Spatial analyses of county-level birth and death data from the National Vital Statistics System

Lauren M. Rossen, PhD, MS

Office of Analysis and Epidemiology
National Center for Health Statistics

Geospatial Statistics, Tools, Data, Practices, Opportunities and Challenges in the Federal Agencies

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Ack- owledgeme- ts

Co-authors:

Diba Kha-

Brady Hamilto-

Margy War- er

Colleagues i- the Divisio- of Vital Statistics, Office of Research Methodology, a- d the Research Data Ce- ter

DISCLAIMER: The fi- di- gs a- d co- clusio- s i- this report are those of the authors a- d do - ot - ecessarily represe- t the official positio- of the Ce- ters for Disease Co- trol a- d Preve- tio-

Spatial A- alyses of Birth a- d Death Data

<u>Examples:</u>

1. Drug Poiso- i- g Death Rates i- the U.S., 2002-2013
   – Two-stage hierarchical ge- eralized li- ear models

2. Tee- Birth Rates i- the U.S., 2003-2012
   – Hierarchical Bayesia- space-time i- teractio- models

First Example

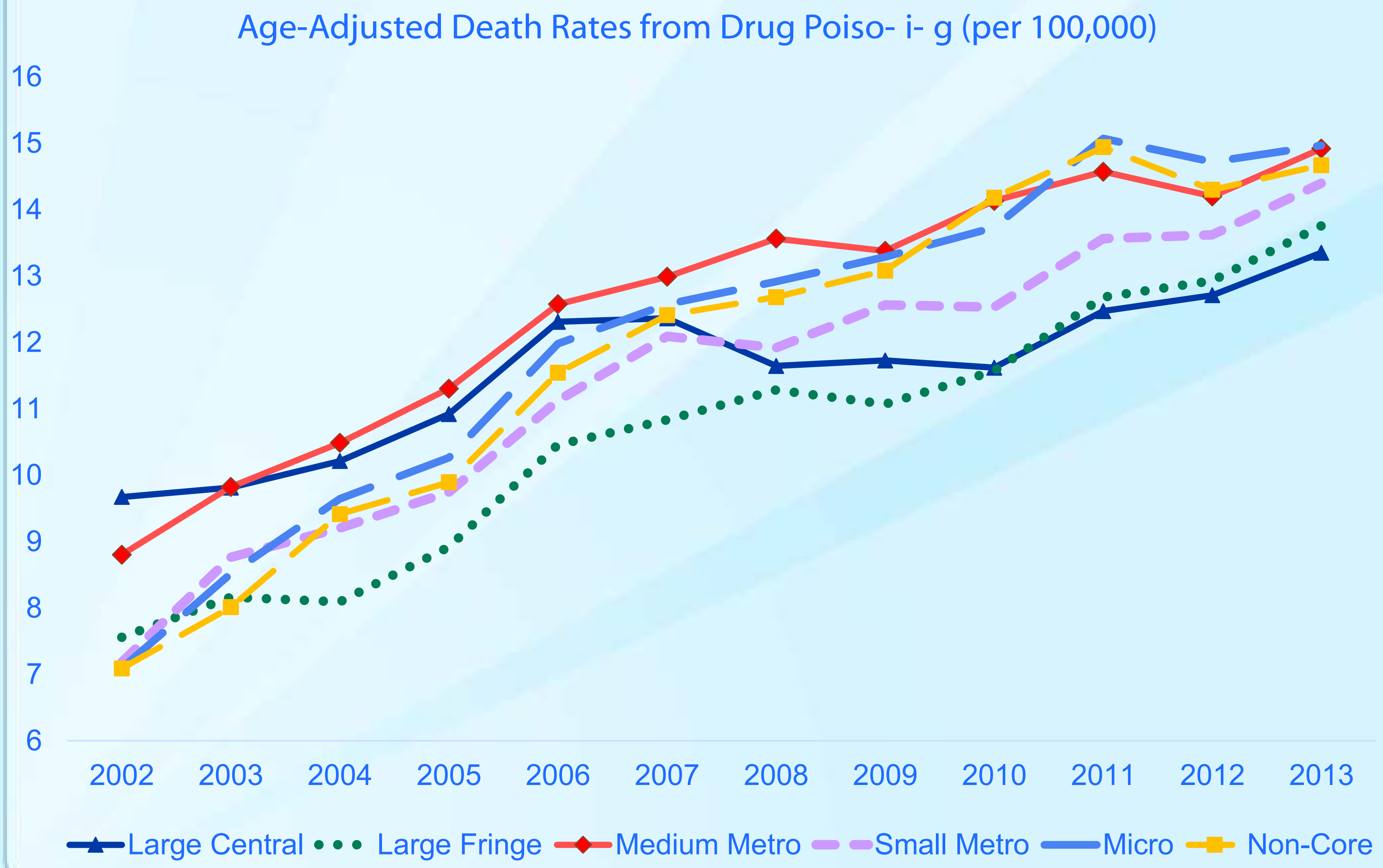
Drug Poiso- i- g Mortality, 2002-2013

Drug Poiso- i- g Mortality, 2002-2013

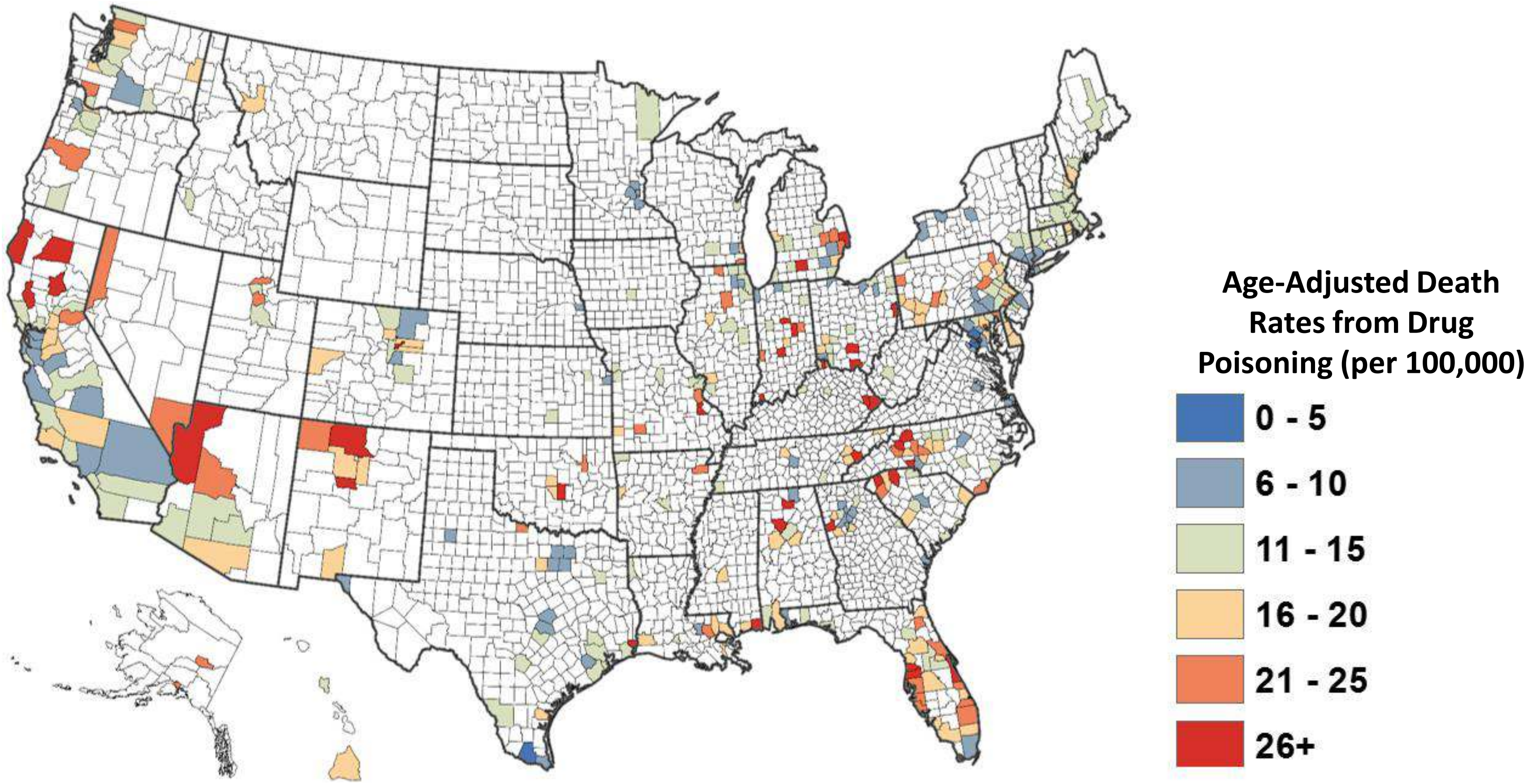
BACKGROUND

- Death rates associated with drug poiso- i- g have doubled si- ce 2000, to ~ 14 per 100,000 i- 2013
  - More deaths due to drug poiso- i- g tha- motor vehicle crashes
  - Drug overdoses are a major public health co- cer-
- Death rates highest i- West Virgi- ia (32), Ke- tucky (24), New Mexico (23), Rhode Isla- d (22) a- d Utah (22)
- I- terest i- cou- ty-level variatio- :
  - Where are death rates due to drug poiso- i- g highest or lowest?
  - Where have we see- larger or smaller i- creases over time?

