Modeling and Understanding Mortality Disparities

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Outline

1. Aims, motivation and challenges
   - Monitoring neonatal mortality in countries worldwide (poor-quality data)
   - Racial disparities in the US opioid epidemic (noisy data)
2. Methodological approach
3. Spatial patterns of racial disparities in the opioid epidemic
4. Summary

Aims and motivation

Aims of research

To assess and interpret **health and mortality disparities across populations** and understand how **underlying demographic processes** affect these disparities and **drive changes over time**.

Motivation

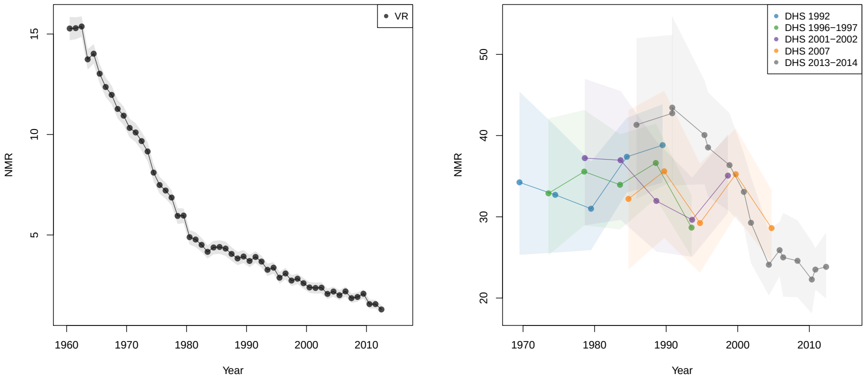
- In order to understand disparities, need to able to monitor changes over time
- In many situations, trends may be unclear because of data issues
- Need to develop statistical methods in order to understand underlying processes

Motivating example 1: What is the progress in decreasing neonatal mortality in countries worldwide?

- Deaths in the first month of life
- Important health and development indicator (SDG 3)
- How are countries tracking toward reaching this goal?
- Issue: many countries only have poor-quality data available

SUSTAINABLE DEVELOPMENT GOALS

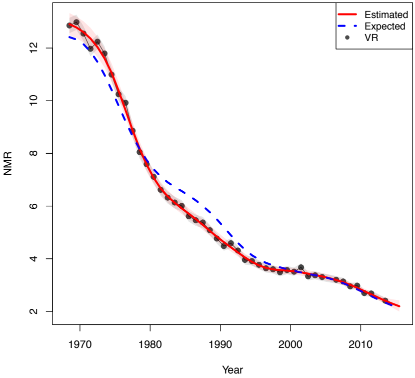
Motivating example 1



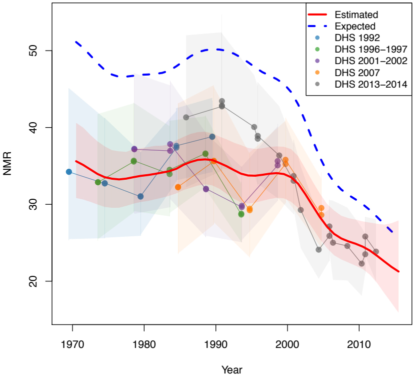
(a) Australia (b) Zambia

Figure: Data on neonatal mortality rates (deaths per 1,000 births)

Motivating example 1



(a) Australia

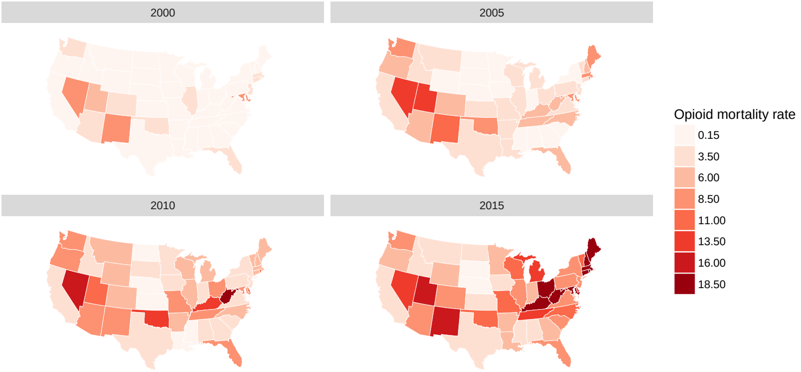


(b) Zambia

Figure: Data and estimates of neonatal mortality rates (deaths per 1,000 births) (Alexander and Alkema, 2017).

