Quantifying Heterogeneity in the Causal Impact of Abortion Restrictions

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2025-04-23

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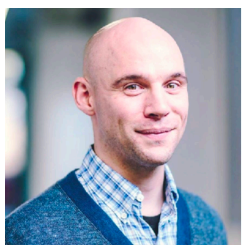

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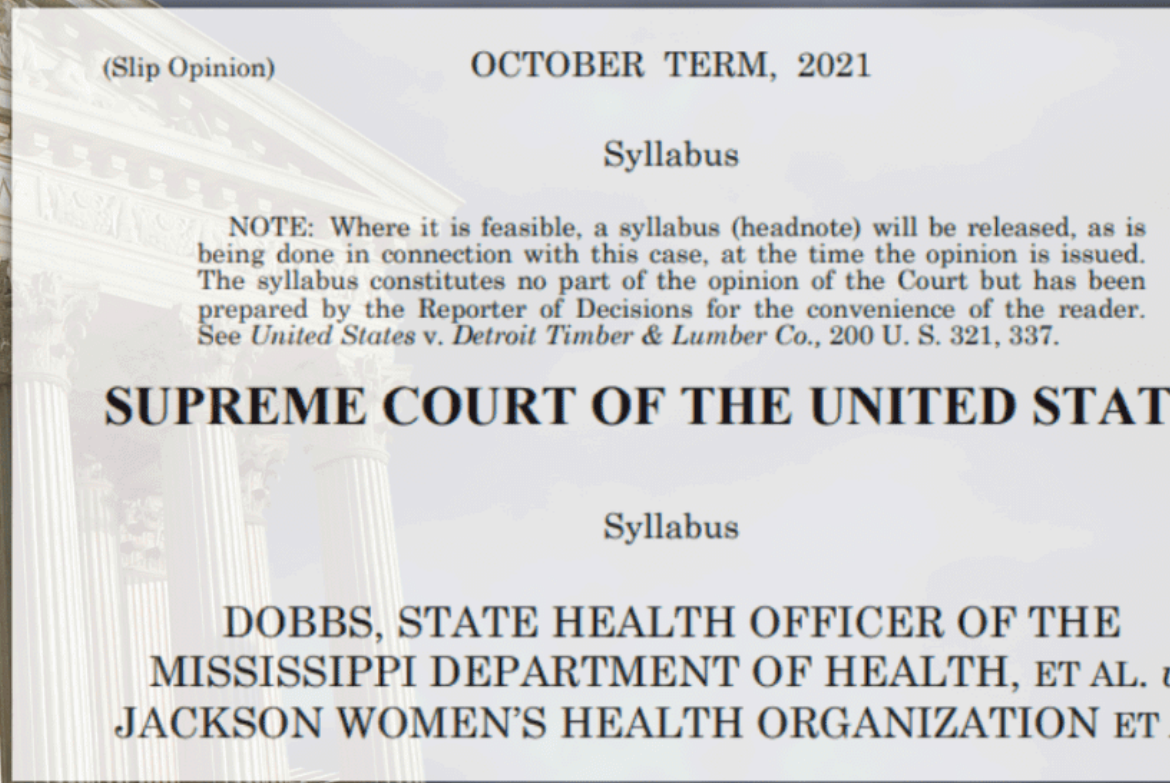
Texas Senate Bill 8
Effectively bans abortion
Sept. 1, 2021

