

MODELING AND UNDERSTANDING MORTALITY DISPARITIES

Monica Alexander

University of California, Berkeley

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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

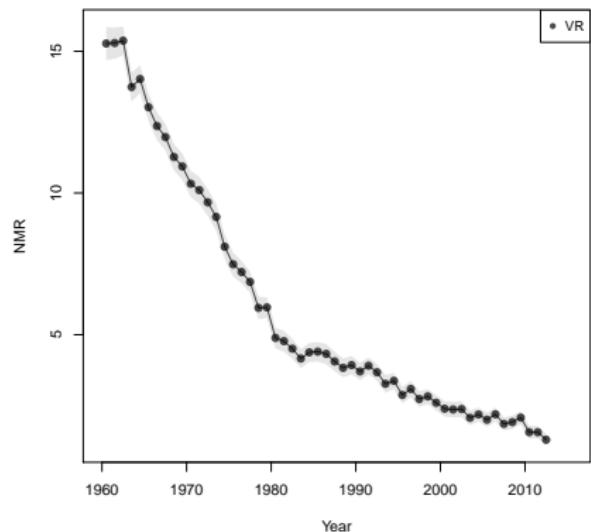
- In order to understand disparities, need to able to monitor changes over time
- In many situations, trends may be unclear because of data issues
- Need to develop statistical methods in order to understand underlying processes

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

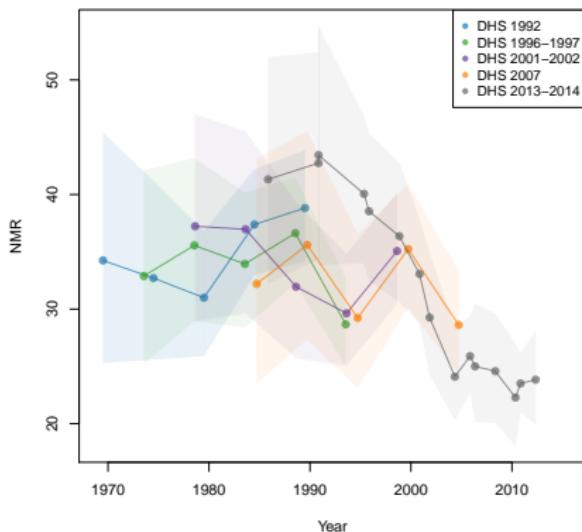
- Deaths in the first month of life
- Important health and development indicator (SDG 3)
- How are countries tracking toward reaching this goal?
- Issue: many countries only have poor-quality data available