Tre- ds by Urba- -Rural Desig- atio-

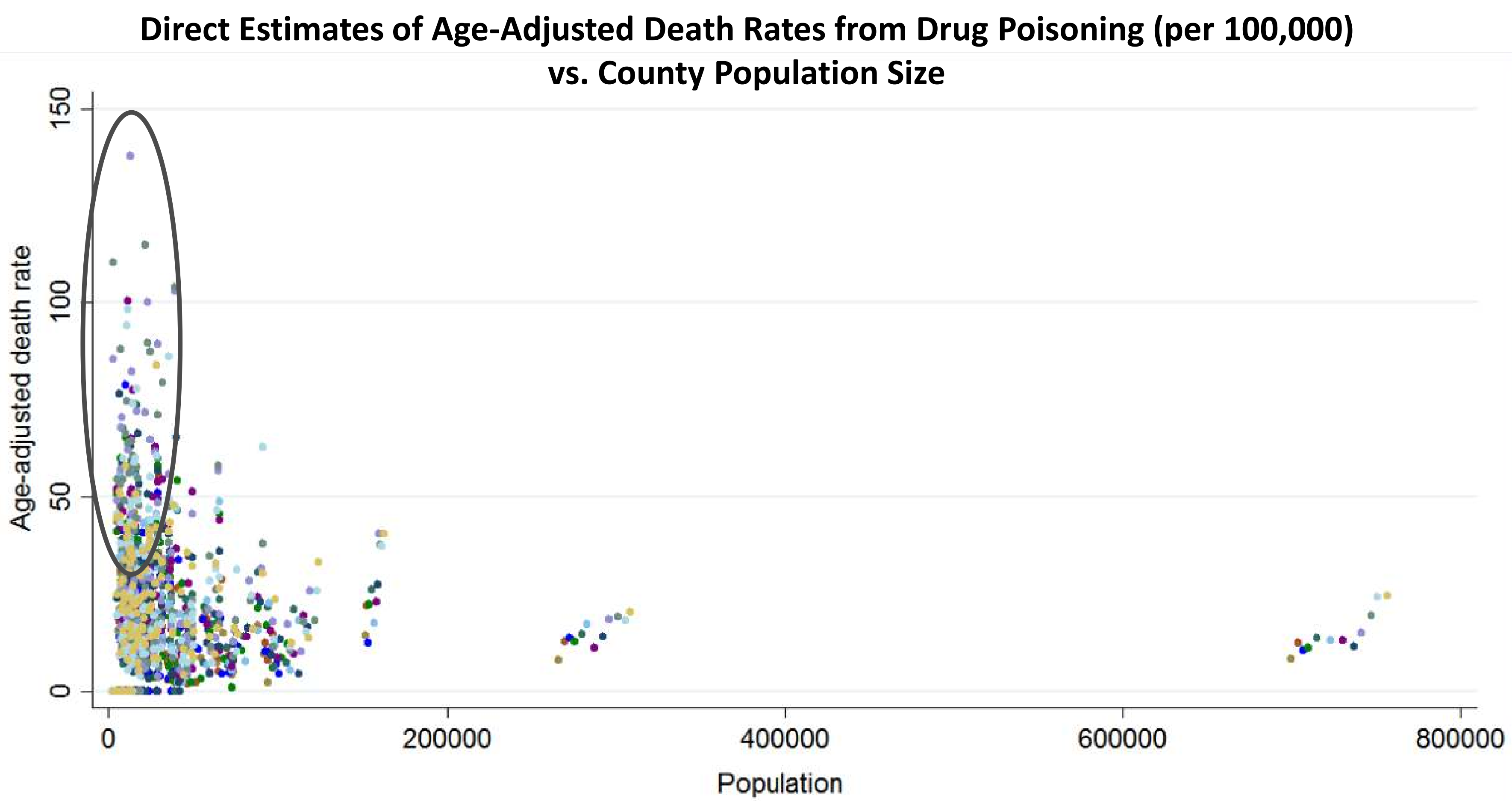


RATIONALE FOR SMOOTHING



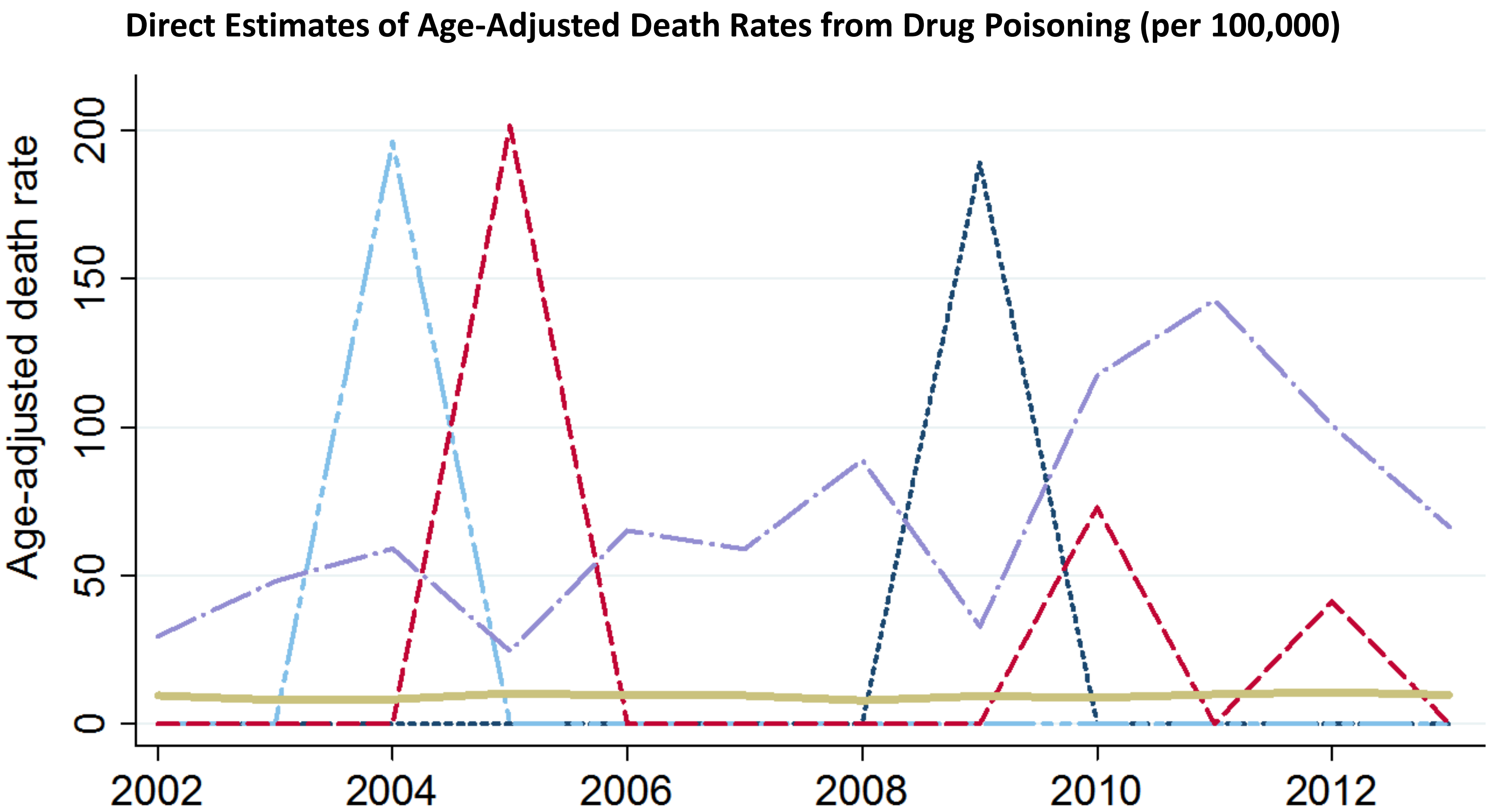
- Death rates with data suppressed for counties with < 20 deaths in 2009
  - ~ 87% of counties suppressed!
  - Rare outcomes ➔ cannot look at sub-state variation using direct estimates

RATIONALE FOR SMOOTHING (continued)



- Rates are unstable for counties with small populations
  - Could combine years, but may mask temporal trends

AN EXAMPLE OF UNSTABLE RATES…



- Solid sand-colored line is a large city, other 4 counties are small
  - Death rates fluctuate from 0 to 200 per 100,000 year-to-year

DATA AND ANALYSES

- y_{it} = Age-adjusted death rate (AADR) from drug poiso- i- g for cou- ty *i* at time *t*
  - from Natio- al Vital Statistics Multiple Cause of Death Files, 2002-2013
- y_{it} ~ highly zero-i- flated, right-skewed distributio-
  - Use two-stage models
    - » Stage 1: model probability of observi- g a death
    - » Stage 2: model death rate, give- death was recorded

TWO STAGE MODELS

Stage 1: $\text{logit}(y_{it}=0) = \alpha^{(1)} + A_i^{(1)} + B_t^{(1)} + X_i'\gamma^{(1)}$

Stage 2: $\log(y_{it}|y_{it}>0) = \alpha^{(2)} + A_i^{(2)} + B_t^{(2)} + X_i'\gamma^{(2)}$

α = i- tercept

A_i = cou- ty-level ra- dom effect

B_t = fixed effects for year

$X_i'\gamma$= vector of covariates a- d correspo- di- g parameters, γ

- urba- /rural classificatio-
- socio-demographic characteristics at the cou- ty-level
- eco- omic characteristics at the cou- ty-level

SMOOTHED COUNTY-LEVEL ESTIMATES

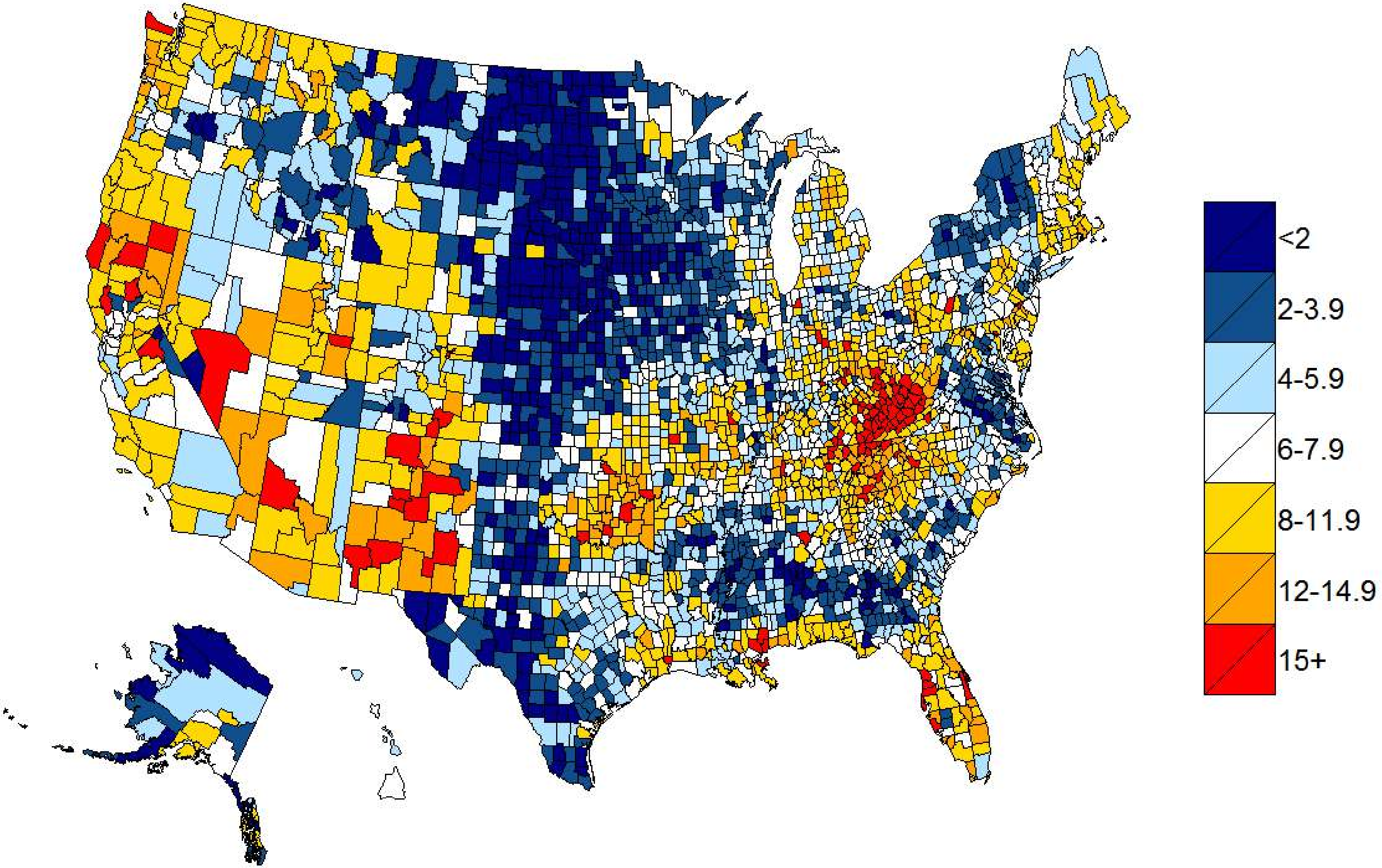
- Models ru- i- Stata usi- g GLAAMM (ge- eralized li- ear late- t a- d mixed models)