Roe v. Wade overturned June 24, 2022



(Slip Opinion) OCTOBER TERM, 2021

Syllabus

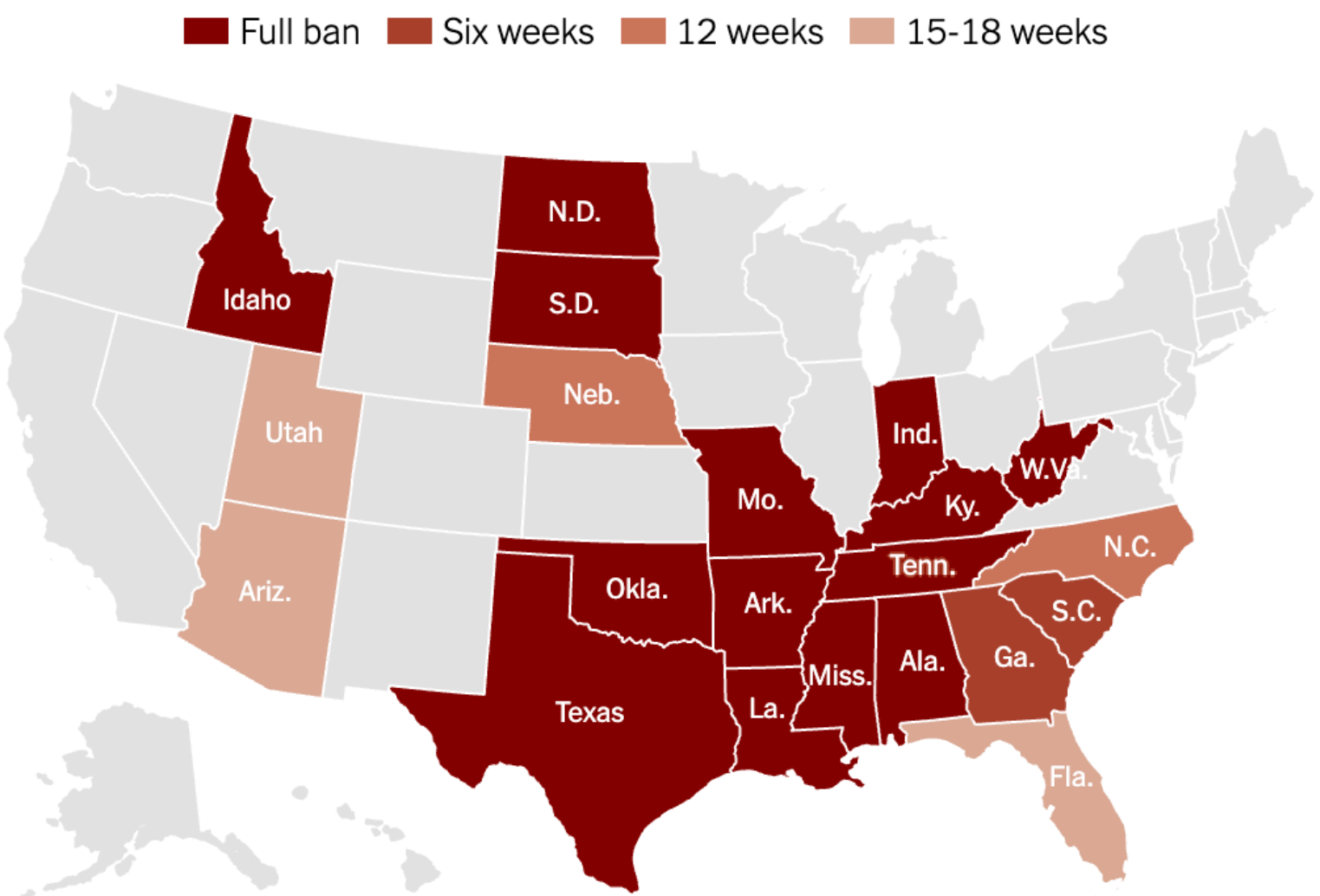
NOTE: Where it is feasible, a syllabus (headnote) will be released, as is being done in connection with this case, at the time the opinion is issued. The syllabus constitutes no part of the opinion of the Court but has been prepared by the Reporter of Decisions for the convenience of the reader. See *United States* v. *Detroit Timber & Lumber Co.*, 200 U. S. 321, 337.