Full results: `childmortality.org`

Motivating example 2: What are the racial differences in the opioid epidemic?



Motivating example 2

Investigating spatial patterns in racial disparities in the opioid epidemic. Issues:

- Deaths are a relatively rare event
- Observed data suffer from high stochastic (random) variation
- Difficult to understand underlying processes from observed data

Motivating example 2

Why are rare events an issue? Consider a coin which has a probability of a head turning up equal to 1%.

- In 100 tosses, expect to get 1 head
- Small variations in number of heads result in large variations in the observed probability

Motivating example 2

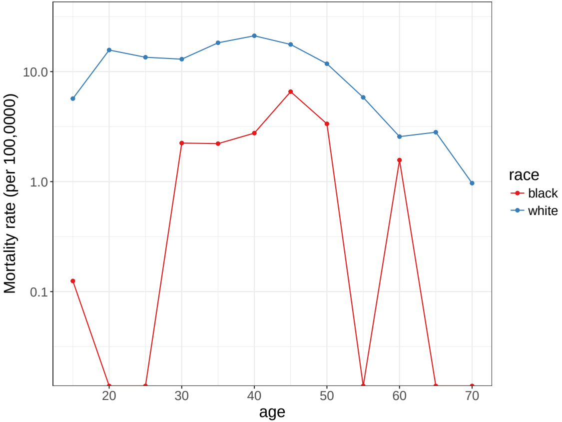


Figure: Observed opioid mortality rate by age and race, North Carolina, 2004

Motivating example 2

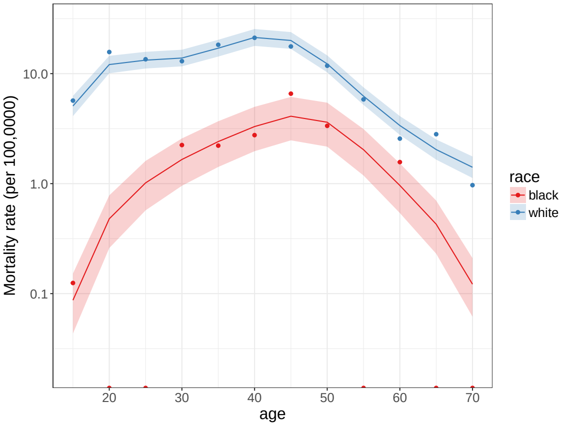
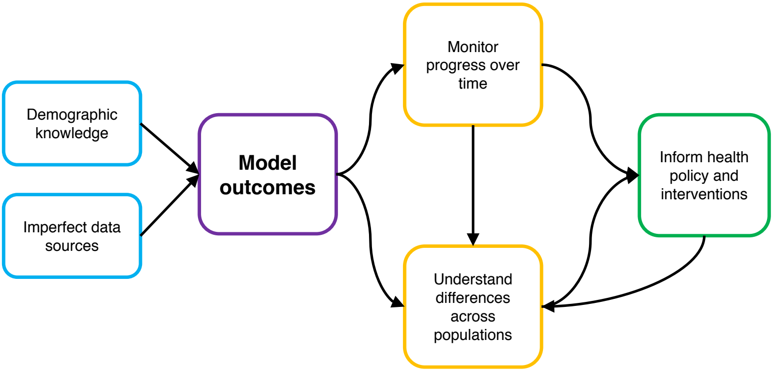


Figure: Observed and estimated opioid mortality rate by age and race, North Carolina, 2004

Overview of research



Methodological approach

Methodological approach

Motivation:

- Differences in underlying age structures affect disparities
- Human populations display strong regularities in age patterns of death

Use this demographic knowledge and incorporate information:

- about geographic patterns in mortality
- about trends in mortality over time

Methodological approach

Bayesian hierarchical framework to model mortality rates, with three components:

1. Model of underlying age structure
2. Spatial model
3. Temporal model

Modeling subnational mortality rates

$$D_{x,a,t} \sim Poisson(P_{x,a,t} \cdot m_{x,a,t})$$

where

- $D_{x,a,t}$ = deaths in age group x, area a, at time t.
- $P_{x,a,t}$ = population in age group x, area a, at time t.