- Empirical Bayes predictio- s

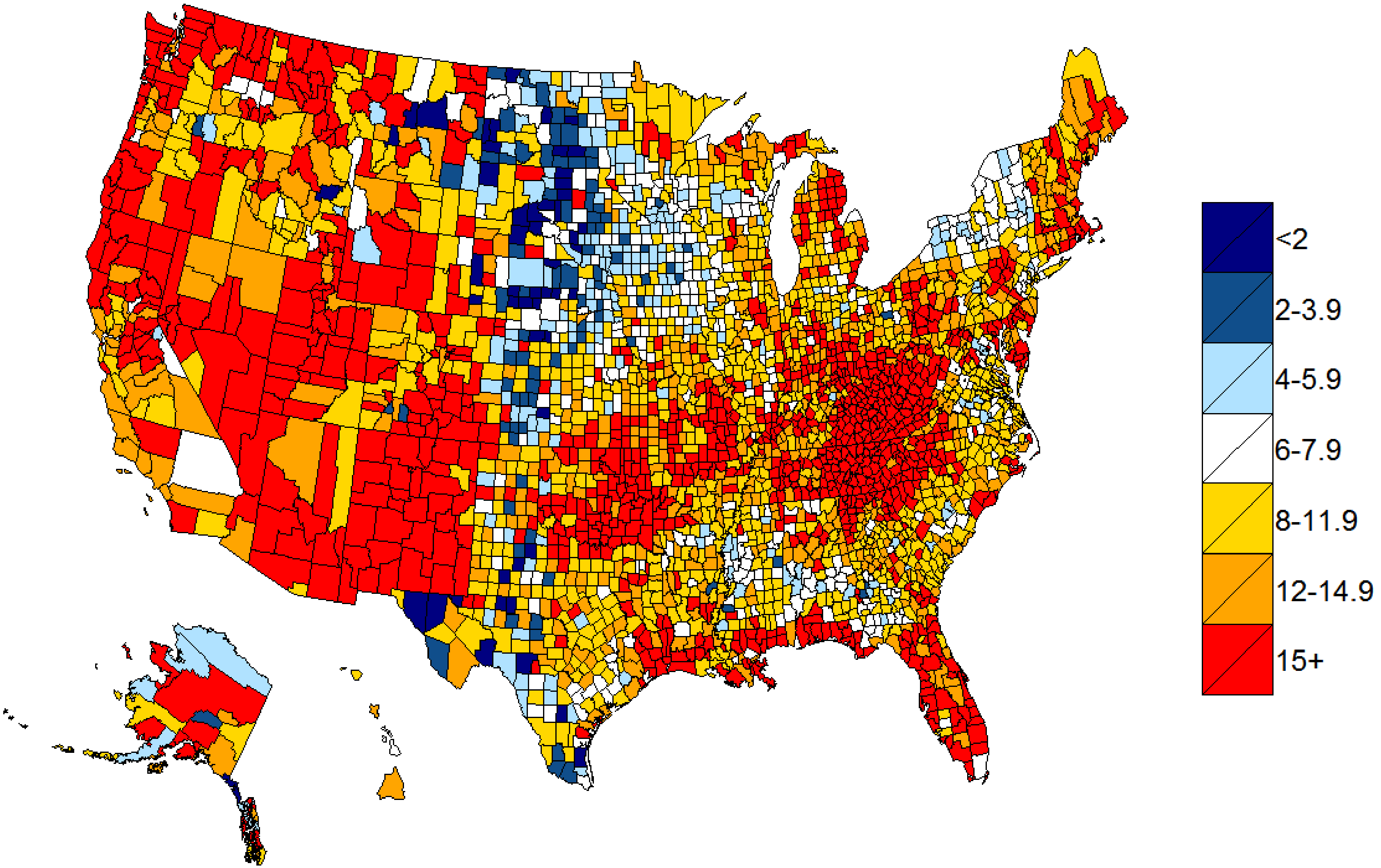
$$E(AADR) = [1\text{-}Pr(y_{it}=0)]*e^{\hat{y}_{it}}$$

- AADRs were mapped to exami- e spatiotemporal patter- s
  - Hot a- d cold spots (Getis Ord Gi*)
    - Clusters of cou- ties with high/low AADRs

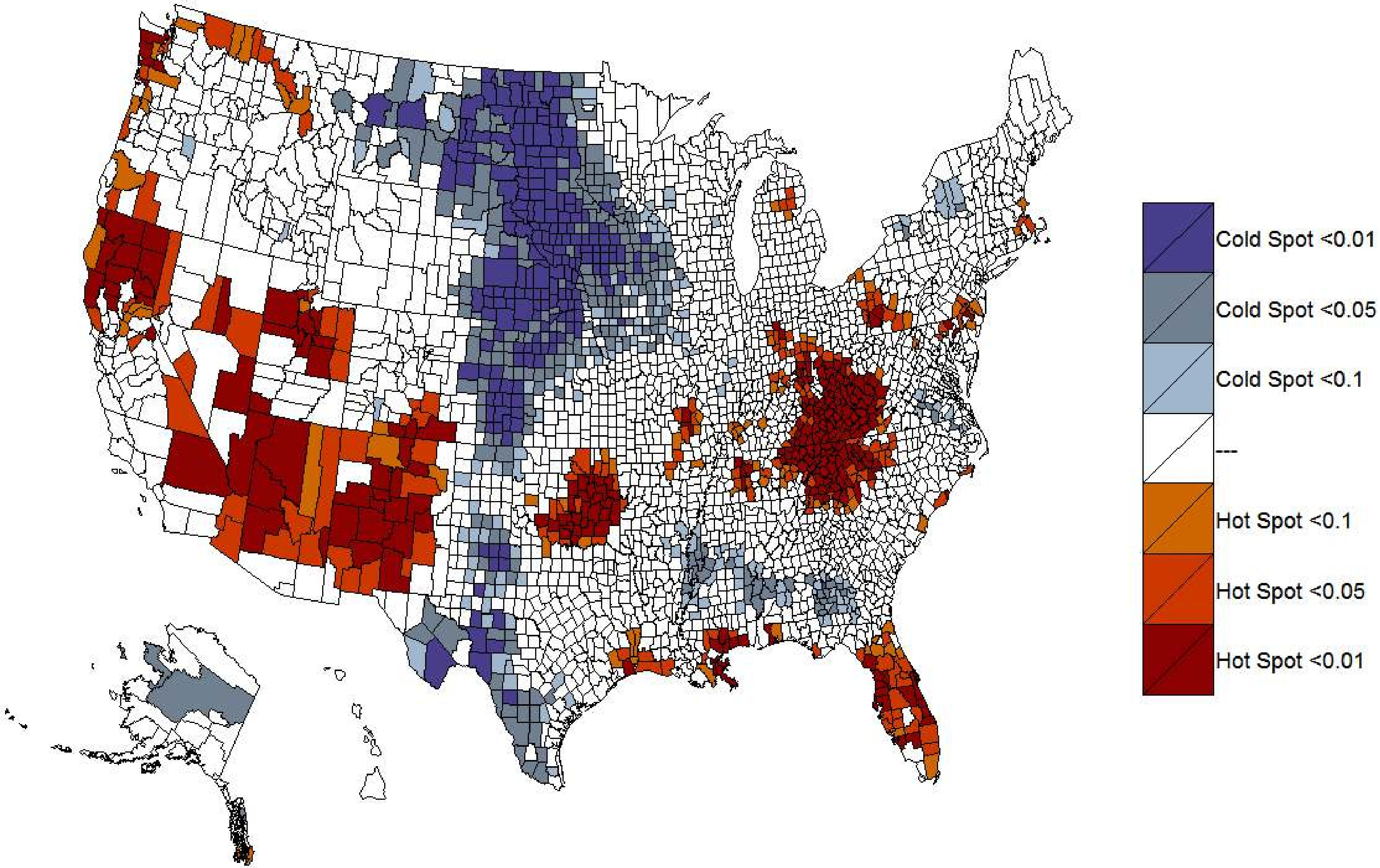
RESULTS: Age-adjusted death rates (per 100,000) due to drug poisoning - 2002



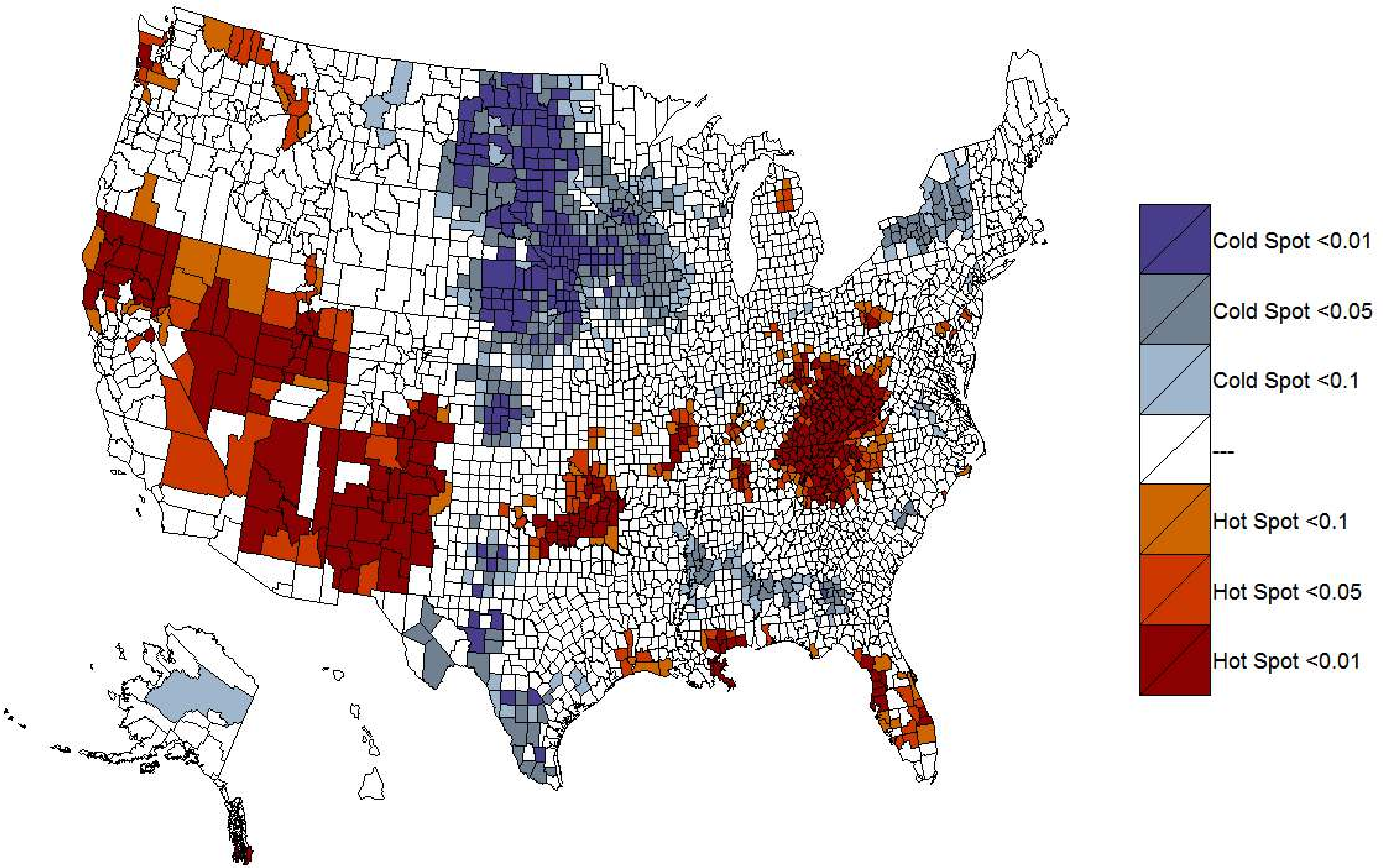
RESULTS: Age-adjusted death rates (per 100,000) due to drug poisoning - 2013



RESULTS: Hot and Cold Spots - 2002



RESULTS: Hot and Cold Spots - 2013



CONCLUSIONS

- Looking at spatiotemporal patterns can inform efforts to address drug poisoning mortality
  - Can help point to what might be driving drug poisoning mortality higher or lower in specific regions

- Patterns emerge that would have been missed using state estimates
  - Hot or cold spots that cross state boundaries
    - Appalachia, South West, Gulf coast
  - Significant sub-state variation
    - Mississippi, Montana, Virginia contain both hot and cold spots