SUPREME COURT OF THE UNITED STAT

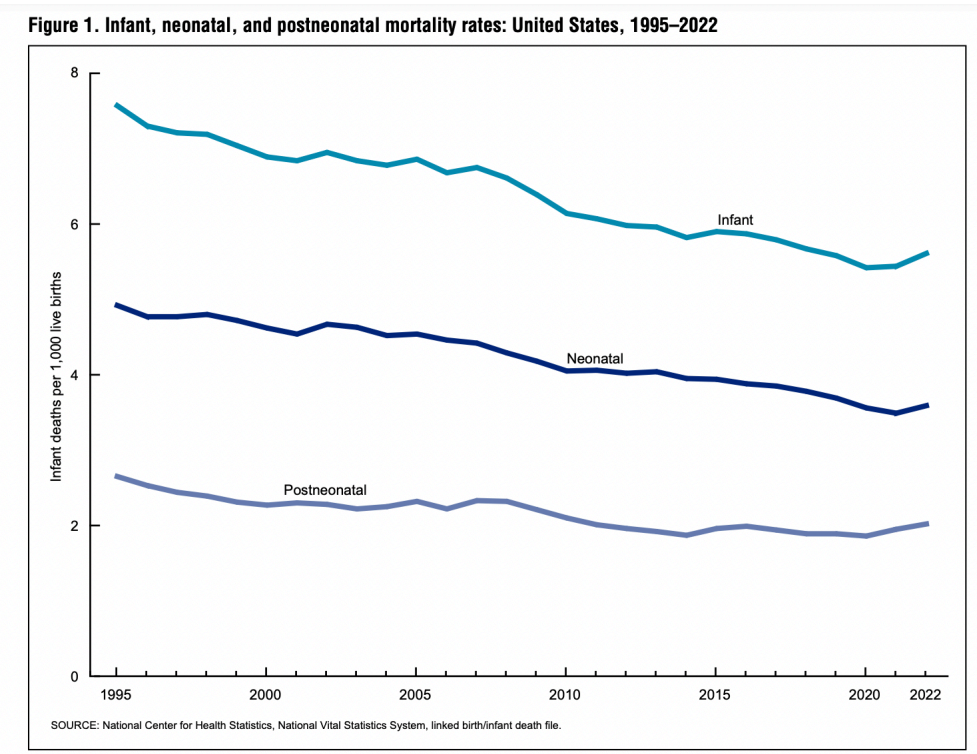
Syllabus

DOBBS, STATE HEALTH OFFICER OF THE MISSISSIPPI DEPARTMENT OF HEALTH, ET AL. v
JACKSON WOMEN'S HEALTH ORGANIZATION ET

Abortion Bans Across the US



US Infant Mortality Rates



	2022 Infant Mortality Rate
Overall	5.6 per 1,000
NH White	4.5
NH Black	10.9
Hispanic	4.9
NH Asian	3.5
NH AI/AN	9.1

Source: Washington Post, August 18, 2022

Early Evidence on Impacts

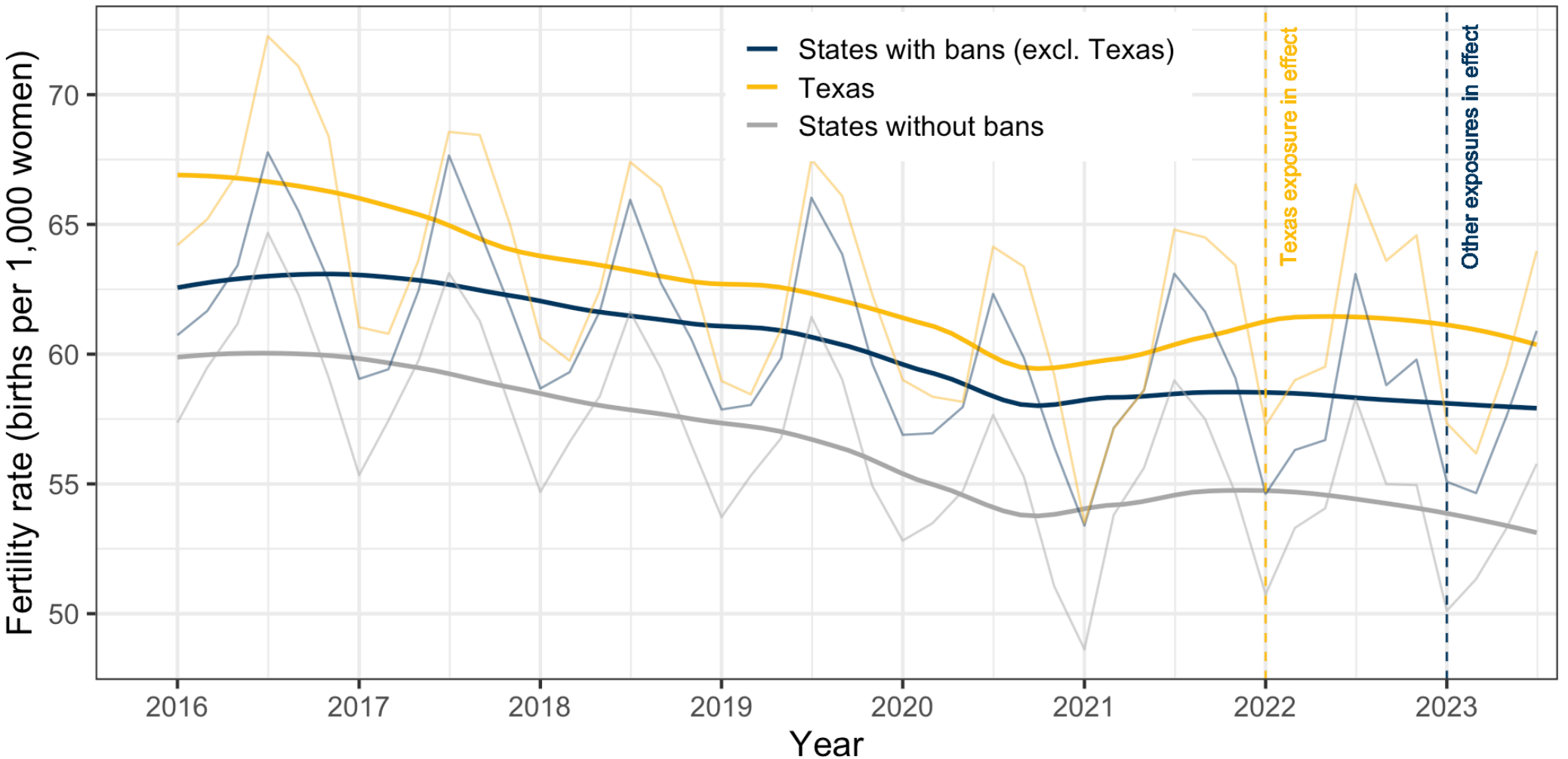
- States with abortion bans experienced an average 2.3% increase in births in first half of 2023 (Dench, Pineda-Torres, and Myers 2024)
- By race/ethnicity: greater impact among non-Hispanic Black and Hispanic individuals (Dench, Pineda-Torres, and Myers 2024; Caraher 2024) and greater impact among 20-24-year-olds (Dench, Pineda-Torres, and Myers 2024)
- ~13% increase in infant deaths; 8% increase in the infant mortality rate (Gemmill et al. 2024)