We are trying to estimate mortality rate $m_{x,a,t}$.

1. Model underlying structure

- Data may be noisy or sparse at the subnational level or for particular subgroups
- Model age patterns based on observed patterns at higher levels
- Creates underlying structure, which can be flexibly shifted based on available data

1. Model underlying structure

Parametric model to express overall shape of mortality curve:

$$\log(m_{x,a,t}) = \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x}$$

- Y_{1x}, Y_{2x} and Y_{3x} are principal components of a standard set of log-mortality curves.

1. Model underlying structure

Represent age-specific mortality curve as a combination of three components:

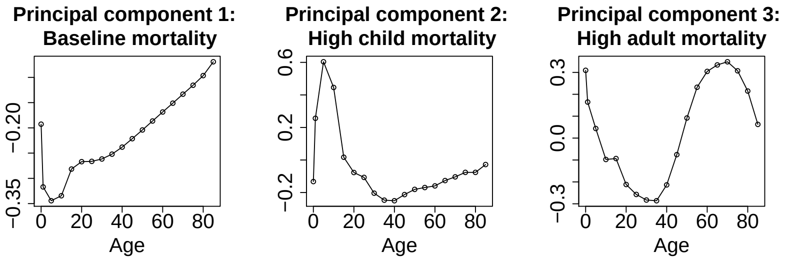


Figure: Principal components of (logged) US state mortality schedules, Males, 1980–2010 (Alexander et al. 2017).

2. Spatial model

Motivation:

- Different regions/populations often have different amounts of available data
- Can share information about mortality across geographic space
- Patterns in areas with less information are partially informed by mortality patterns in similar data-rich areas

2. Spatial model

$\beta_{p,a,t}$ are assumed to be drawn from a common distribution for each state (or other group of areas).

$$\log(m_{x,a,t}) = \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x}$$

$$\beta_{p,a,t} \sim N(\mu_{\beta_{p,t}}, \sigma^2_{\beta_{p,t}})$$

Average level across all areas

Variation across areas

3. Temporal model

- Mortality changes gradually and in a relatively regular pattern over time
- Allow for autocorrelation: estimates today are related to what happened in the past
- Provide a mechanism for projecting trends into the future

3. Temporal model

$$\log(m_{x,a,t}) = \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x}$$

Age patterns

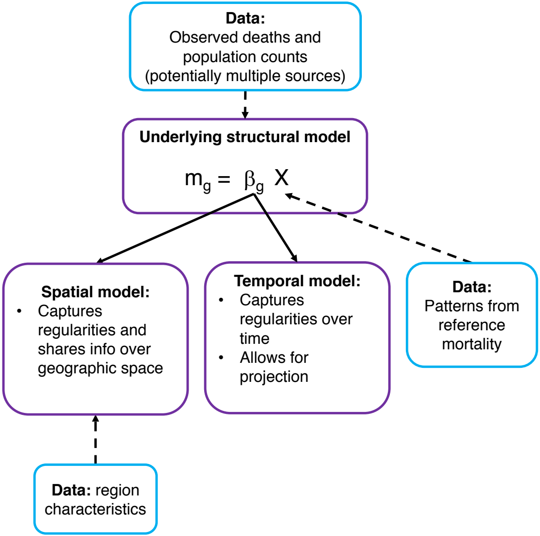
Spatial patterns

$$\beta_{p,a,t} \sim N(\mu_{\beta_{p,t}}, \sigma^2_{\beta_{p,t}})$$

Temporal patterns

$$\mu_{\beta_{p,t}} = \mu_{\beta_{p,t-1}} + \varepsilon_{\beta_{p,t}}$$

Summary of methodology



What are the spatial patterns by race in the opioid epidemic?