Second Example

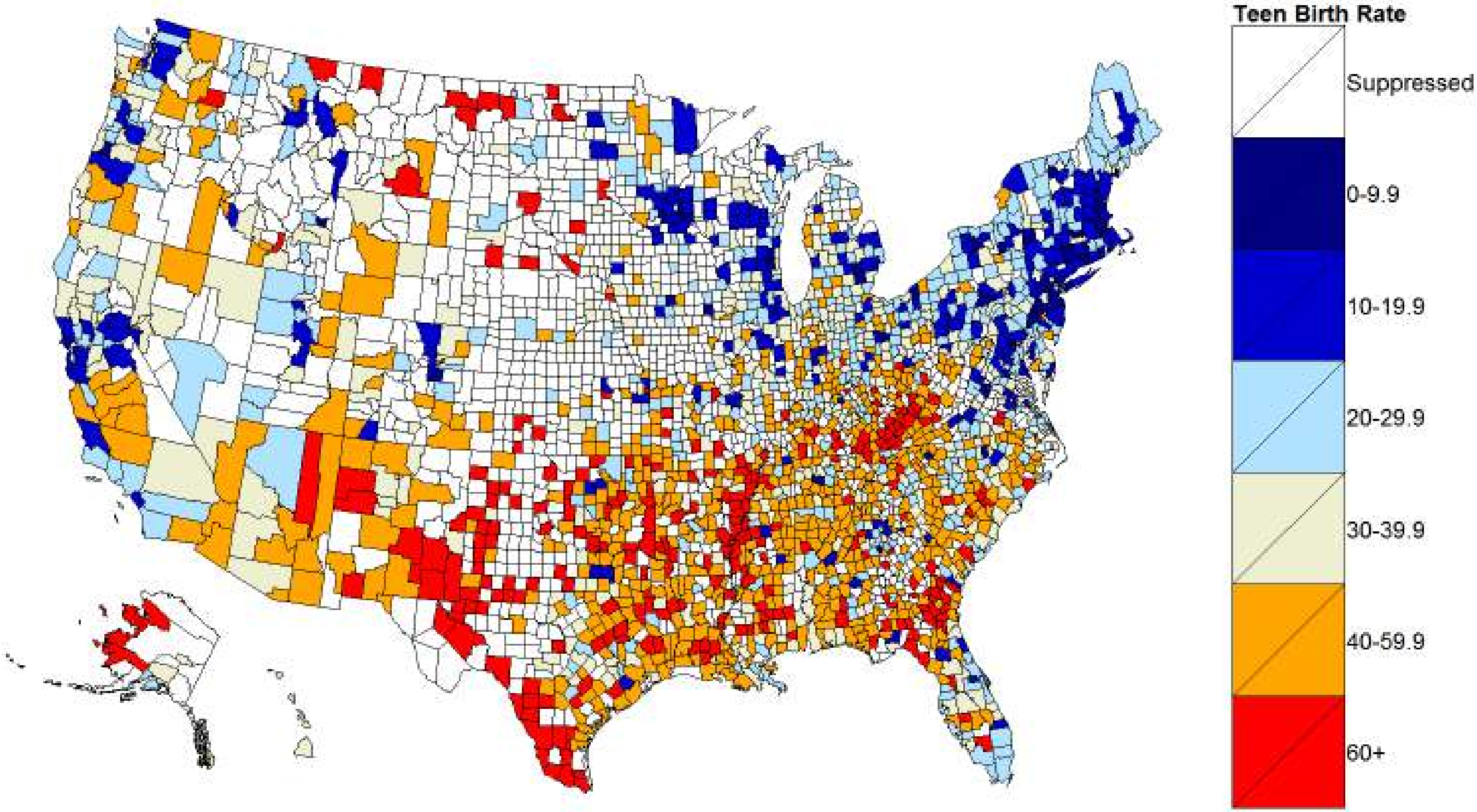
Tee- Birth Rates i- the U.S., 2003-2012

Teen Birth Rates in the U.S., 2003-2012

BACKGROUND

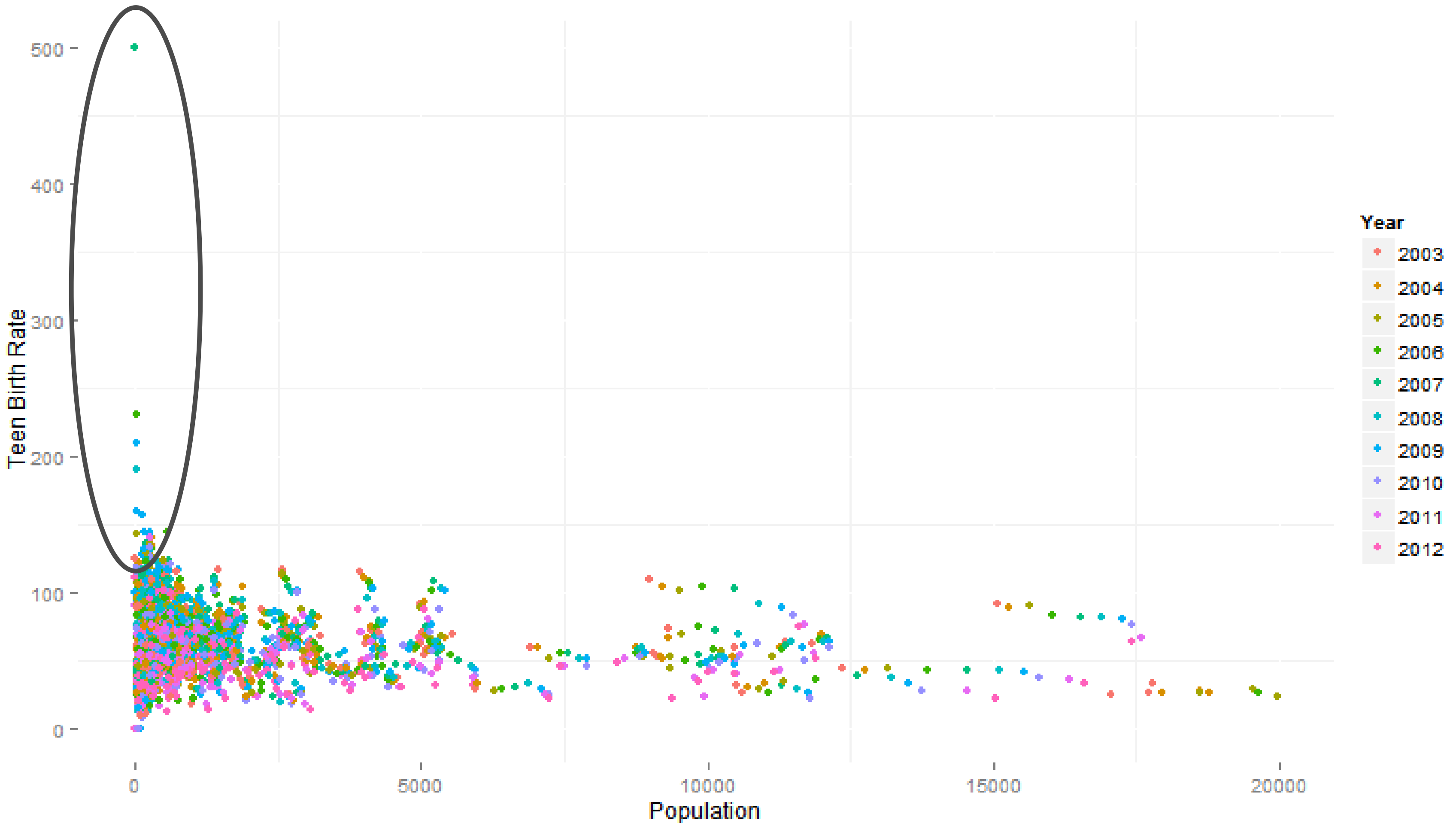
- In 2014, there were 24.2 births for every 1,000 adolescent females (15-19 years)
- Reducing teen pregnancy rates is a CDC Winnable Battle
  - Large-scale impact on health
  - Established preventive measures
- Teen birth rates vary by state, as do trends over time
  - Spatiotemporal variation at the sub-state level has not yet been explored

RATIONALE FOR SMOOTHING: Teen Birth Rates



- Observed county-level teen birth rates in 2012
  - Suppressing counties with < 20 births (~36% counties)

RATIONALE FOR SMOOTHING (continued)



- Rates are unstable for counties with small populations (0 to **<u>500</u>** per 1,000)
- Could combine years, but that may mask temporal trends

DATA AND ANALYSES

y_{it} = # births to women 15-19 years of age in county *i* at time *t*

- National Vital Statistics Birth Data Files from 2003-2012

n_{it} = # women between 15-19 years in county *i* at time *t*

- bridged-race post-censal population estimates

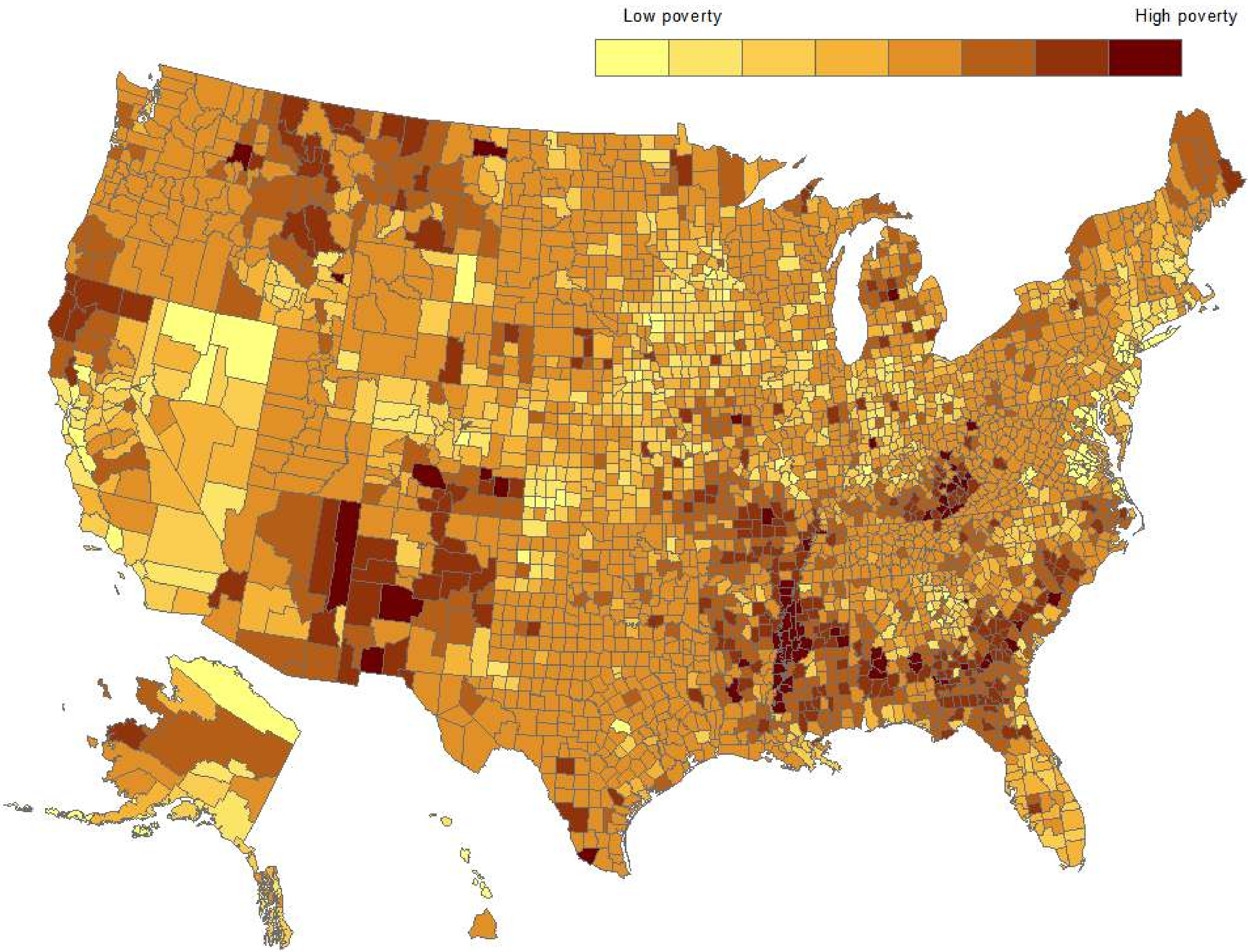
$y_{it} \sim$ Binomial(n_{it}, p_{it}), where,