Study Objectives

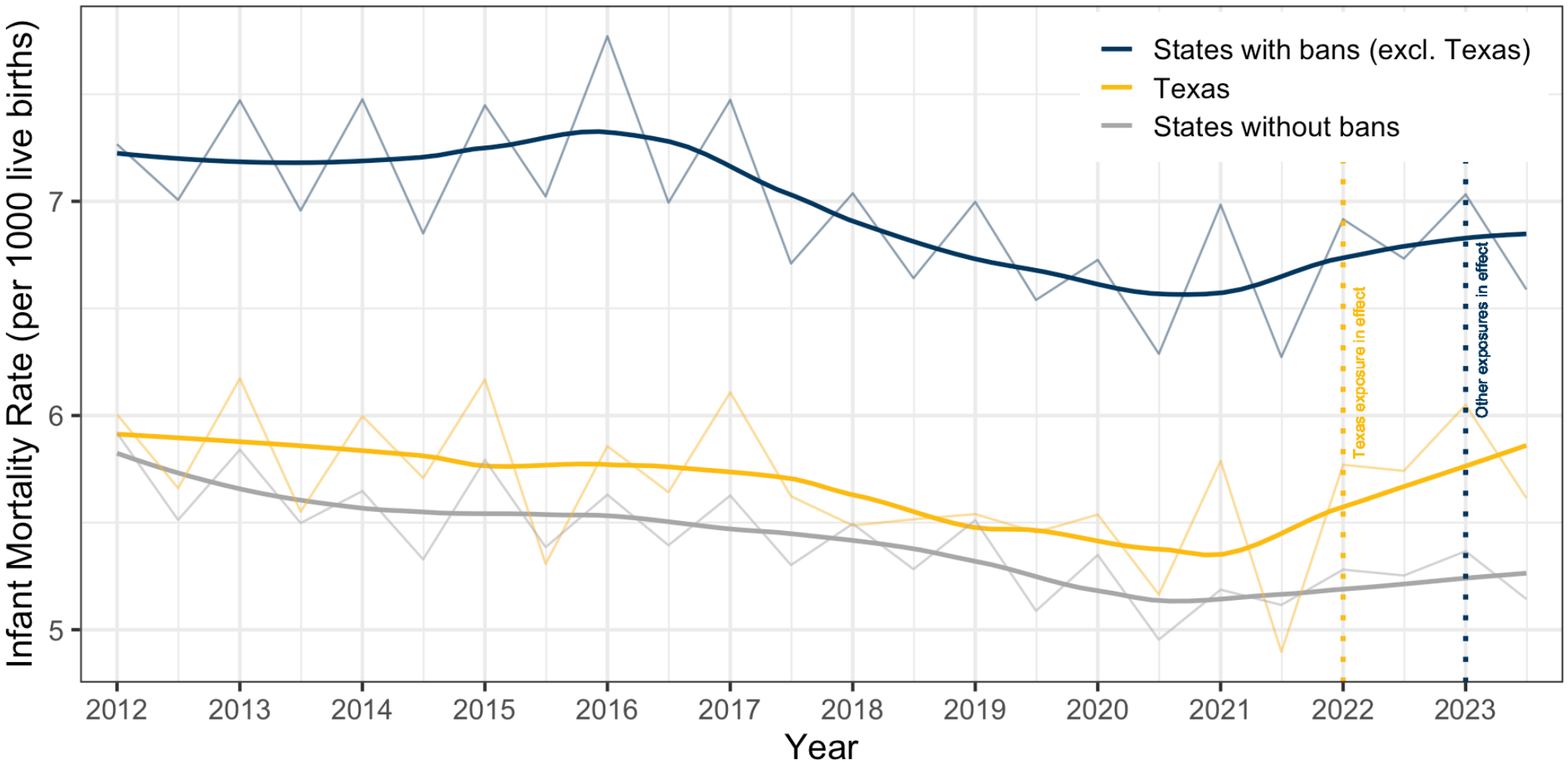
- To estimate sociodemographic variation in the impact of abortion bans on subnational **birth rates** in the US through the end of 2023
  - By age, race/ethnicity, marital status, educational attainment, insurance type