Opioid mortality by race, 1979–2015

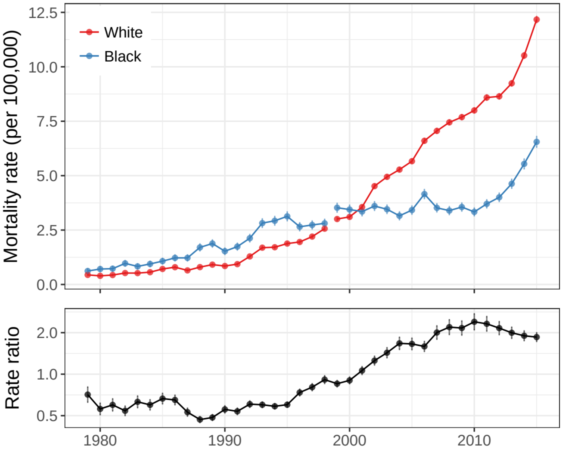


Figure: Top: Opioid mortality rate for white and black populations. Bottom: Rate ratio (white / black) of opioid mortality rates. (Alexander et al. 2017).

The US opioid epidemic by race

- Opioid epidemic has shifted from prescription opioids to heroin/fentanyl
- Reversal of usual racial inequality observed in mortality
  - Low opioid prescription rates in black population (Frenck et al. 2015)
  - Lower access to healthcare; differing attitudes of patients and doctors (Pletcher et al. 2008; Singhal et al. 2016)
- However, epidemic is increasingly affecting the black population
  - Increased supply, affordability, potency of heroin

Why has the opioid epidemic changed?

Three potential mechanisms:

1. Substitution effect painkillers to heroin (concentration) (Alpert et al. 2017)
2. New effects on existing users (concentration) (CDC 2015; Slavova et al. 2017)
3. New users (diffusion) (Cicero et al. 2017)

Racial disparities by state

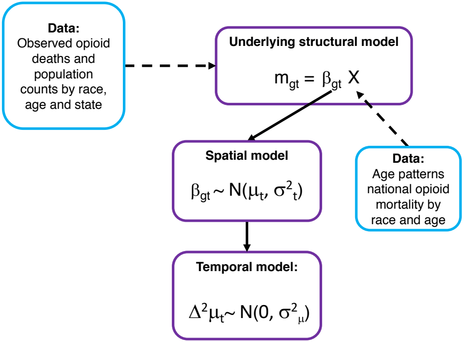
- How do racial patterns in opioid mortality vary by state?
- How have they evolved over time?
- Evidence for potential mechanisms of change?

Data

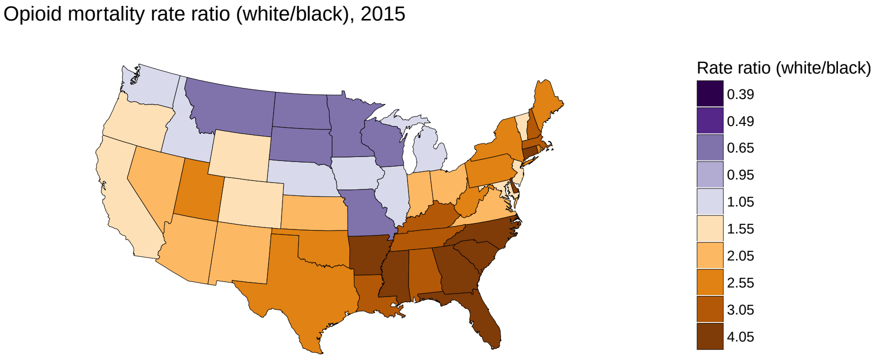
- NCHS multiple cause of death microdata from 1999–2015 (ICD-10)
- Restrict to non-hispanic white and black populations
- Opioid deaths defined as a combination of
    - underlying cause of X40-X44, X60-X64, X85 and Y10-Y14.
    - drug poisoning code of T40.0-4, T40.6
- Age-specific mortality for five-year age groups between ages 15–75
- Death rates standardized using 2000 US Census population