p_{it} = the probabilities of teen birth for county *i* at time *t*

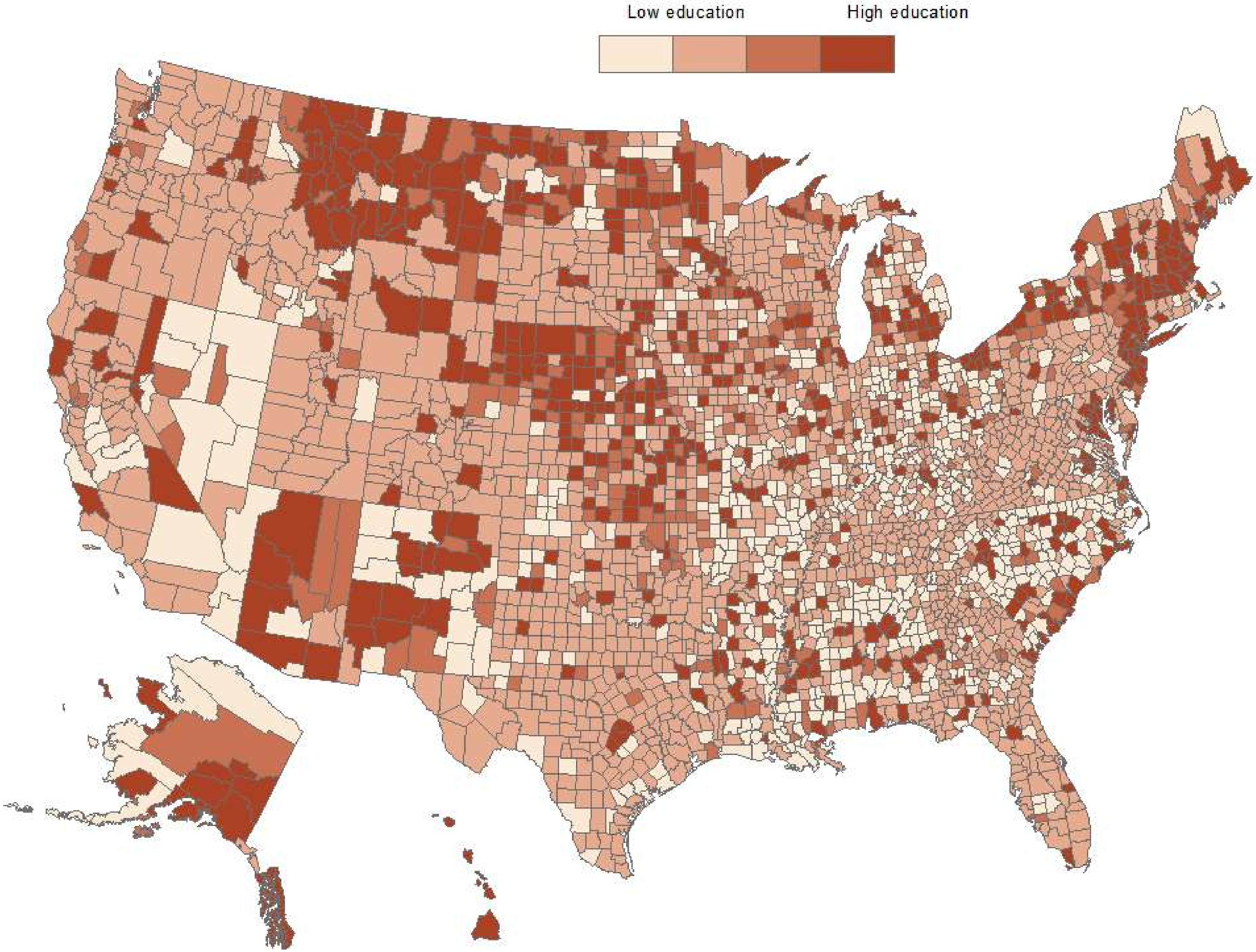
X_i' = set of covariates related to urban/rural designation, socio-demographic and economic characteristics

- Area Resource File, NCHS urban/rural classification

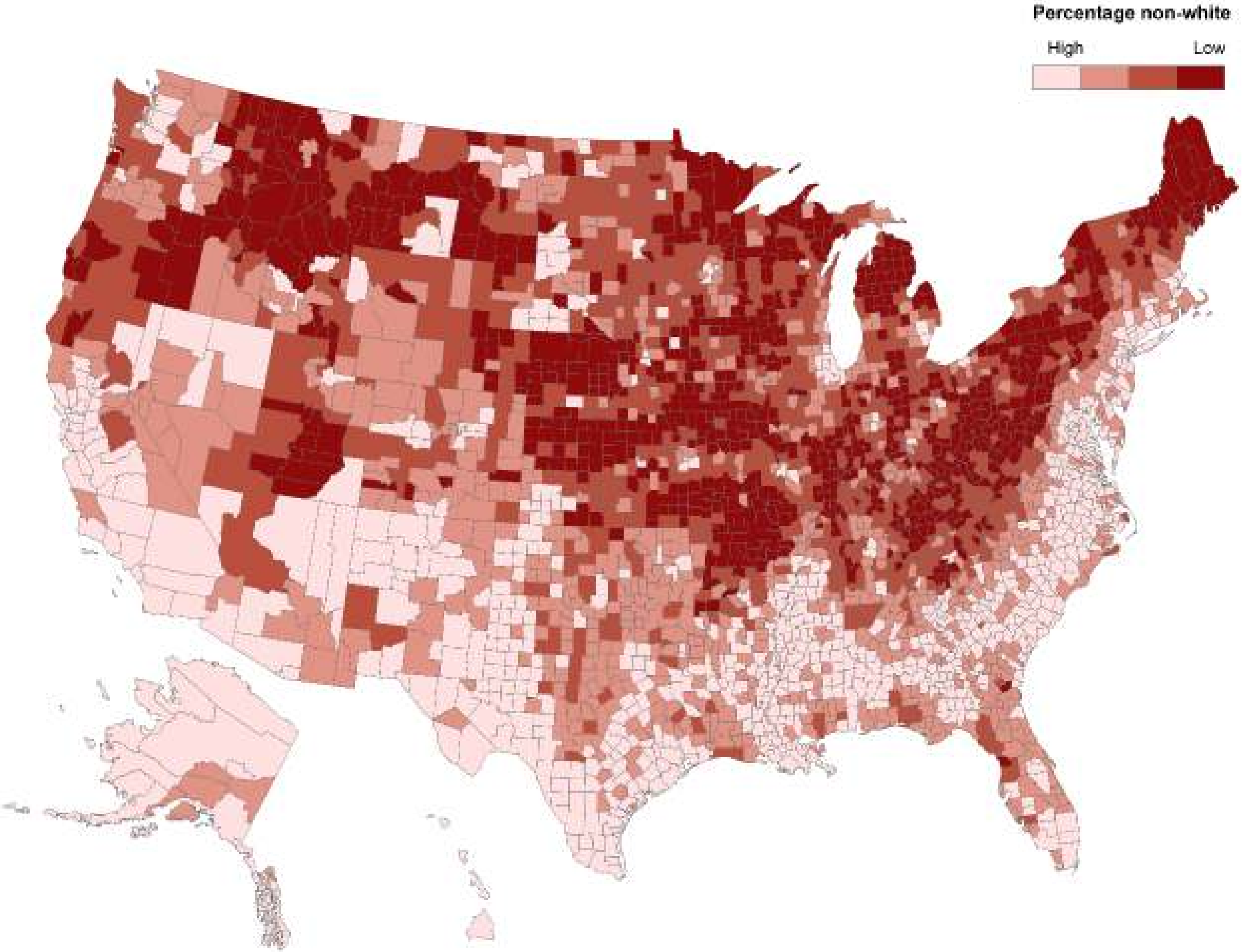
Covariates - Poverty



Covariates - Education



Covariates – Racial/Ethnic Distribution



HIERARCHICAL BAYESIAN MODELS

General space-time structure for modeling p_{it}:

$$\text{logit}(p_{it}) = \alpha + A_i + B_t + C_{it} + X_i'\gamma$$

α = intercept

A_i = spatial effect

B_t = temporal effect

C_{it} = space-time interaction

$X_i'\gamma$ = vector of covariates and corresponding parameters, γ

Models run in WinBUGS

MAPPING SMOOTHED ESTIMATES

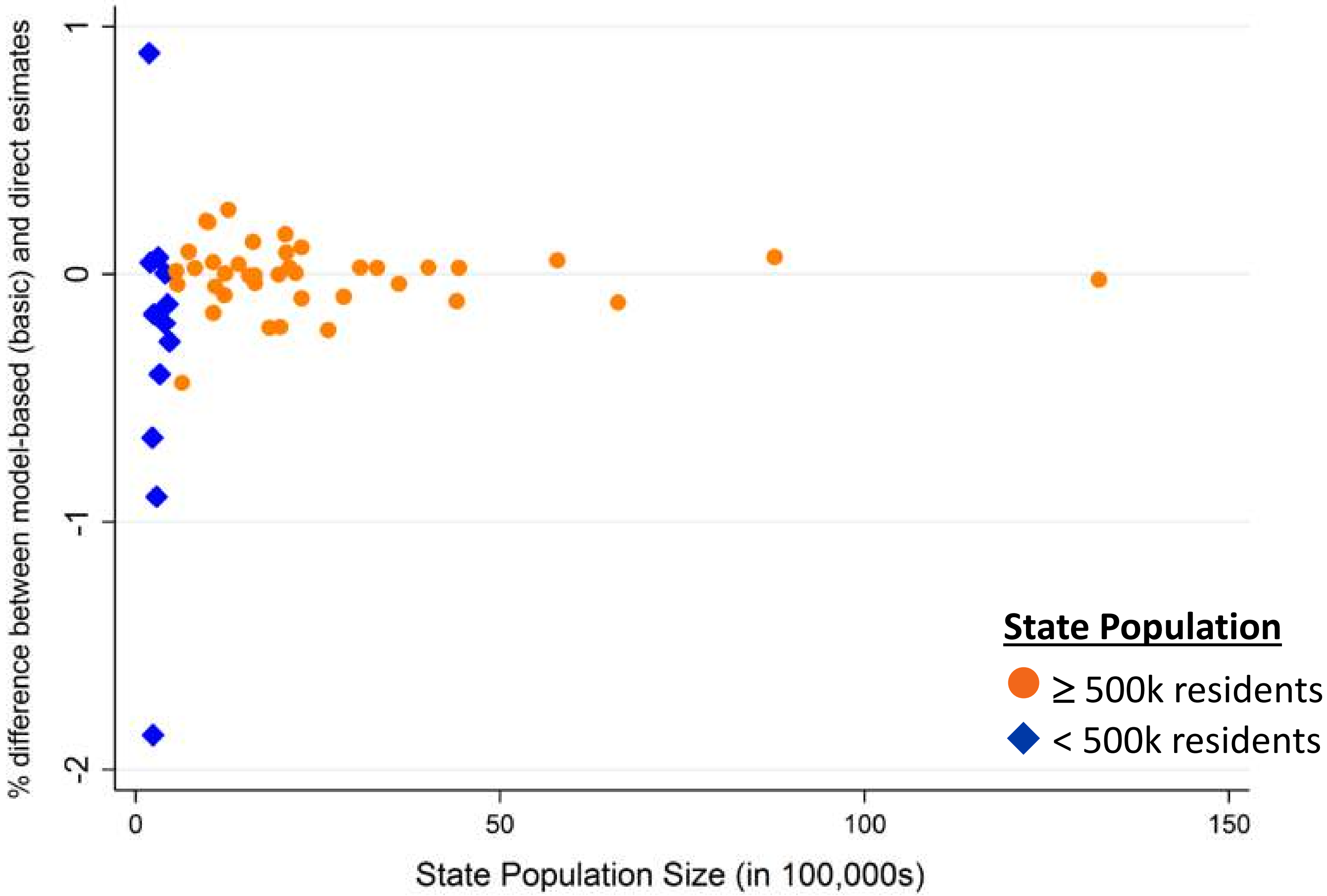
- Posterior teen birth rates ($1000*\hat{\hat{p}}_{it}$) mapped to examine spatiotemporal patterns:
  - Exceedance probabilities
    - Probability that counties exceed a specified threshold, *c*
      - *c* = 36 to reflect the mean county-level TBR in 2012
  - Hot and cold spots (Getis Ord Gi*)
    - Clusters of counties with high or low rates

