The Association between Temperature Variation and the Outcomes of Hospitalized Cardiovascular Disease Patients in Shanxi, China

PHS6060 Grantwriting Presentation

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Background

- CVD is the leading cause of death worldwide in 2016
- long time exposure in extreme temperature
- a more comprehensive understanding on the effect of temperature variation

Overall goal: to explore the association between temperature variation and the outcomes of CVD patients in Shanxi, China

The long-term goal to reduce CVD hospitalizations and mortality due to weather changes in China

Aims

1. Determine the association between temperature variation and the hospitalization rates of chronic CVD patients

Hypothesis: more regional temperature variation is associated with a higher rate of chronic CVD hospitalizations

2. Examine the association between temperature variation and the mortality of chronic CVD patients

Hypothesis: temperature variation is independently associated with patients' in-hospital mortality after adjusting for the covariates.

Significance

- CVD is the leading cause of death worldwide and in China
- Dramatic weather changes and human activities
- Little evidence exists on the association between temperature variation and CVD outcomes

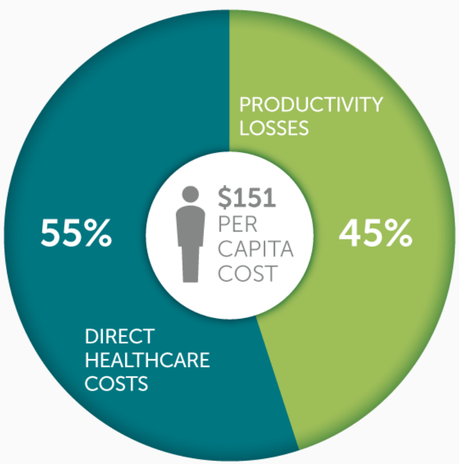

Figure 1 CVD disease burden

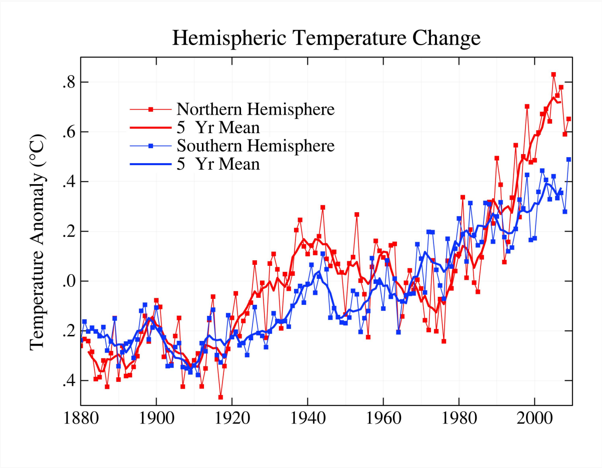

Figure 2 Global temperature pattern

Innovation

- A generally overlooked area
- A decomposition of temperature variation into vertical and horizontal variation
- Bayesian statistical models
- 127 regions or districts in a populous province