- To estimate variation in the impact of abortion bans on subnational **infant mortality** in the US through the end of 2023
  - By race/ethnicity, timing of death, cause of death

Fertility Trends



Infant Mortality Trends



Overall Analytic Approach

- Today: focus methods discussion on infant mortality data
- Models for the fertility data are very similar
- Bayesian panel data approach

- Poisson latent factor model
  - Fertility: model bimonthly number of births with population offset
  - Infant mortality: model biannual number of deaths with live birth offset
- Model state-by-subgroup-specific impacts separately by characteristic
- States without bans and pre-exposure outcomes in all states inform counterfactual

Infant Mortality Approach

- Outcome: infant mortality rate (deaths per 1,000 live births)
- Exposure: 6-week or complete abortion ban (14 states[1]), staggered adoption
- Pre-policy period: January 2012 through ~December 2022
- Treated period: ~January 2023 through December 2023

- Subgroups
  - Race/ethnicity: non-Hispanic White, non-Hispanic Black, Hispanic, and Other
  - Timing: neonatal (<28 days), non-neonatal
  - Cause of death: congenital, non-congenital

Panel Data

- Panel with n states and T time periods
- Potential outcomes $Y_{it}(0), Y_{it}(1)$ and a binary exposure indicator $W_{it} \in \{0, 1\}$
- We observe for each unit the pair Y_i, W_i where

$$Y_{it} \equiv Y_{it}(W_{it}) = \begin{cases} Y_{it}(0) & \text{if } W_{it} = 0 \\ Y_{it}(1) & \text{if } W_{it} = 1 \end{cases}$$

Causal Inference for Panel Data

Assumptions:

- Well-defined exposure: {any complete or 6-week abortion ban} vs {no ban}
- No anticipation: no effect of abortion restrictions prior to exposure
- No spillovers across states: outcomes only depend on own state's policy

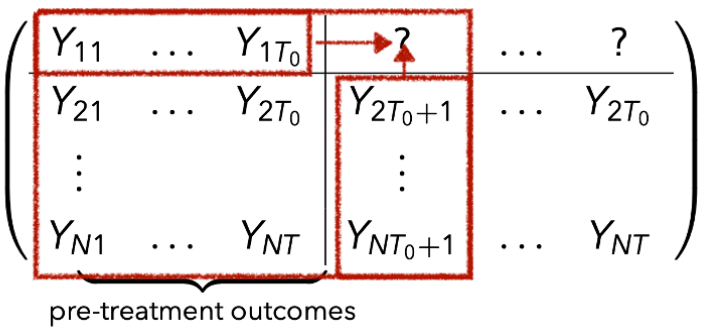
$$\mathbf{Y}(\mathbf{0}) = \left(\begin{array}{ccc|ccc} Y_{11} & \cdots & Y_{1T_0} & Y_{1T_0+1} & \cdots & Y_{1T} \\ \vdots & & \vdots & \vdots & & \vdots \\ Y_{(N-1)1} & \cdots & Y_{(N-1)T_0} & Y_{(N-1)T_0+1} & \cdots & Y_{(N-1)T} \\ \hline Y_{N1} & \cdots & Y_{NT_0} & ? & \cdots & ? \end{array}\right) \equiv \left(\begin{array}{cc} \mathbf{Y}^{\text{obs}} & \\ & \boxed{\mathbf{Y}^{\text{mis}}} \end{array}\right)$$