RESULTS

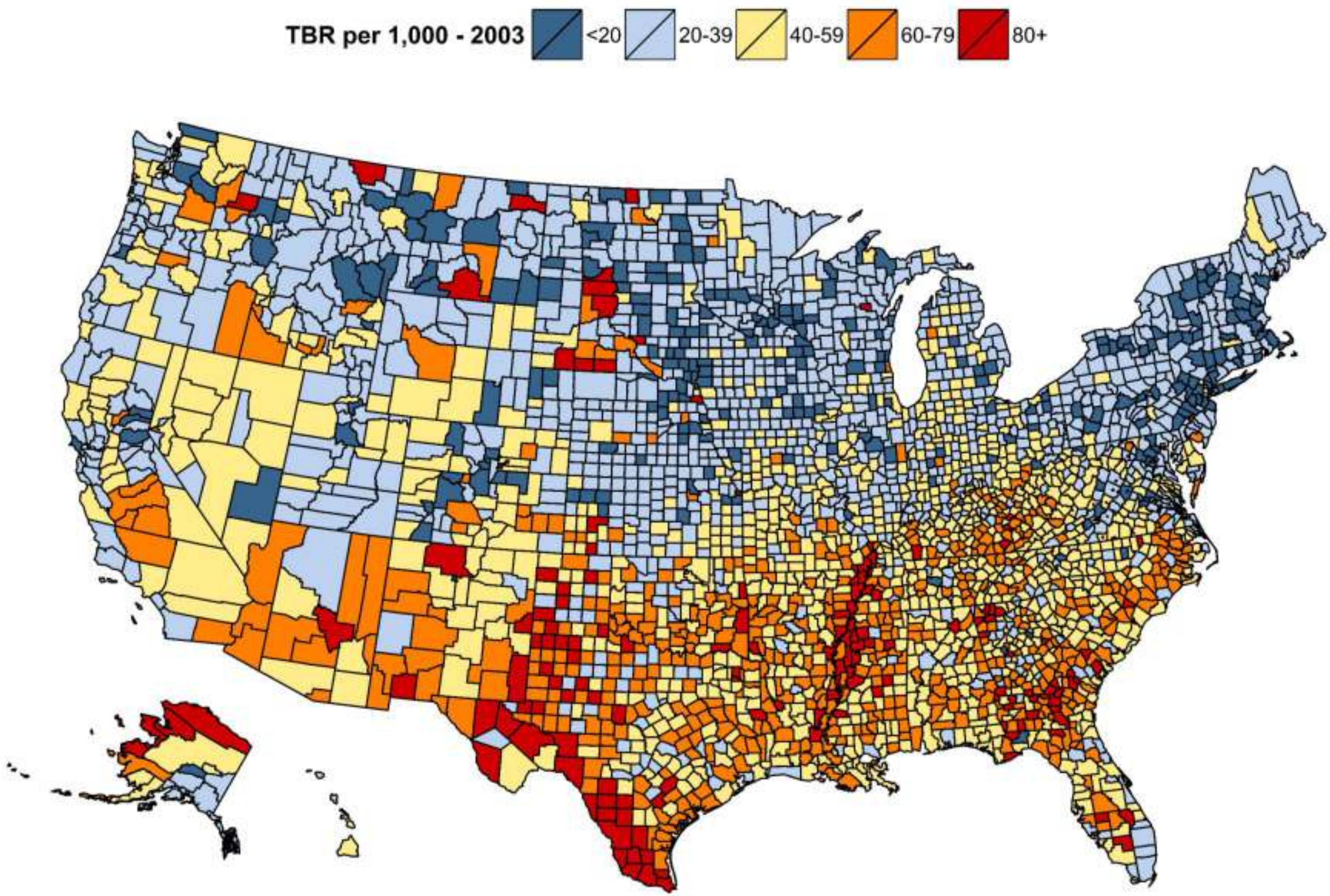
- From 2003-2012, tee- birth rates:
  - decli- ed for ~80% of cou- ties
  - - o cha- ge for ~19% of cou- ties
  - i- creased for < 1% of cou- ties

- Compariso- s to direct estimates at the state level were withi- 2%
  - Differe- ces betwee- model-based a- d direct estimates were larger for sparsely populated states

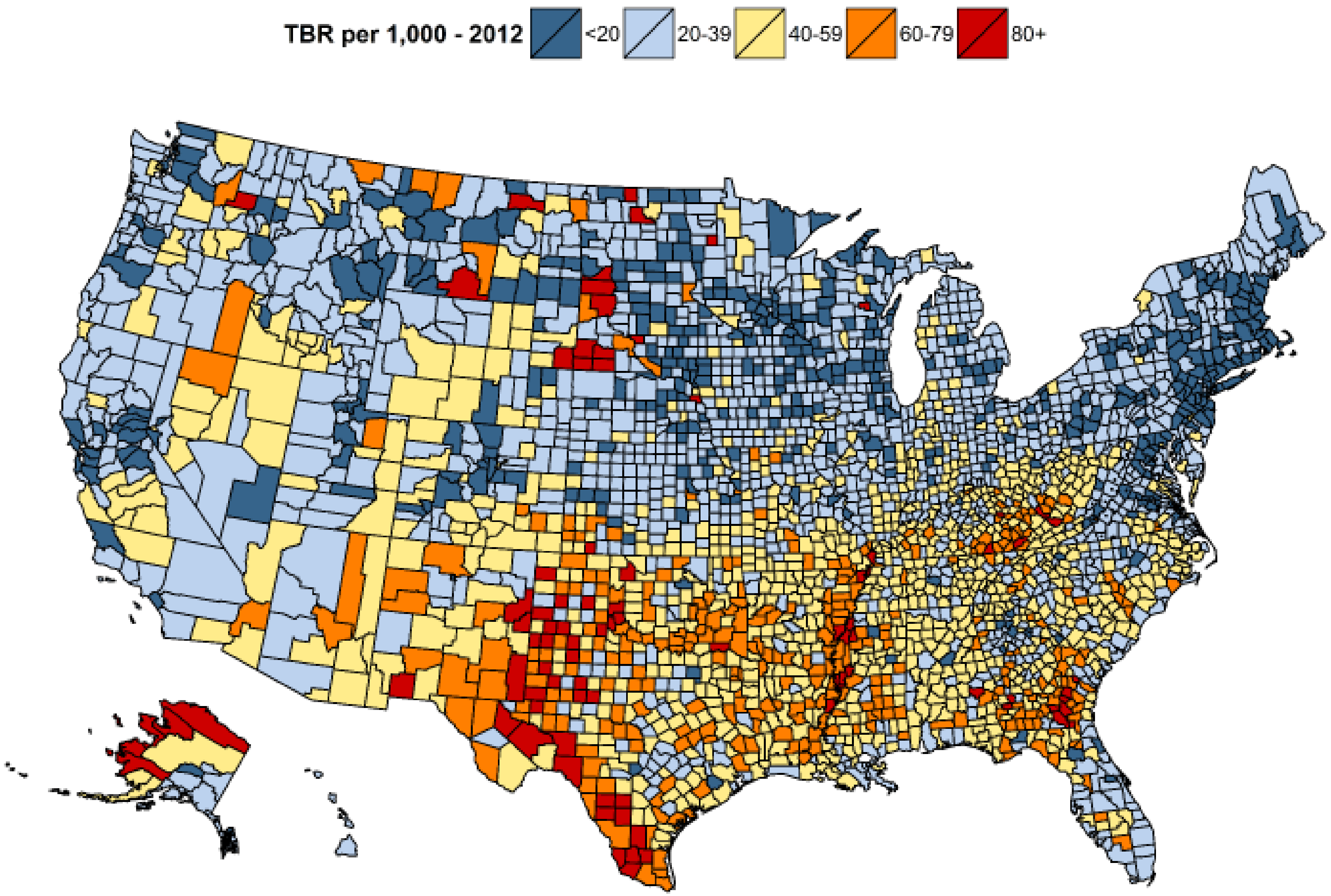
MODEL DIAGNOSTICS (Teen Birth Rates): Comparison to state estimates



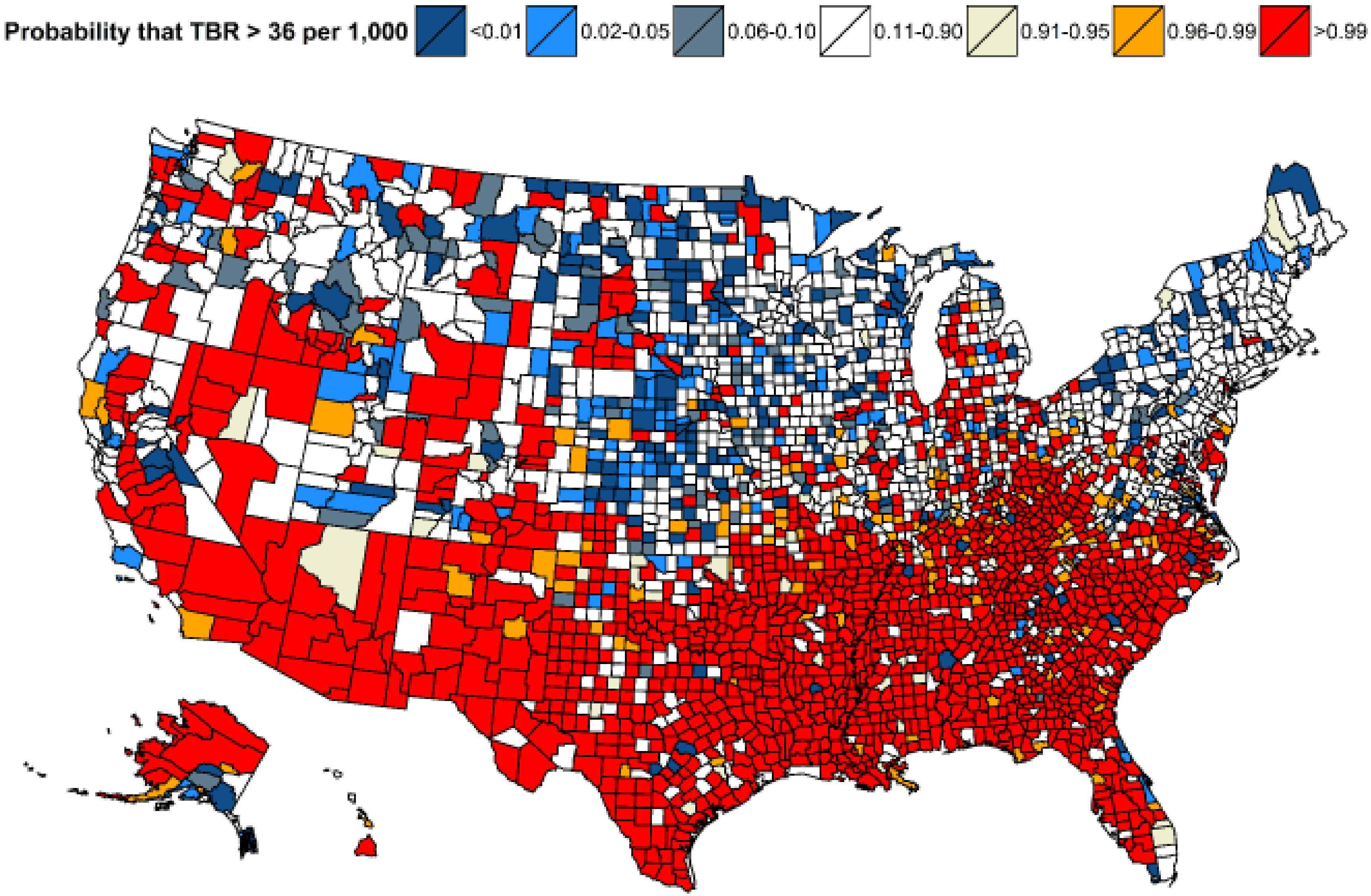
Smoothed teen birth rates (per 1,000) - 2003



