models have been exhaustively explored but yielded economically insignificant effect sizes or suffered from incompatible covariates.

This research provides a Python code repository to allow other researchers to apply this framework. Using Python allows for efficient large-scale data management and estimation across various data types. Processed data sources include monthly decedent data (CDC-MCD, CDC-WONDER), demographic data (SEER), income data (BEA-CAINC1), GIS data (TIGER), and hourly weather station readings (NCEI-ISD). In addition, adopting GPU computation dramatically reduces estimation time for bootstrapping procedures.

[1]Chang, Kim, Miller, Park, and Park., *A New Approach to Modeling the Effects of Temperature Fluctuations on Monthly Electricity Demand.*, **Energy Economics.**, 2016.