$\underbrace{\qquad\qquad}_{\text{pre-treatment outcomes}}$

Causal Inference for Panel Data

Some common strategies:

- Interrupted Time Series (horizontal)
- Synthetic Control Methods and Factor Models (vertical)
- Differences in Differences(DID) and Two-Way-Fixed-Effects (TWFE)



Challenges with Infant Death Data

- Infant death counts are small and discrete
- Missing data: CDC Wonder excludes counts between 1 and 9
  - Implications for level of temporal aggregation
- States and subgroups vary in size and mortality rates
- Staggered Adoptions
  - Bans were imposed at different times

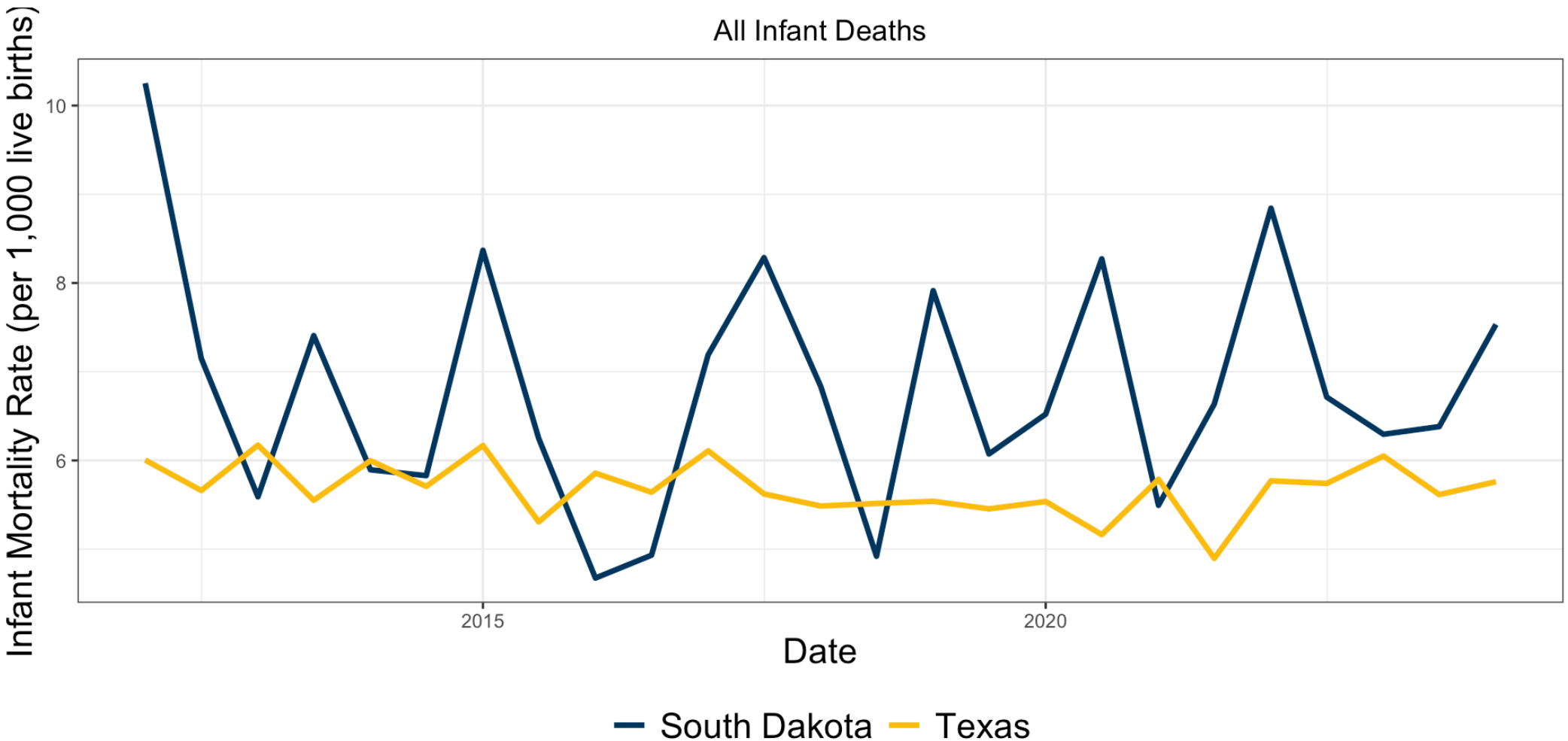
Temporal Aggregation

- Missingness → CDC Wonder suppresses counts 1, …, 9 (but not 0!)