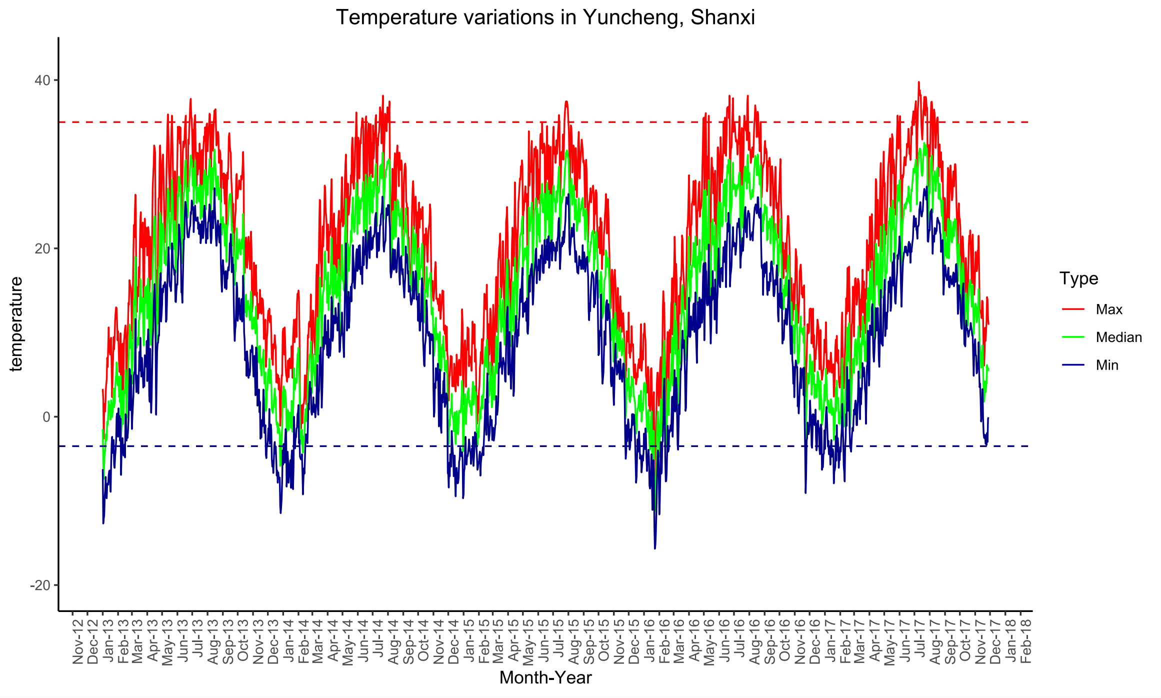

Figure 3 Temperature variation in Yucheng, Shanxi

Approach

The Shanxi Chinese population

- Large sample size: **36 million** residents, **1.2 million** CVD inpatients
- very different temperature patterns
- long observation window: year 2013 to 2017
- regional variation: **127 districts or counties**

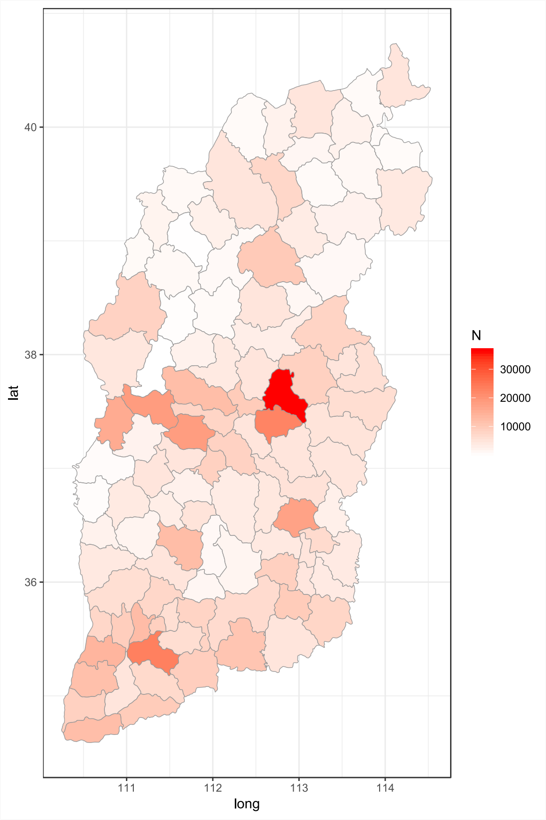

Figure 4 Patient volume distribution in 127 cities or counties

Different temperature patterns

- Average temperature difference within a day is **12 Celsius degrees**
- Average temperature difference between summer and winter is **28.1 Celsius degrees**