Motivating example 1



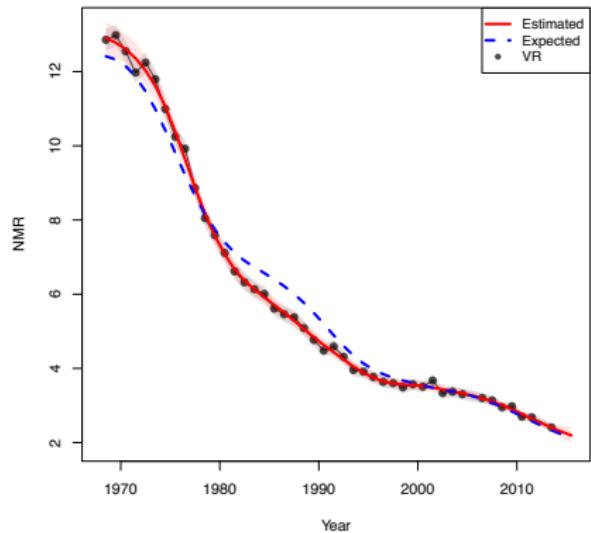
(a) Australia



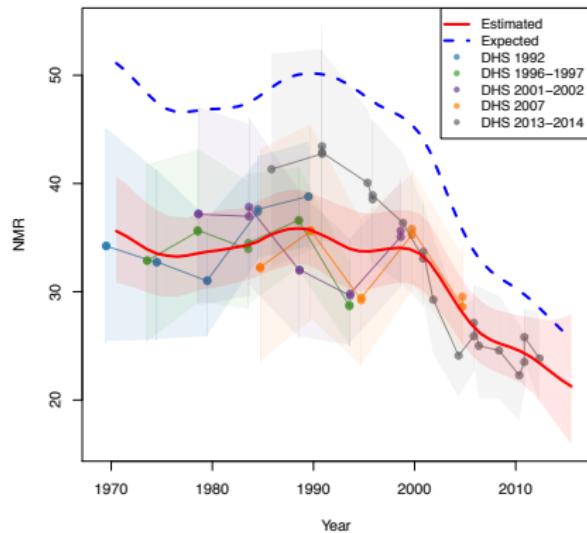
(b) Zambia

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

Motivating example 1



(a) Australia

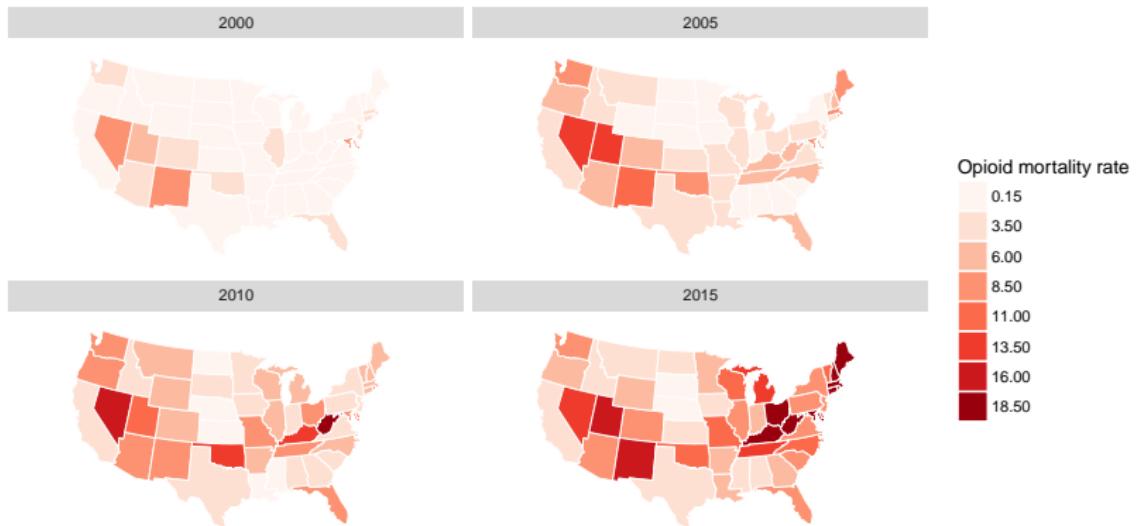


(b) Zambia

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

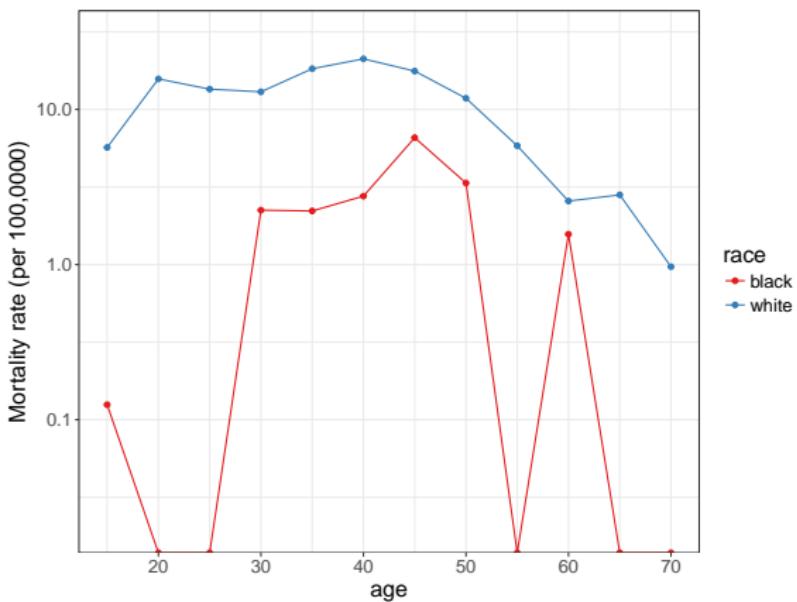


Figure: Observed opioid mortality rate by age and race, North Carolina, 2004

Motivating example 2

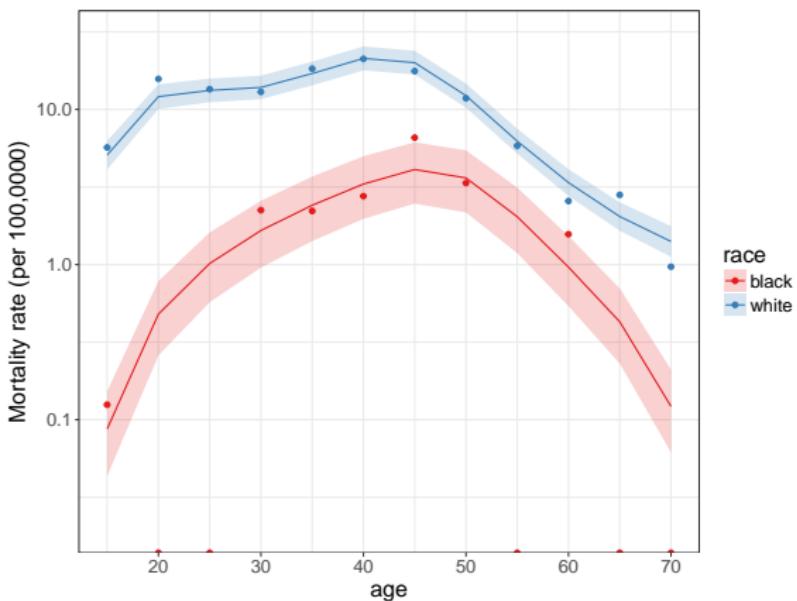
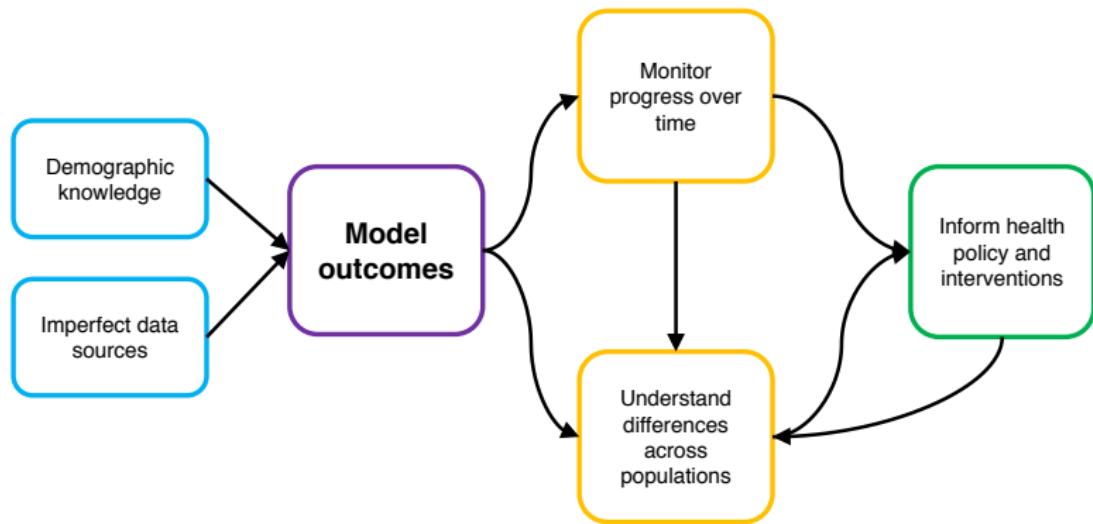


Figure: Observed and estimated opioid mortality rate by age and race, North Carolina, 2004

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

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

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:

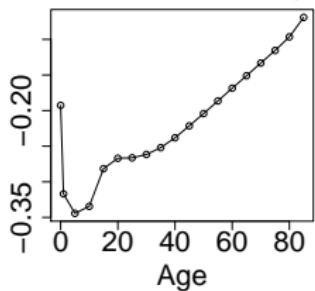
$$\log(m_{x,a,t}) = \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x}$$

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

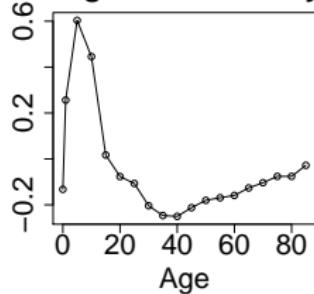
1. Model underlying structure

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

**Principal component 1:
Baseline mortality**



**Principal component 2:
High child mortality**



**Principal component 3:
High adult mortality**

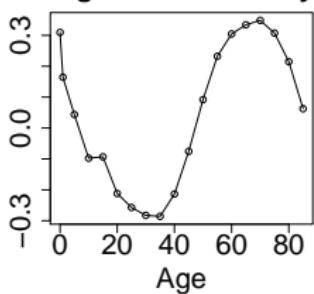


Figure: Principal components of (logged) US state mortality schedules, Males, 1980–2010 (Alexander et al. 2017).