  - e.g., annual → no missingness; daily → high missingness
  - Later: imputation approach
- Noise → noise for (avg) annual counts ≪ (avg) monthly counts (see Sun, Ben-Michael, and Feller 2024)
  - Further complicated by seasonality
- Fertility → 2 month intervals (e.g., Jan-Feb 2023)
- Mortality → 6 month intervals (e.g., Jan-June 2023)

Subgroup Inference

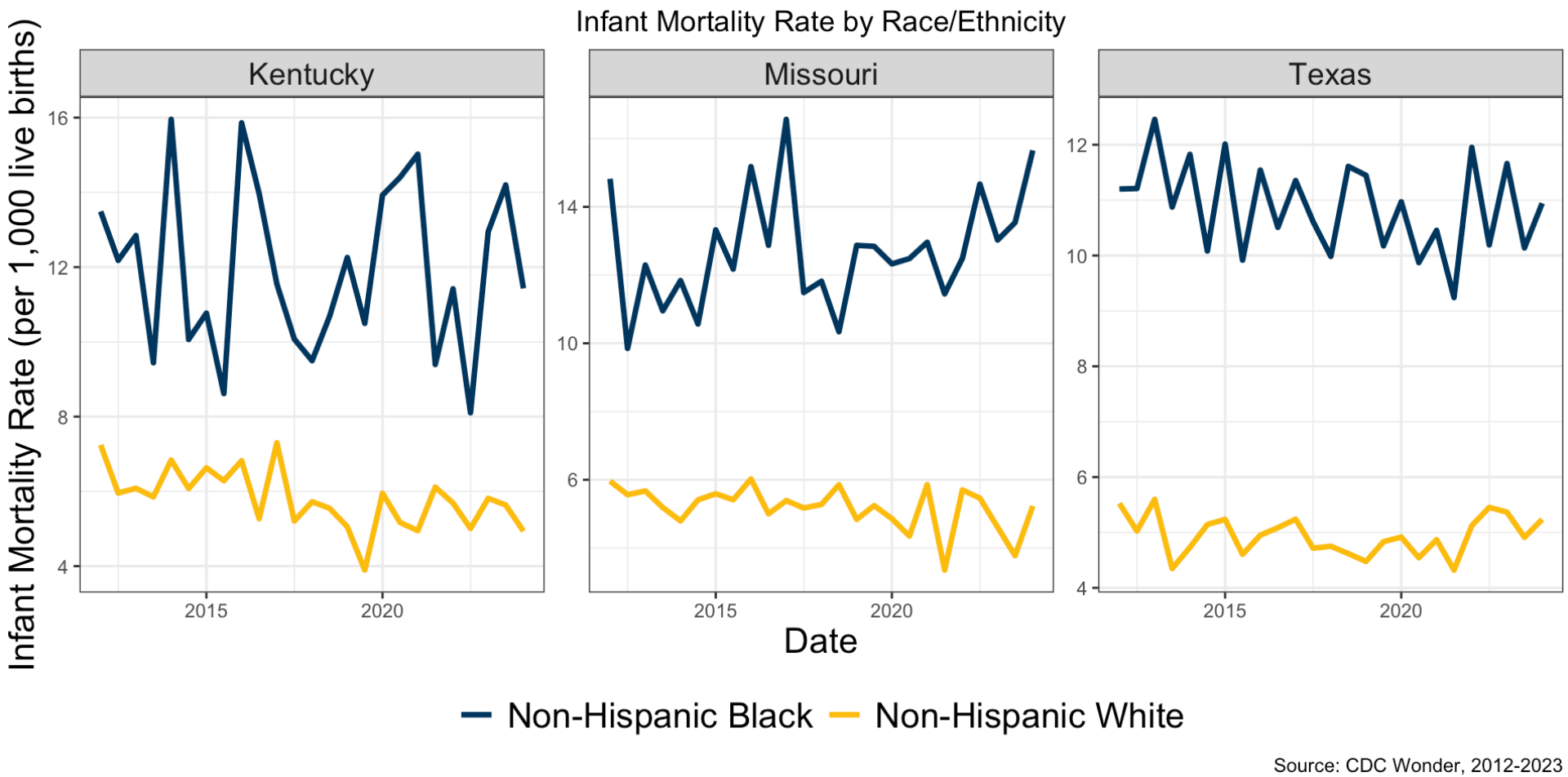
- Summing infant deaths over subroups yields total infant deaths
- Inferred total infant mortality rates by differ depending on which subgroups are considered
- Better to estimate the total effect by estimating the subgroup effects and summing or modeling the total effect directly?