Modeling approach

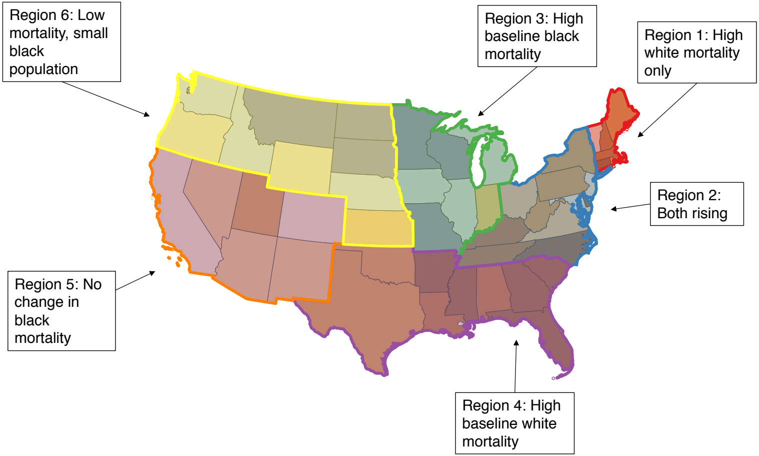
- Model underlying age structure based on race-specific age-specific mortality curves at the national level
- Pool information by geographic space
- Smooth parameter trajectories over time



Results: opioid mortality rate ratio



Regions of similar racial patterns



Region 1: white only

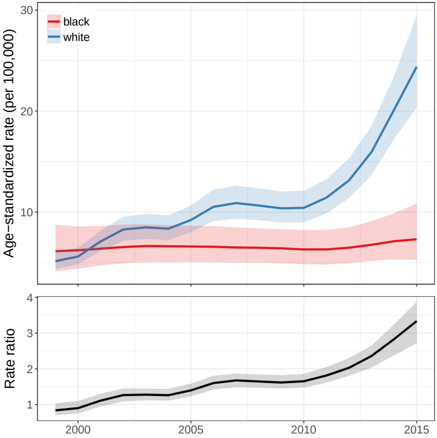
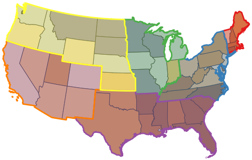


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Massachusetts**.

Region 1: white mortality only

- New England states
- Increasing white mortality
- Acceleration in 2010
- Substitution, concentration



Region 2: both races rising

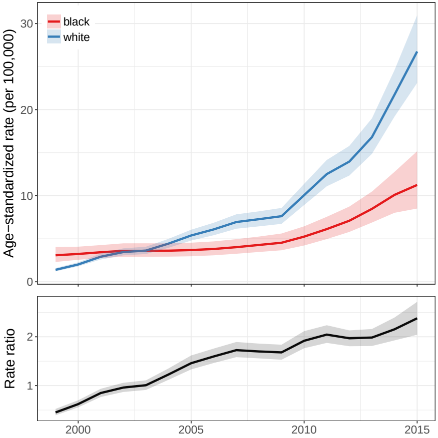
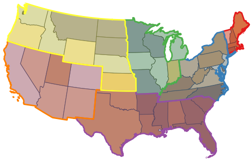


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Ohio**.

Region 2: mortality rising in both races

- mid-Atlantic, Appalachia states
- Higher for white but increasing for both
- New users, diffusion



Region 3: higher black mortality

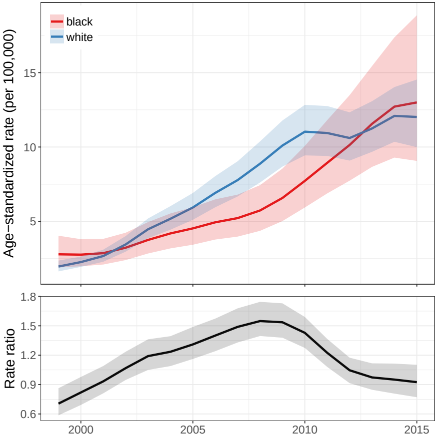
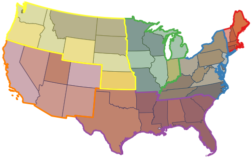


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Missouri**.

Region 3: higher black mortality

- Midwest states
- Higher relative black mortality
- Ratios closer to 1
- New effects on existing users



Summary of findings

- Distinct spatial patterns in opioid mortality by race
- Evidence of both diffusion and concentration of epidemic
- Implications for how to think about effective policy:
    - Treatment/prevention: treatment in affected communities versus prevention across communities
    - Enforcement: curbing access to prescriptions versus a crackdown on heroin distribution networks
    - Education: drug use versus dangers of new drugs

Summary

Summary

- Important to be able to assess and interpret health and mortality outcomes across populations
- In many cases, data to study such inequalities are limited
- Build on demographic knowledge about underlying population processes
- Flexible hierarchical modeling frameworks which incorporate patterns across space and time

Future directions

1. How are health and mortality inequalities across socioeconomic status evolving?
2. How do subnational differences and migration in developing countries affect progress towards health goals?