2. Spatial model

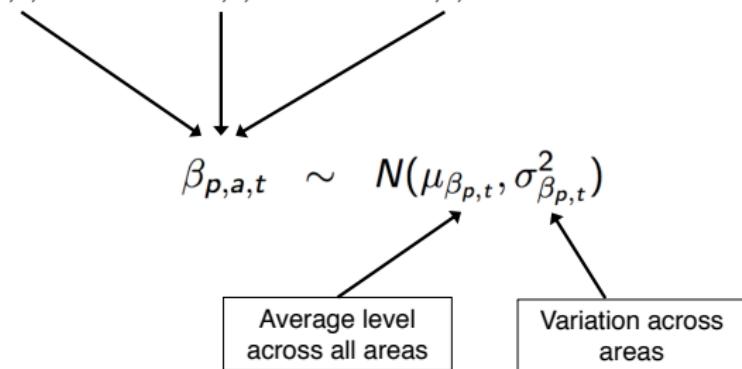
Motivation:

- 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).

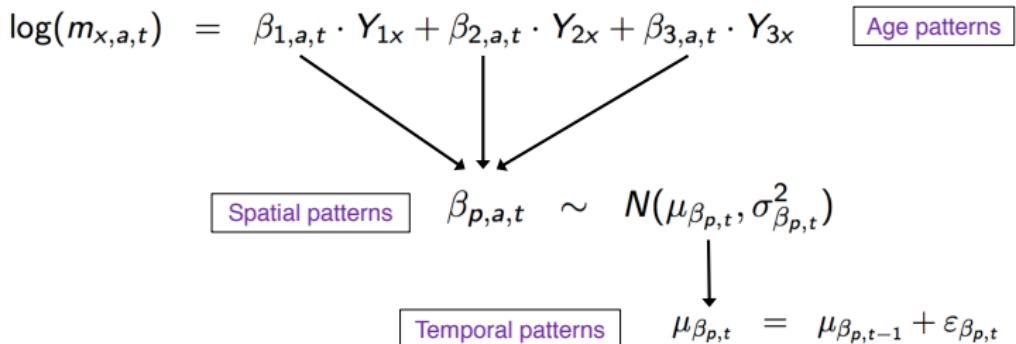
$$\log(m_{x,a,t}) = \beta_{1,a,t} \cdot Y_{1x} + \beta_{2,a,t} \cdot Y_{2x} + \beta_{3,a,t} \cdot Y_{3x}$$



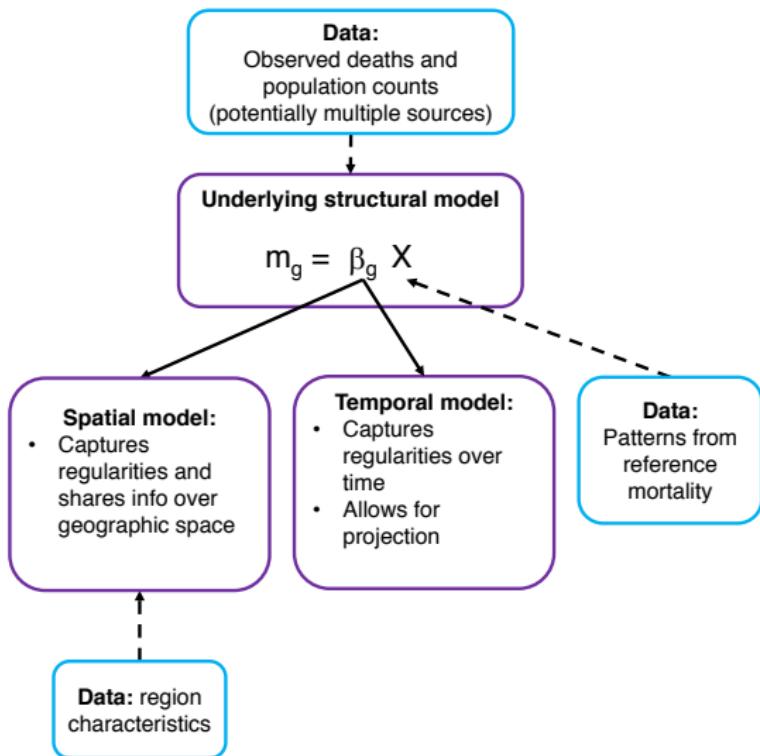
3. Temporal model

- 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



Summary of methodology



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

Opioid mortality by race, 1979–2015

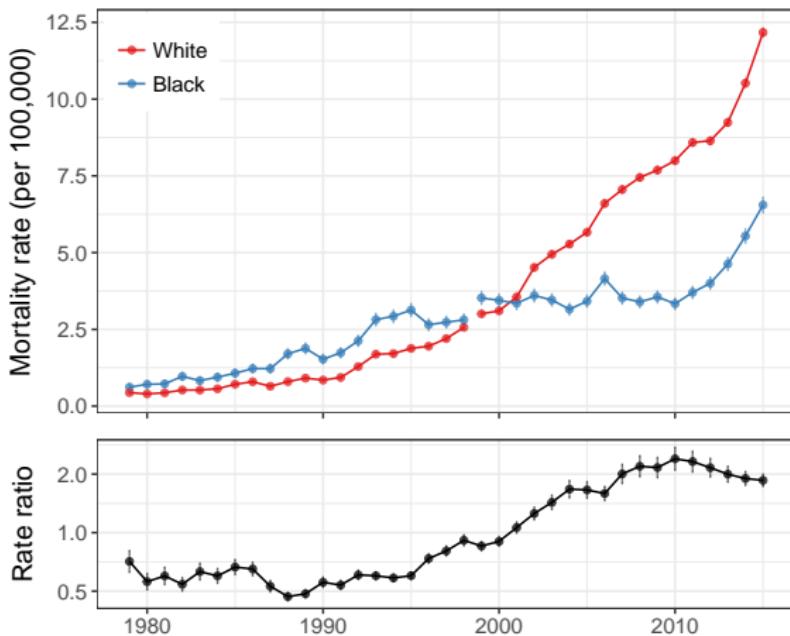


Figure: Top: Opioid mortality rate for white and black populations.