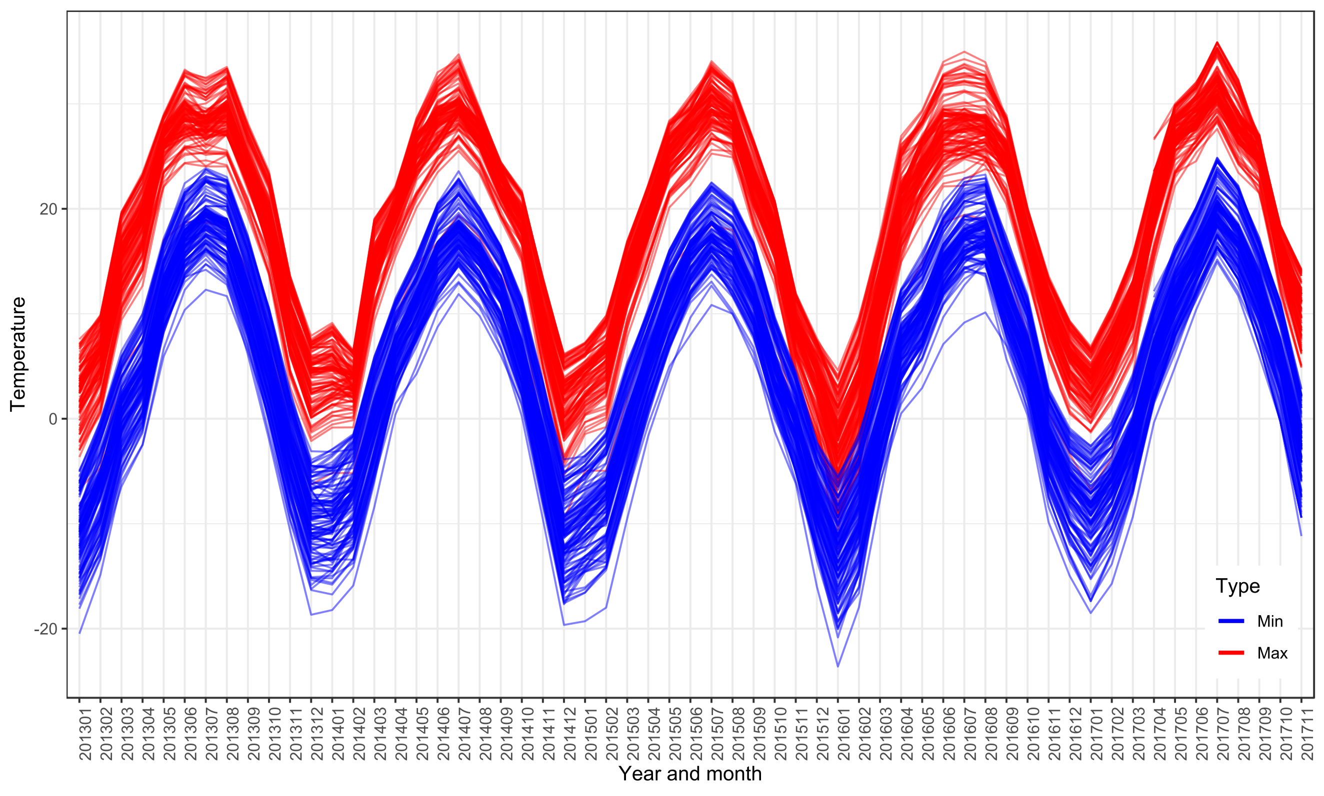

Figure 5 Temperature variation across 127 counties and districts

Data

The Shanxi hospitalized patient Database

- All patients hospitalized in secondary and tertiary hospitals

- socio-demographic status (age, sex, marital status, occupation)
- admission and discharge status
- up to 10 secondary ICD-10 diagnosis codes
- outcome upon discharge

China Meteorological Database

- Maximum temperature,
- Average temperature,
- Minimum temperature,
- Wind speed,
- Humidity,
- Air quality index (AQI): SO_2, NO_2, $pm10$, $pm2.5$, CO, and O_3.