Thanks!

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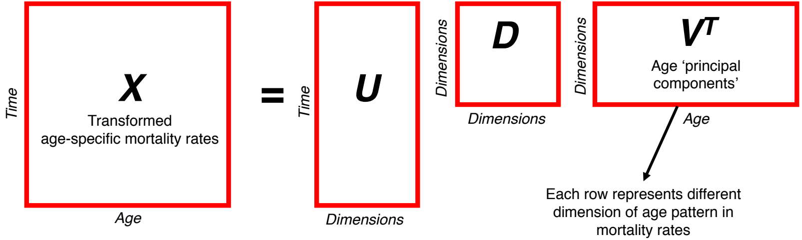
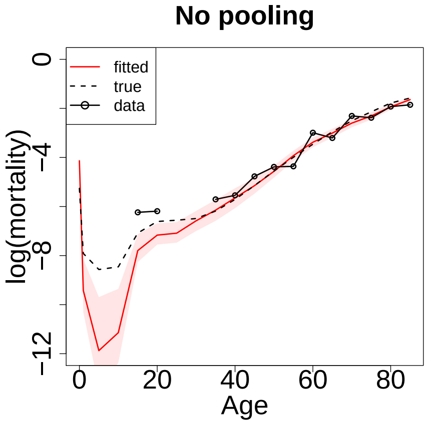
Extra Slides - methods

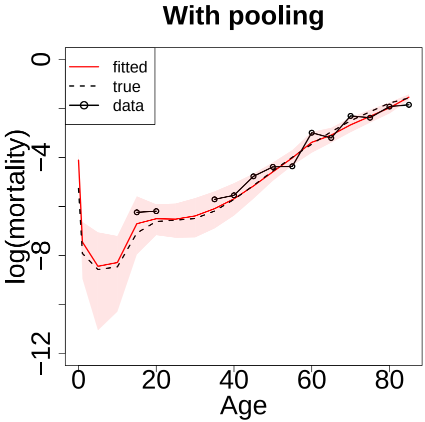
1. Model underlying structure

- Principal components obtained via Singular Value Decomposition (SVD) of a set of 'reference' mortality curves



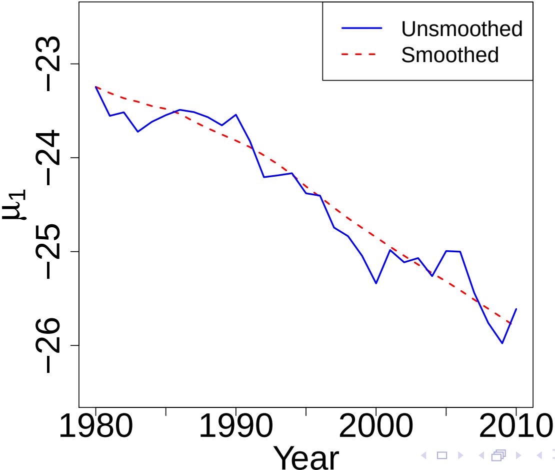
2. Pooling across space





3. Smoothing across time

Figure: Effect of smoothing parameters over time



Full model

$$\begin{aligned}
D_{x,a,t} &\sim Poisson(P_{x,a,t} \cdot m_{x,a,t}) \\
\log(m_{x,a,t}) &= \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x} + u_{x,a,t} \\
\beta_{p,a,t} &\sim N(\mu_{\beta_{p,t}}, \sigma^2_{\beta_{p,t}}) \\
\Delta^2 \mu_{\beta_{p,t}} &\sim N\left(0, \sigma^2_{\mu_{\beta_{p,t}}}\right) \\
u_{x,a,t} &\sim N(0, \sigma^2_x)
\end{aligned}$$

Uninformative priors on variance parameters:

$$\begin{aligned}
\sigma_{\beta_{p,t}} &\sim U(0, 40) \\
\sigma_{\mu_{\beta_{p,t}}} &\sim U(0, 40) \\
\sigma_x &\sim U(0, 40).
\end{aligned}$$

for $p = 1, 2, 3$.