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

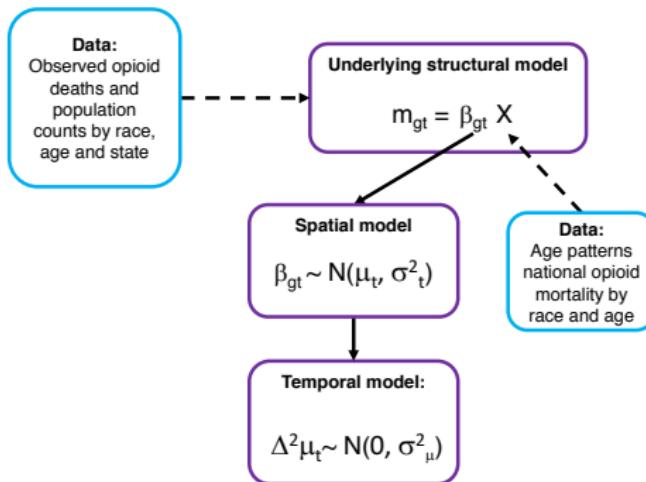
- How do racial patterns in opioid mortality vary by state?
- How have they evolved over time?
- Evidence for potential mechanisms of change?

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

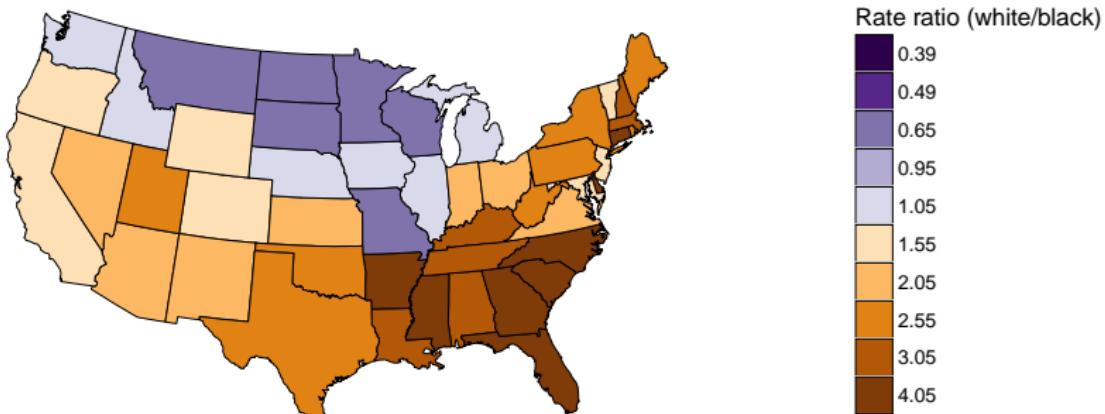
Modeling approach

- 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

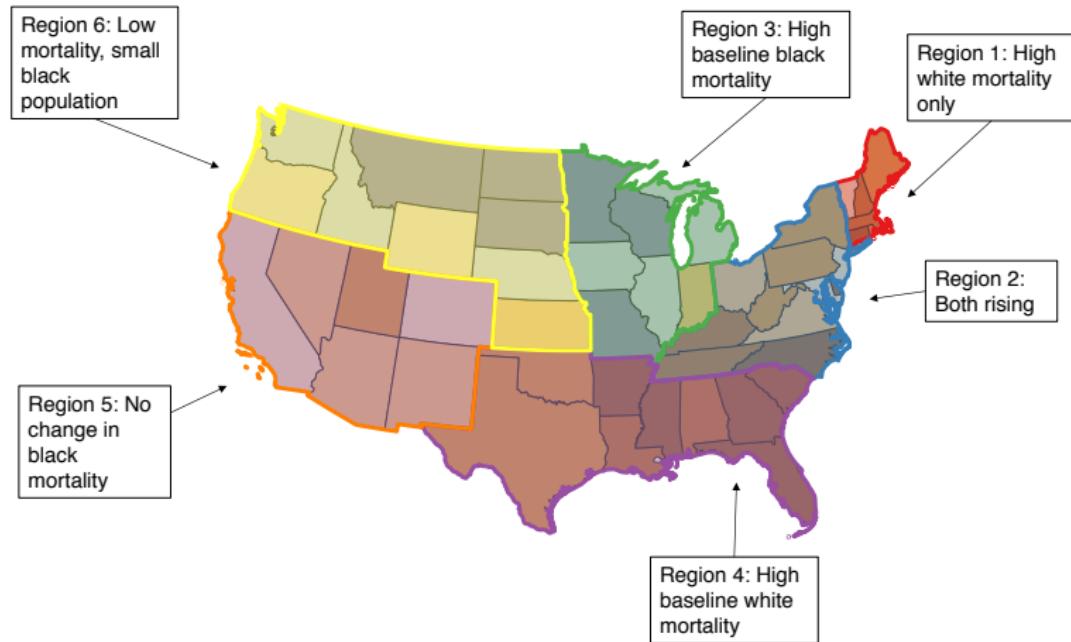


Results: opioid mortality rate ratio

Opioid mortality rate ratio (white/black), 2015



Regions of similar racial patterns



Region 1: white only

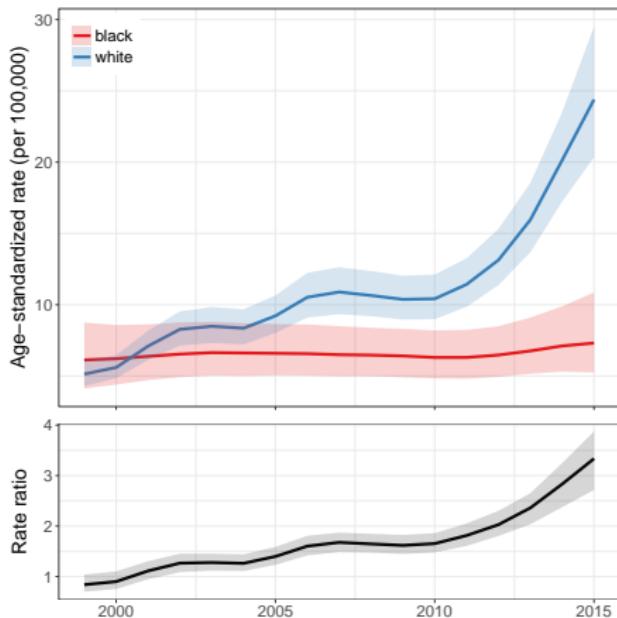


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Massachusetts**.