Conceptual framework

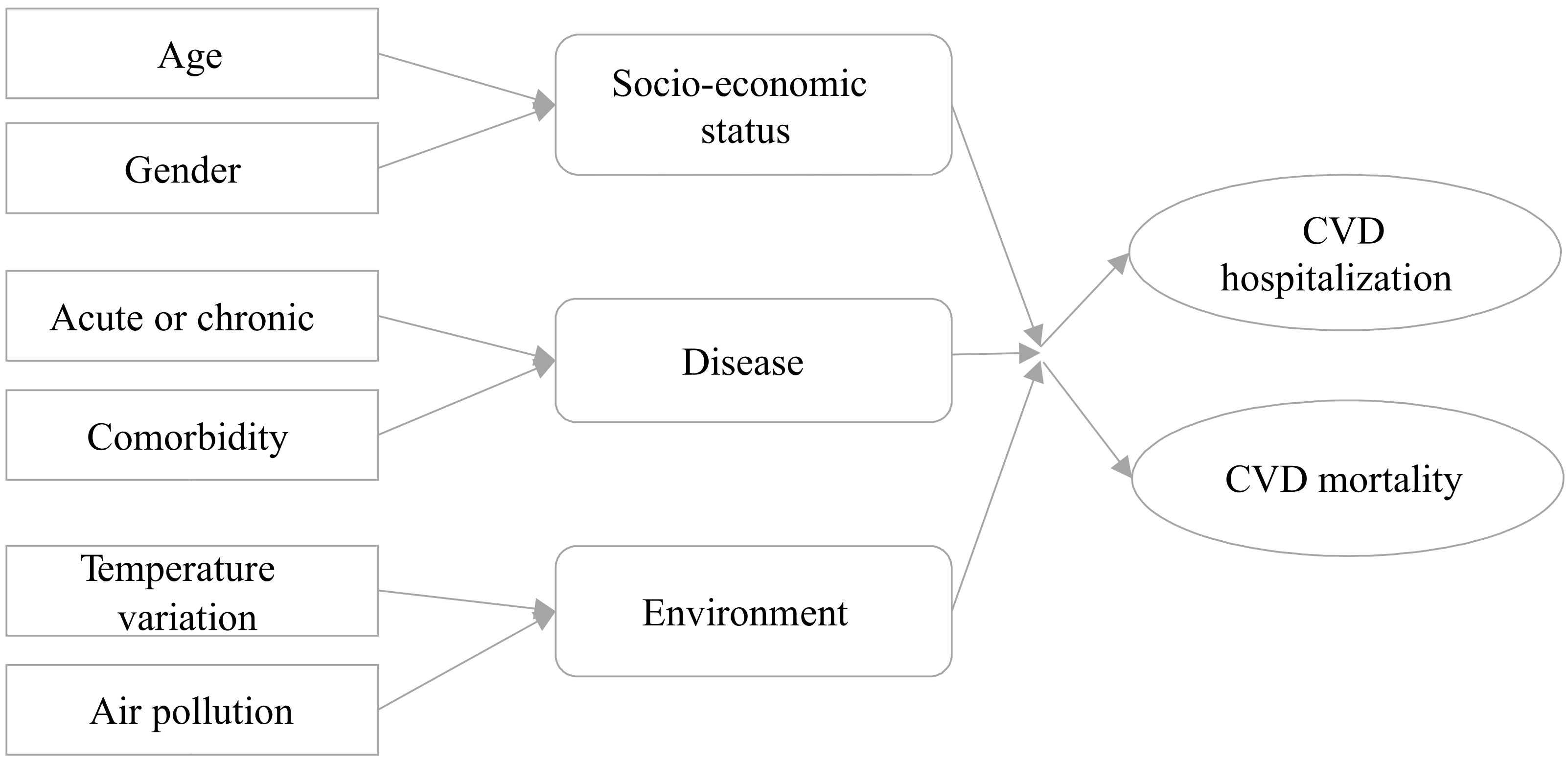

Figure 6 Conceptual framework

Statistical analysis - Aim 1

$$
\begin{aligned}
Y_{jt} &\sim \mathrm{POI}(Pop_{jt} * \lambda_{jt}) \\
\log(\lambda_{jt}) &= \beta_{0j} + \beta_{1j} HV_{jt} + \beta_{2j} VV_{jt} + \beta_3 Tem_{jt} + \beta_4 Old_{jt} \\
&\quad + \beta_5 Edu_{jt} + \beta_6 Air_{jt} + \beta_7 Season_{jt} \\
\beta_{0j} &\sim N(\mu_0, \sigma_0) \\
\beta_{1j} &\sim N(\mu_1, \sigma_1) \\
\beta_{2j} &\sim N(\mu_2, \sigma_2)
\end{aligned}
$$

- j: index for region (districts/counties)
- t: a certain time during 2013 and 2017
- Y_{jt}: total number of CVD hospitalization in district j, time t
- Pop_{jt}: total number of population
- HV_{jt}: Horizontal temperature variation
- VV_{jt}: Vertical temperature variation
- Tem_{jt}: Average temperature at that time

Statistical analysis - Aim 2

$$
\begin{aligned}
D_{ijt} &\sim \mathrm{POI}(\theta_{ijt}) \\
\mathrm{logit}(\theta_{ijt}) &= \beta_{0j} + \beta_{1j} HV_{jt} + \beta_{2j} VV_{jt} + \beta_3 Tem_{jt} + \beta_4 Age_i + \beta_5 Gender_{jt} \\
&\quad + \beta_6 Occupation_i + \beta_7 Comorbidity_i + \beta_8 Gravity_i + \beta_9 Season_{jt} \\
\beta_{0j} &\sim N(\mu_0, \sigma_0) \\
\beta_{1j} &\sim N(\mu_1, \sigma_1) \\
\beta_{2j} &\sim N(\mu_2, \sigma_2)
\end{aligned}
$$

- j: index for patient
- D_{ijt}: Whether patient i died during hospitalization or not,
- θ_{ijt}: The probability of in-hospital death for patient i,
- $Gravity_i$: Gravity of disease.

Estimation method

- Stan: Hamiltonian Markov chain Monte Carlo
- Non-informative priors
- 3000 burn-in
- 7000 simulations per chain
- 4 chains
- Gelman-Rubin statistics and posterior convergence checks

Potential Problems and Solutions

Incomplete air pollution data

- Air pollution data prior to 2015 may be missing.
- separate analysis for complete and non-complete air pollution data

Non-convergence for the Bayesian models

- Non-convergence due to large sample size
- Frequentist methods or firefly MCMC (subsampling)

Missing data

- missing completely at random (MCAR) - exclude these missing cases
- missing at random (MAR) - analysis based on the complete sample

Adjacency of regions

- Bayesian Gaussian model
- geographically weighted regression

Questions and Answers