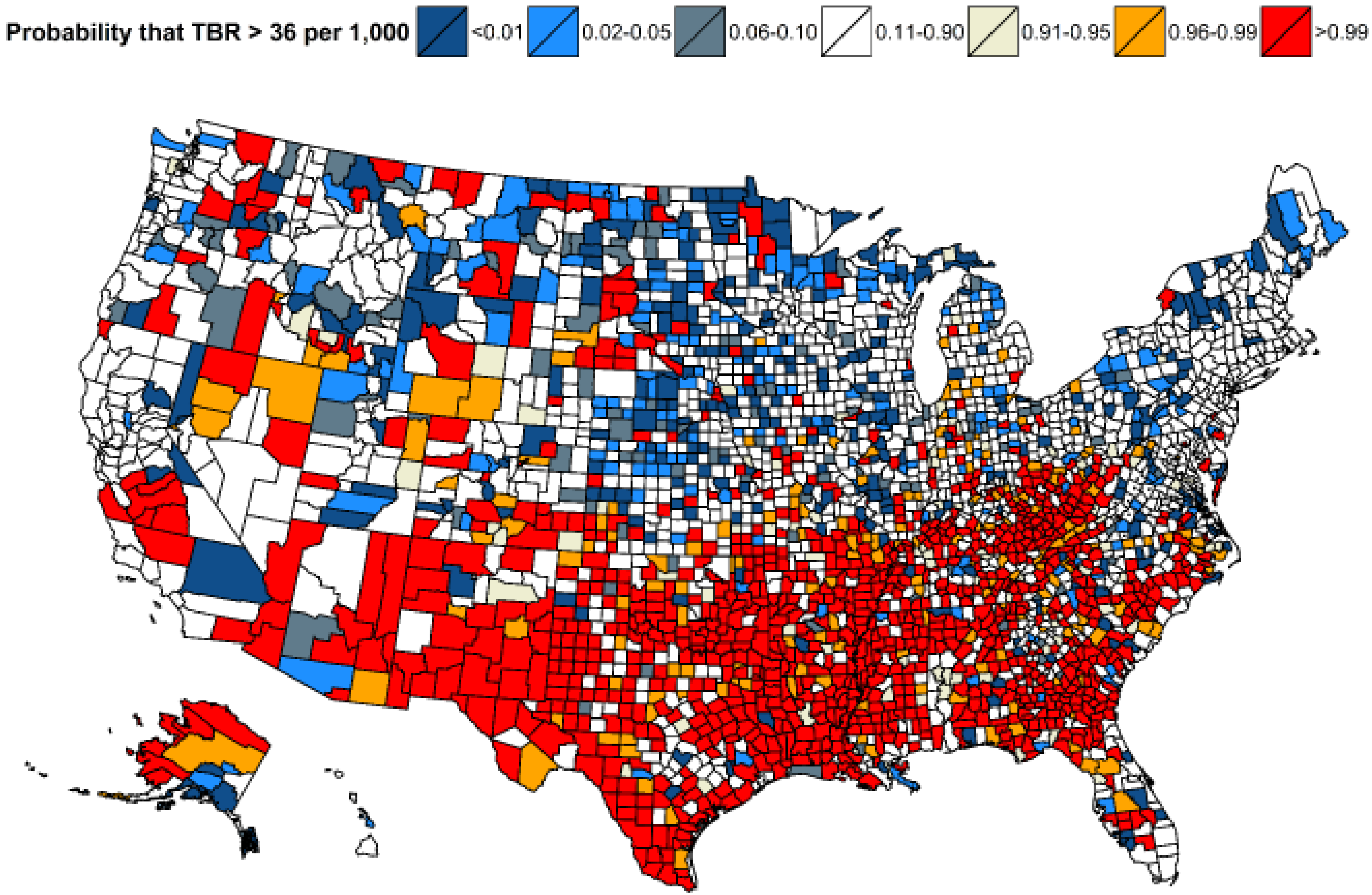
Smoothed teen birth rates (per 1,000) - 2012