Region 1: white mortality only

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



Region 2: both races rising

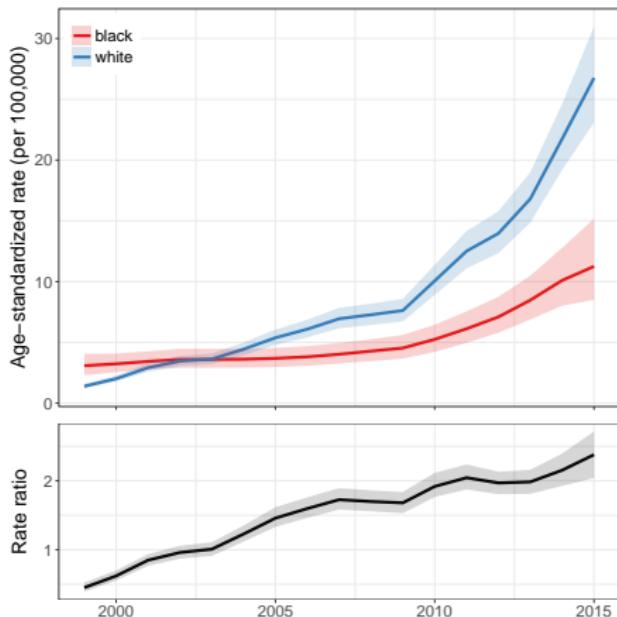


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Ohio**.

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

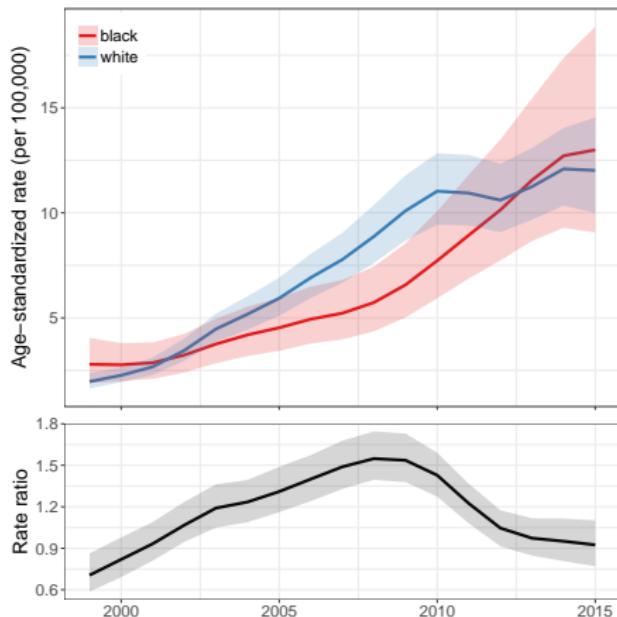


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Missouri**.

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

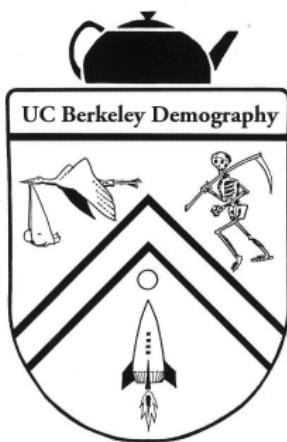
Summary

- 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!



monicaalexander.com

monicaalexander@berkeley.edu

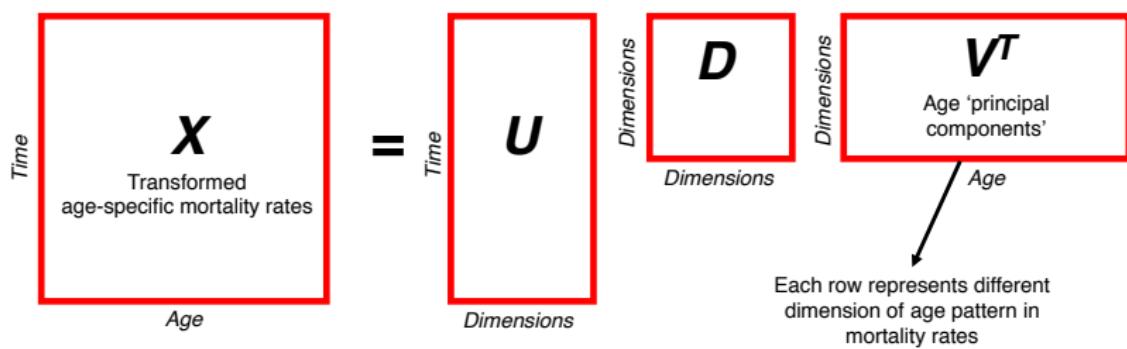
Papers cited:

- Alexander, M., and Alkema, L., 'Global Estimation of Neonatal Mortality using a Bayesian Hierarchical Splines Regression Model', <https://arxiv.org/abs/1612.03561> (forthcoming, *Demographic Research*).
- Alexander, M., Zagheni, E., and Barbieri, M., 'A Flexible Bayesian Model for Estimating Subnational Mortality', <https://link.springer.com/article/10.1007/s13524-017-0618-7> (forthcoming, *Demography*).
- Alexander, M., Barbieri M., and Kiang, M.V., 'Opioid deaths by race in the United States, 2000–2015.', <https://osf.io/preprints/socarxiv/jm38s>.
- Alpert A, Powell D and Pacula RL (2017); 'Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids', RAND Working Paper, WR-1181, January 2017.
- Centers for Disease Control and Prevention. Increases in Fentanyl Drug Confiscations and Fentanyl-related Overdose Fatalities. CDC Health Alert Network; 2015.
- Cicero TJ, Ellis MS, Kasper ZA. 'Increased use of heroin as an initiating opioid of abuse.' *Addict Behav.* Elsevier; 2017;74:63–6.
- Frenk SM, Porter KS, Paulozzi LJ. 'Prescription opioid analgesic use among adults: United States, 1999–2012.' *NCHS Data Brief* 2015 Feb 1;(189):1–8.
- Pletcher MJ, Kertesz SG, Kohn MA, Gonzales R. 'Trends in opioid prescribing by race/ethnicity for patients seeking care in US emergency departments.' *JAMA* 2008 Jan 2;299(1):70–8.
- Singhal A, Tien Y-Y, Hsia RY. 'Racial-Ethnic Disparities in Opioid Prescriptions at Emergency Department Visits for Conditions Commonly Associated with Prescription Drug Abuse.' *Public Library of Science*; 2016 Jan 1;11(8):e0159224.
- Slavova S, Costich JF, Bunn TL, Luu H, Singleton M, Hargrove SL, et al. 'Heroin and fentanyl overdoses in Kentucky: Epidemiology and surveillance'. *Int J Drug Policy*. 2017;46:120–9.

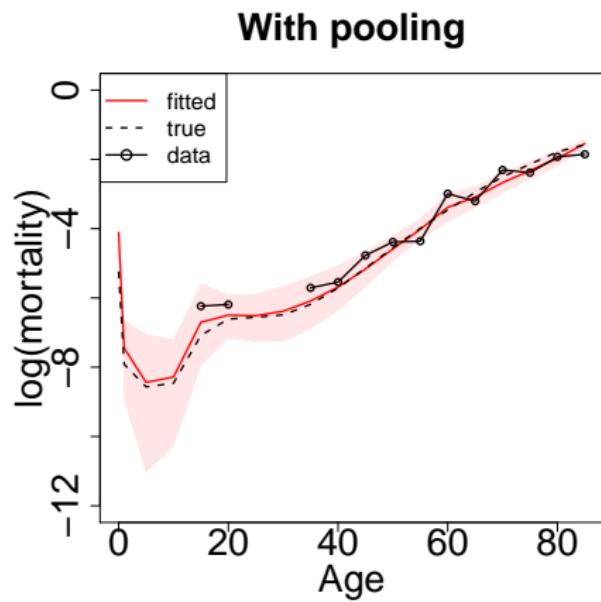
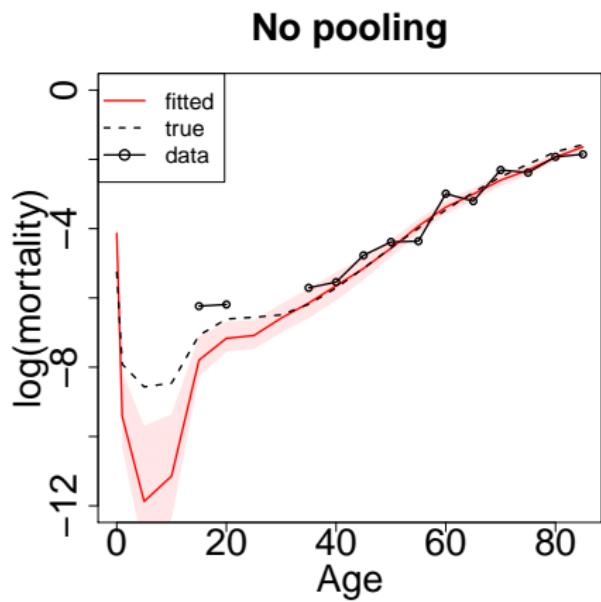
Extra Slides - methods

1. Model underlying structure

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

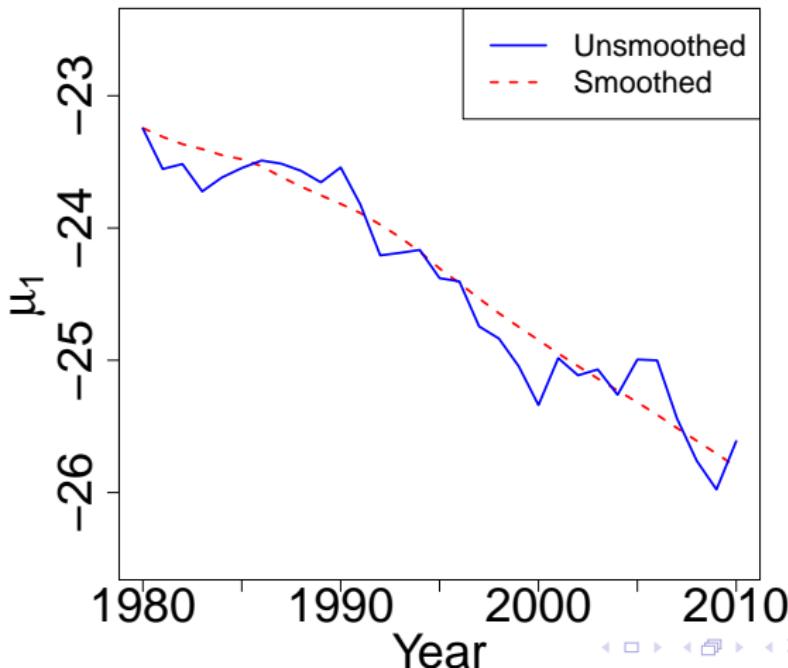


2. Pooling across space



3. Smoothing across time

Figure: Effect of smoothing parameters over time



Full model

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

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 $p = 1, 2, 3$.