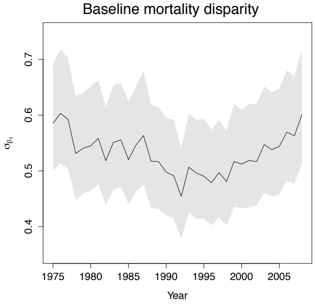
Parameterizing disparities

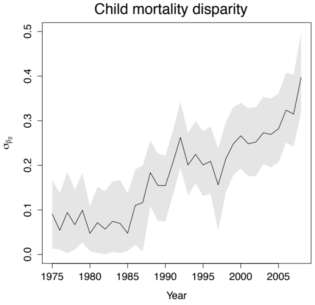
$$\beta_{p,a,t} \sim N(\mu_{\beta_{p,t}}, \sigma^2_{\beta_{p,t}})$$

Average level across all areas

Variation across areas

Variation across French *départements*:





Extra Slides - opioids

The US opioid epidemic

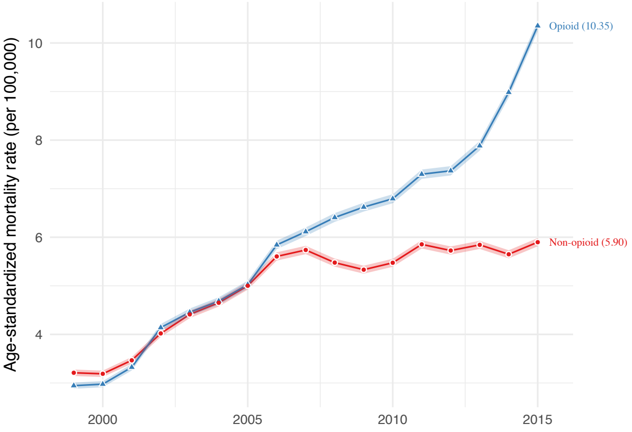


Figure: Drug-related mortality in the United States, 1999–2015 (Alexander et al. 2017)

A changing epidemic

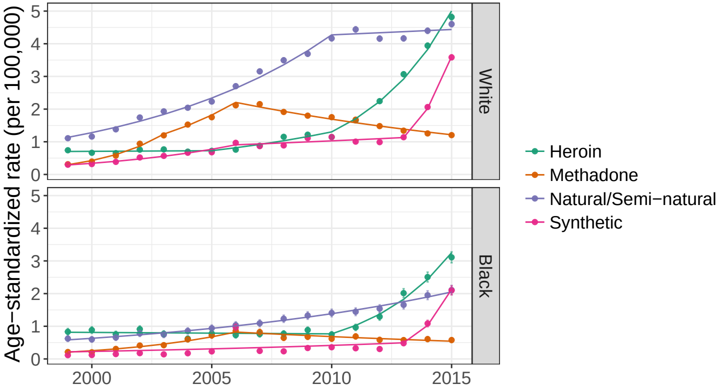


Figure: Opioid mortality rates by general type of opioid for white (top) and black (bottom) populations. Lines are joinpoint model fits (Alexander et al. 2017).

Estimation issues

- Death rates by race and state can be noisy
- Use modeling approach described above
- Model based on structural age patterns; pool across space and time

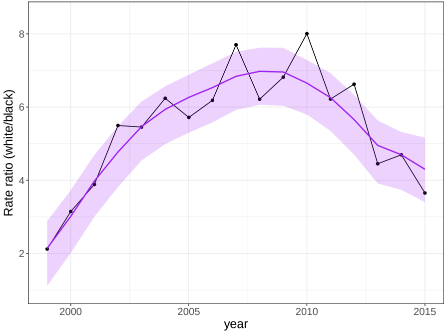
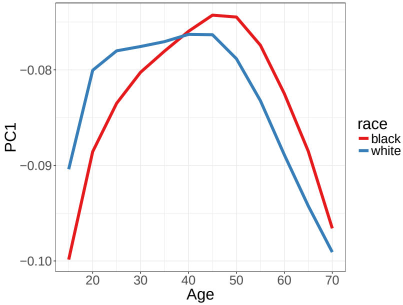