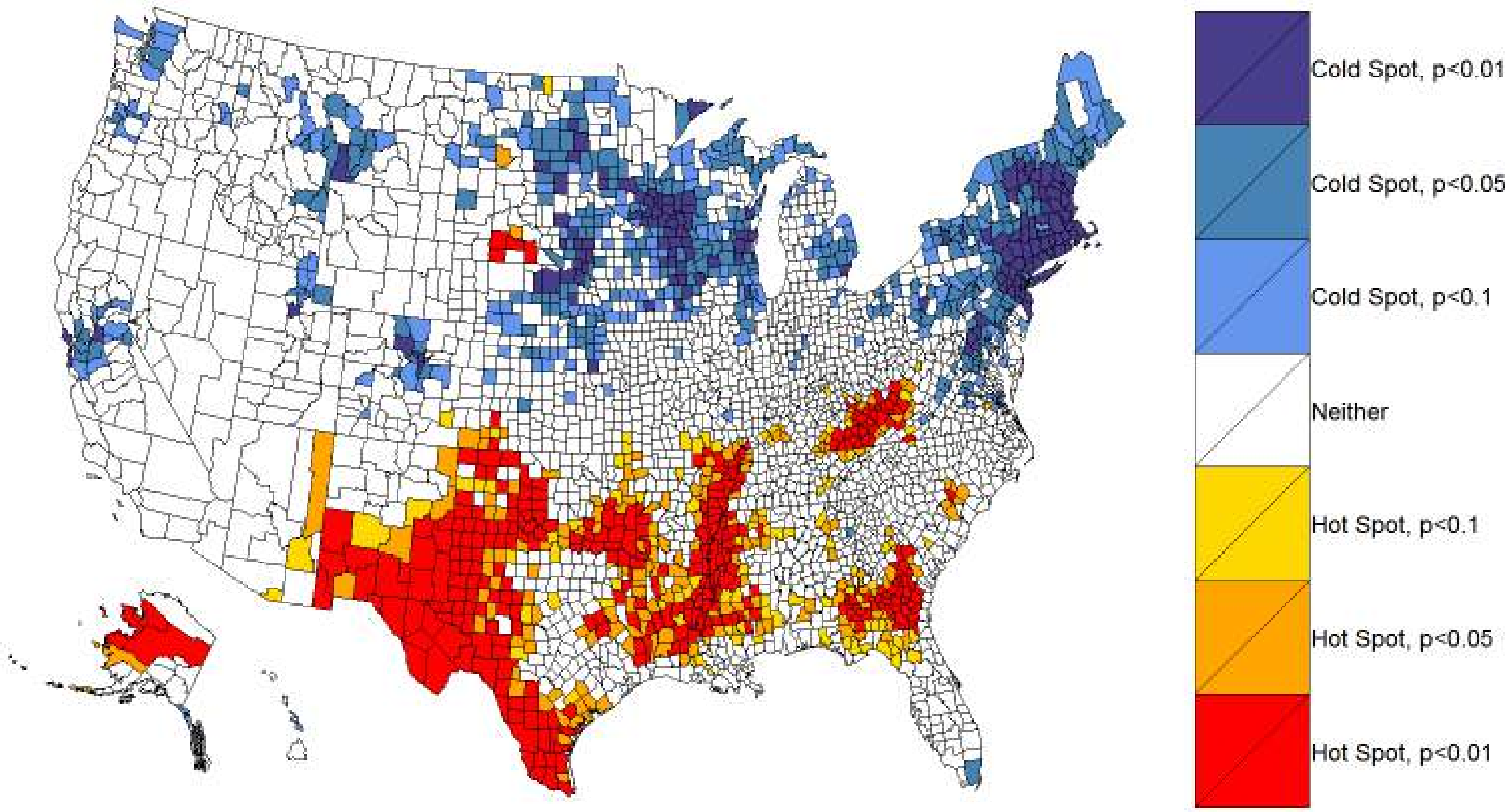
Exceedance Probabilities - 2003



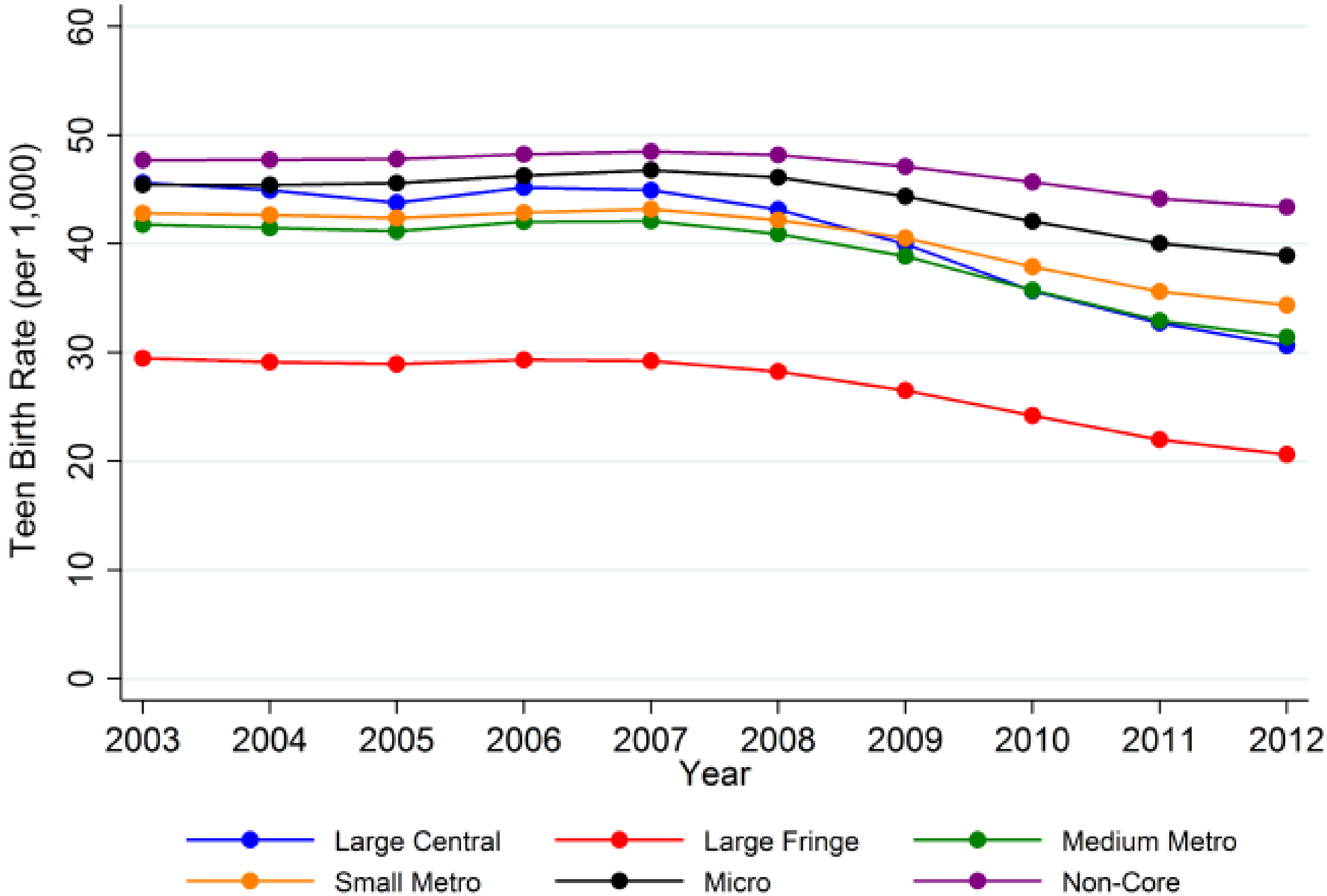
Exceedance Probabilities - 2012



Hot and Cold Spots - 2012



Trends by Urban/Rural Designation, Teen Birth Rates 2003-2012



CONCLUSIONS

- Findings highlight counties where teen birth rates are relatively higher or lower
  - How trends over time vary geographically
- Patterns emerge that we would have missed using state estimates
  - For example, the hot spot along the Mississippi River crosses state boundaries
- Examination of spatiotemporal patterns may inform efforts to further reduce birth rates to adolescents in the U.S.
  - Can look at where teen birth rates are higher than a given ‘target’

SOME CONSIDERATIONS

- Strengths and opportunities:
  - Can see and examine variation across the U.S.
  - Pick up on important patterns that might be masked by state estimates or other groupings (urban/rural)
  - Provide information relevant to public health efforts at the state or local level
  - Shed light on risk/protective factors associated with population health outcomes

SOME CONSIDERATIONS

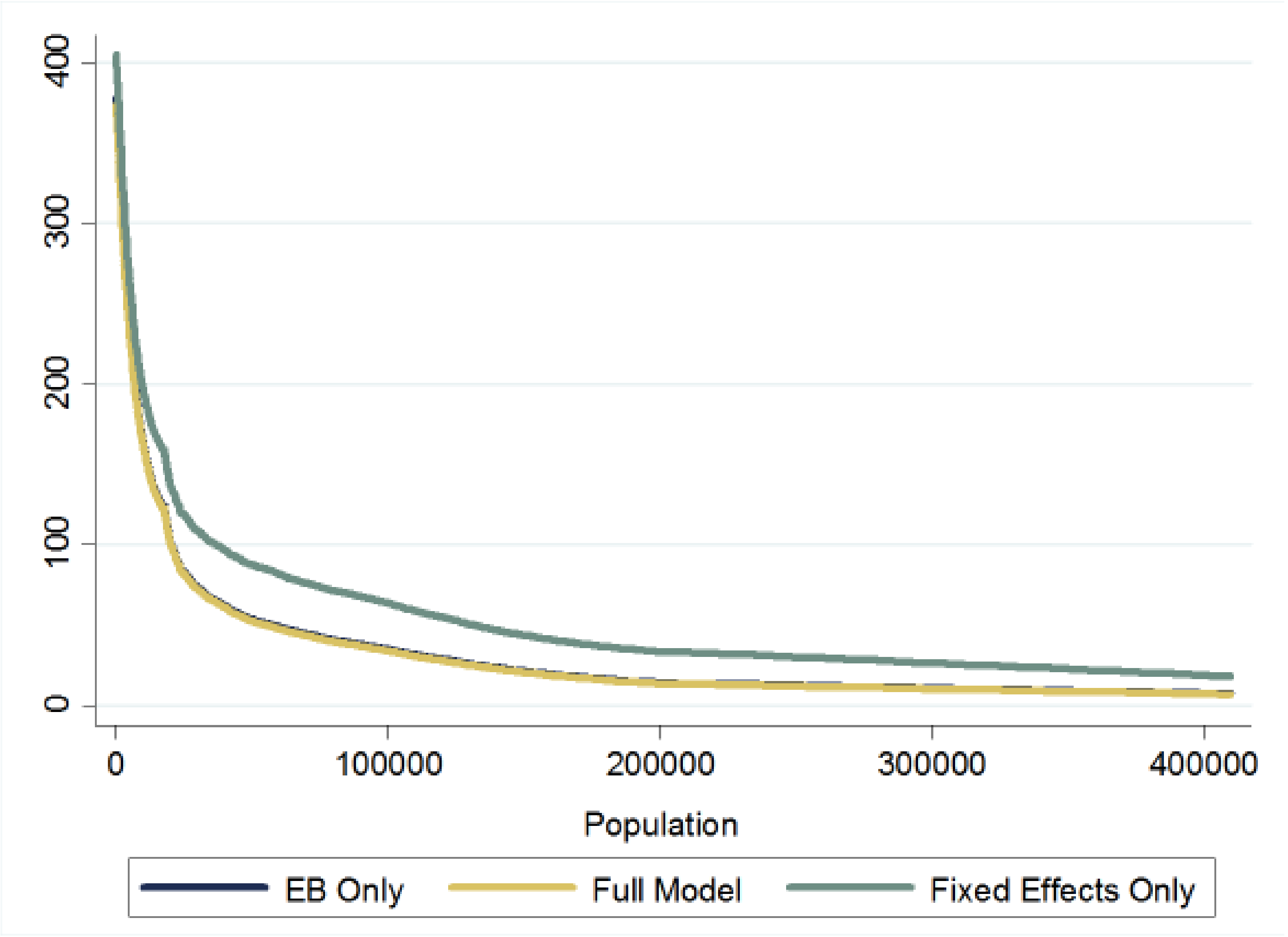
- Limitations and challenges:
  - Model-based estimates might smooth away important effects (either in space or time)
  - Some analyses are <u>VERY</u> computer intensive
    - 6+ weeks running on a 32 GB machine
  - Might not have the level of geography we want
    - Is county the appropriate unit of geography?
  - Data are typically restricted-use
    - Implications for access, confidentiality

QUESTIONS?

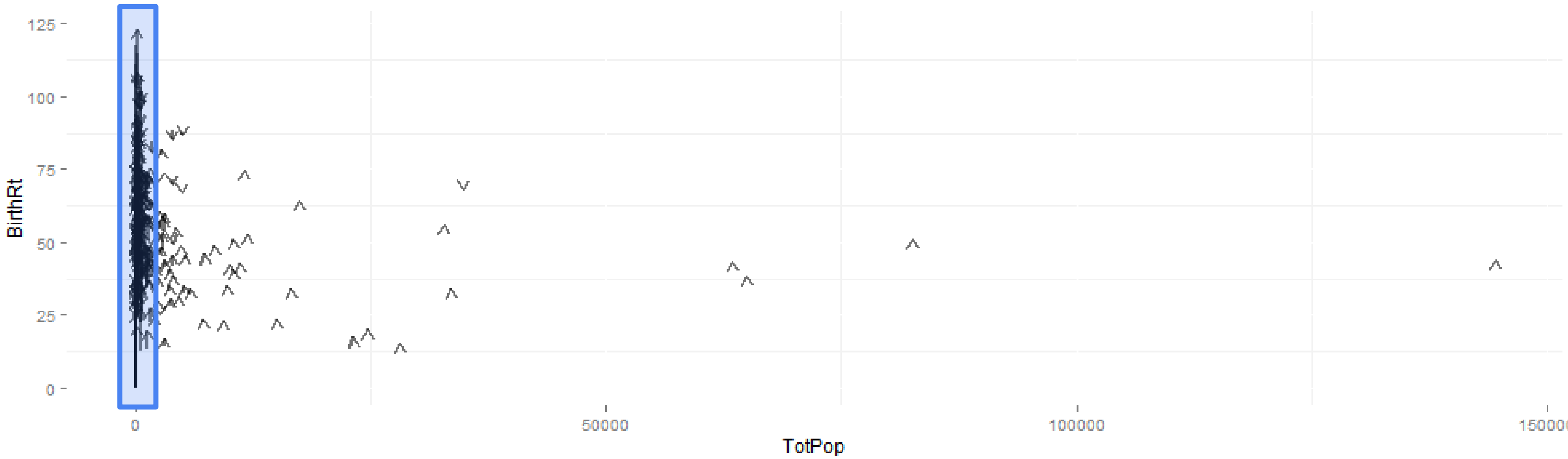
Email: LRosse- @cdc.gov

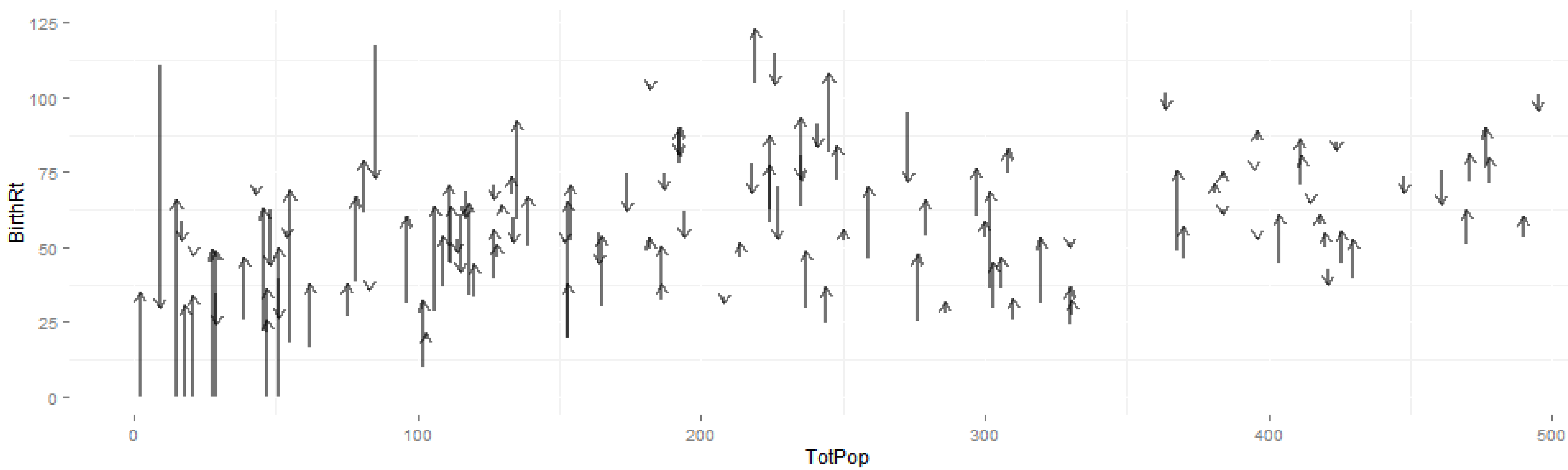
EXTRA SLIDES

MODEL DIAGNOSTICS (Drug Poisoning): $(Y_{obs} - Y_{pred})^2$ vs. Population Size



MODEL DIAGNOSTICS (Teen Birth): Effects of shrinkage





Helpful Refere- ces

NCHS Fact Sheet: Data o- Drug Poiso- i- g Deaths. Ju- e 2015. http://www.cdc.gov/- chs/data/factsheets/factsheet_drug_poiso- i- g.pdf

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