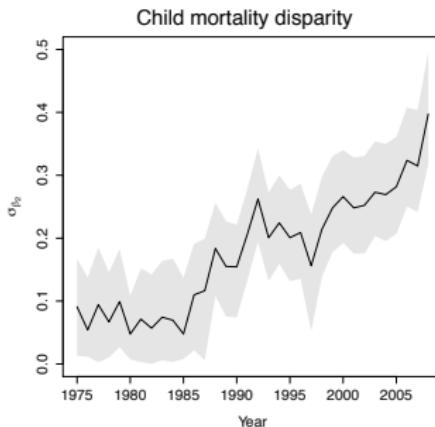
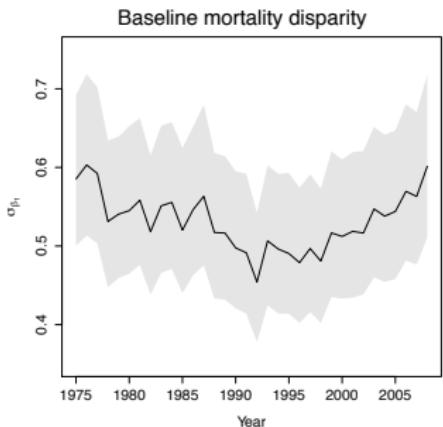
Parameterizing disparities

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

Average level across all areas

Variation across areas

Variation across French *départements*:



Extra Slides - opioids

The US opioid epidemic

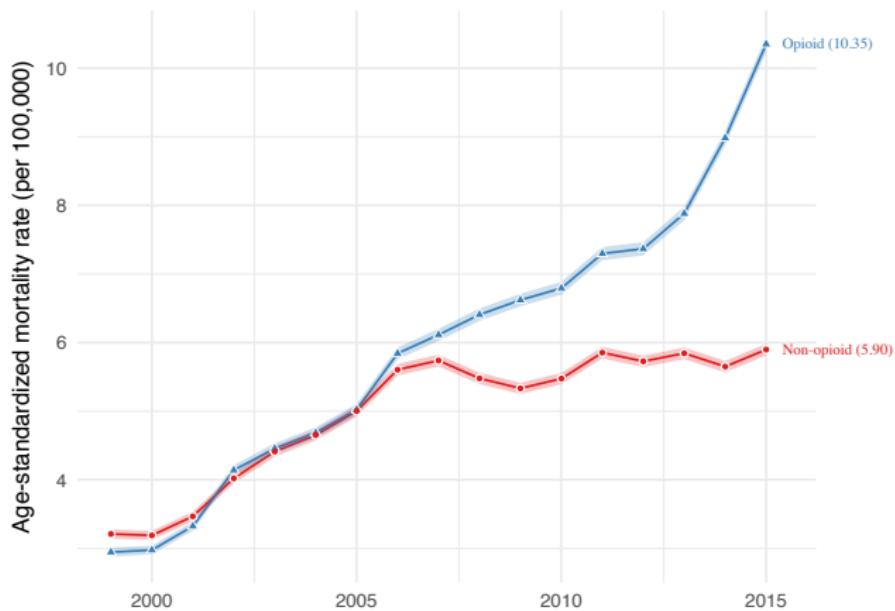


Figure: Drug-related mortality in the United States, 1999–2015
(Alexander et al. 2017)

A changing epidemic

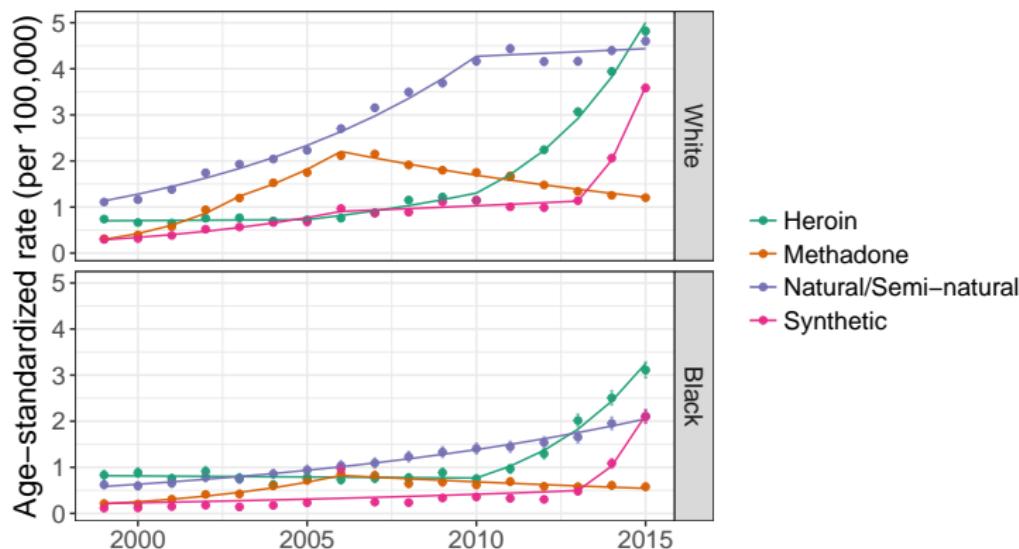


Figure: Opioid mortality rates by general type of opioid for white (top) and black (bottom) populations. Lines are joinpoint model fits (Alexander et al. 2017).

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

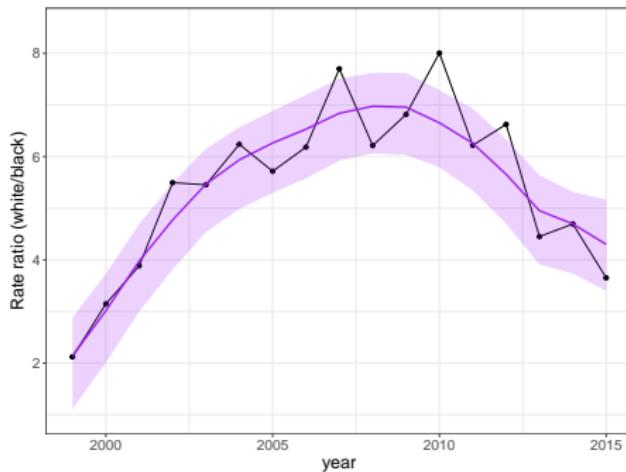
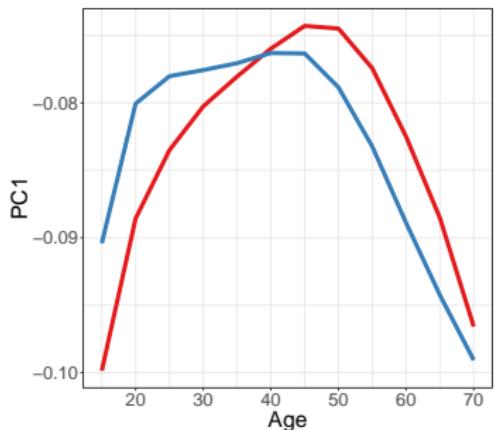