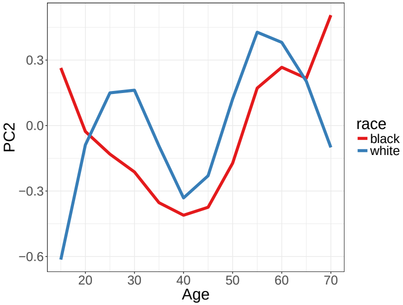
Figure: Opioid mortality ratio ratio (white/black), observed and fitted, North Carolina

Inputs to model

Figure: Principal components of race-specific opioid mortality, US, 1999–2015.



(a) PC1: Baseline mortality



(b) PC2: Contribution of each age group to change

Region 4: higher white mortality

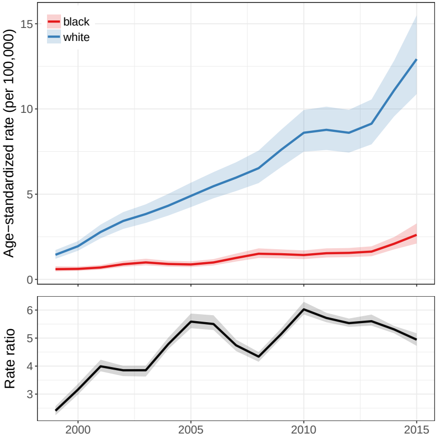
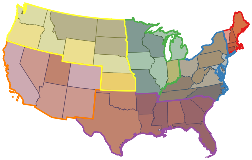


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Georgia**.

Region 4: higher white mortality

- Southern states
- Higher relative white mortality
- Large rate ratios
- Some increase in black population, but mostly concentration



Region 5: no change in black mortality

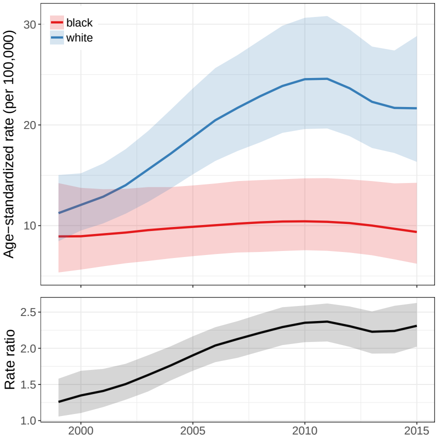
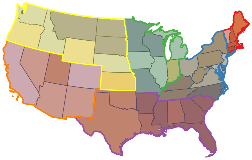


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Nevada**.

Region 5: no change in black mortality

- Western states
- no change in black mortality
- no evidence of recent spike



Region 6: low mortality

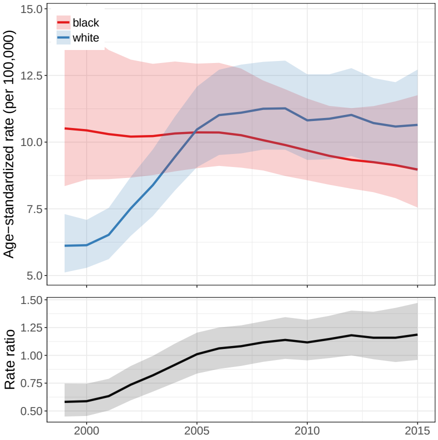
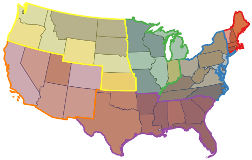


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Washington**.

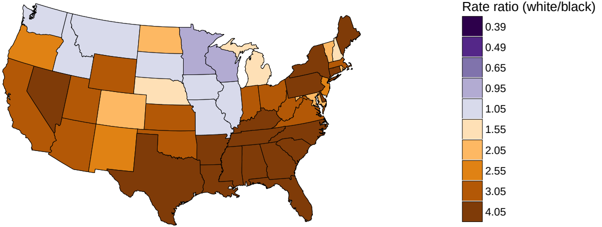
Region 6: low mortality

- NW states
- relatively small black populations
- no evidence of recent spike



Big differences in age structure

Opioid rate ratio (white/black) 15−39 years, 2015



Opioid rate ratio (white/black) 40+ years, 2015