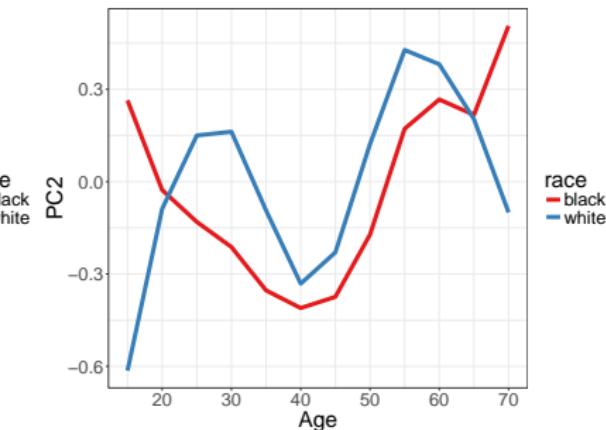
Figure: Opioid mortality ratio ratio (white/black), observed and fitted, North Carolina

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

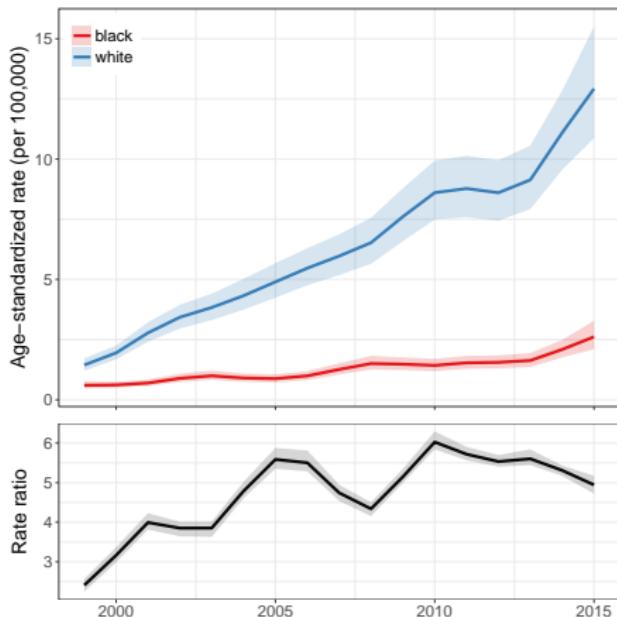


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Georgia**.

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

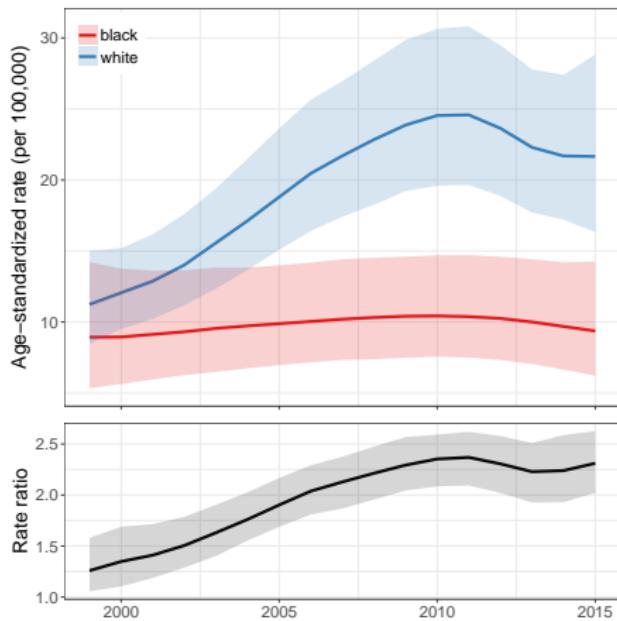
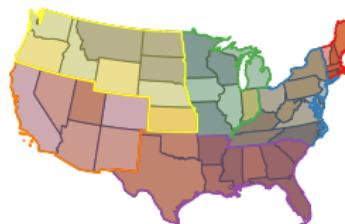


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Nevada**.

Region 5: no change in black mortality

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



Region 6: low mortality

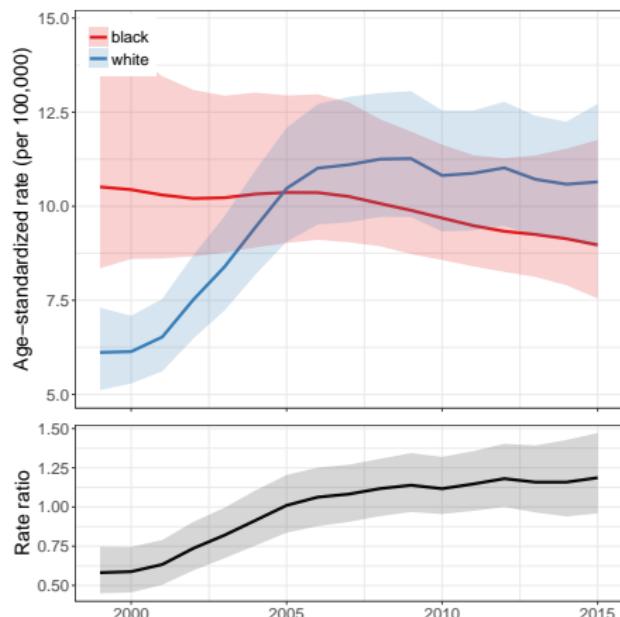


Figure: Opioid mortality rates by race and ratio ratio (white/black) for **Washington**.

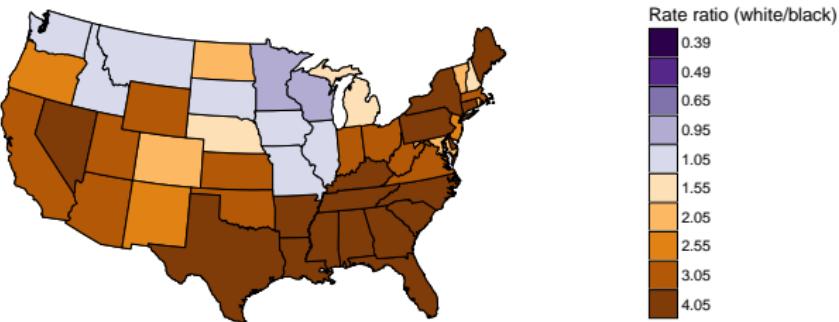
Region 6: low mortality

- 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