State Size and Sampling Variance



Source: CDC Wonder, 2012-2023

Subgroup Size and Variability



Source: CDC Wonder, 2012-2023

In these states population white ≈ 5-15x population black

Implications

- Pre-treatment balance should depend on state and subgroup size
- Avoid overfitting to noise when groups are small
- The difference between realized and counterfactual infant deaths, $Y_{it}(1) - Y_{it}(0)$, will be more variable for smaller states and subgroups
- Suggests a need to regularize causal effect estimates
- Want to encourage estimated infant mortality rates to be similar for the same state or same subgroup, while still allowing for the possibility of differences

A Probabilistic Bayesian Model

- Explicitly incorporate a missing data model
- Staggered adoption accounted for in the likelihood
- Count data modeled via Poisson with offset based on state/group size
- Hierarchical prior stabilize treatment effect estimates and partially pool effects by state and category
- Uncertainty quantification for “free”

Panel Model for Infant Deaths

$$Y_{ijt}(1) \sim \text{Poisson}(\tau_{ijt} \cdot \rho_{ijt} \cdot B_{ijt})$$
$$Y_{ijt}(0) \sim \text{Poisson}(\rho_{ijt} \cdot B_{ijt})$$

for unit i, subgroup j, time t

- B_{ijt} is births (in thousands)
  - Scales mortality rate to account for variability in state size
- ρ_{ijt} is the infant mortality rate **without** bans
- $\tau_{ijt}\rho_{ijt}$ is the infant mortality rate **with** bans
- τ_{ijt} is the multiplicate change in infant mortality rate due to bans

Poisson Latent Factor Model

We assume the infant mortality rate in the “no ban” condition can be expressed as

$$\rho_{ijt} = \alpha_{ij}^{\text{state}} \cdot \alpha_{jt}^{\text{time}} \cdot \left(\sum_{k=1}^{K} \lambda_{ijk} \eta_{jkt} \right),$$

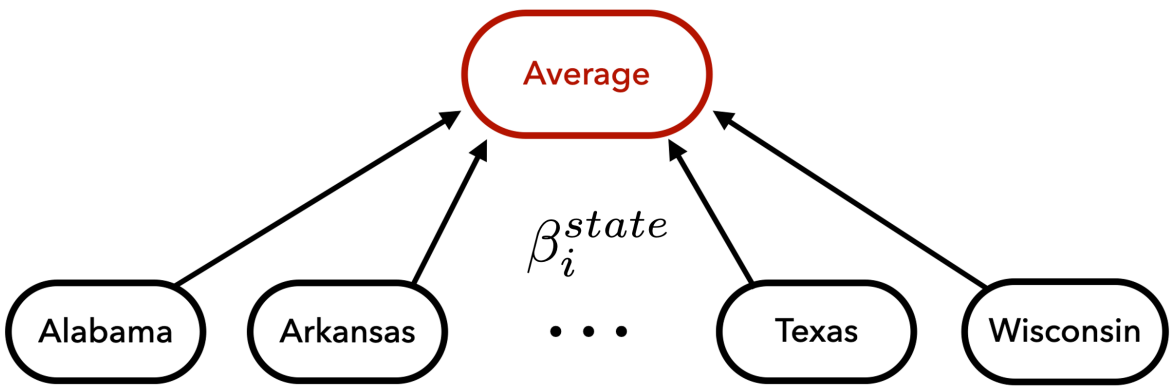
- $\alpha_{ij}^{\text{state}}$ and $\alpha_{jt}^{\text{time}}$ are state and time-specific intercept
- $\eta_{jkt} \in \mathbb{R}^{+}$ is the kth latent factor at time t, common to all states but unique to subcategory j
- $\lambda_{ij.} \sim \text{Dirichlet}$ are the factor loadings for state i and category j
- Model selection problem: choosing K (rank)

Hierarchical Prior on Causal Effects

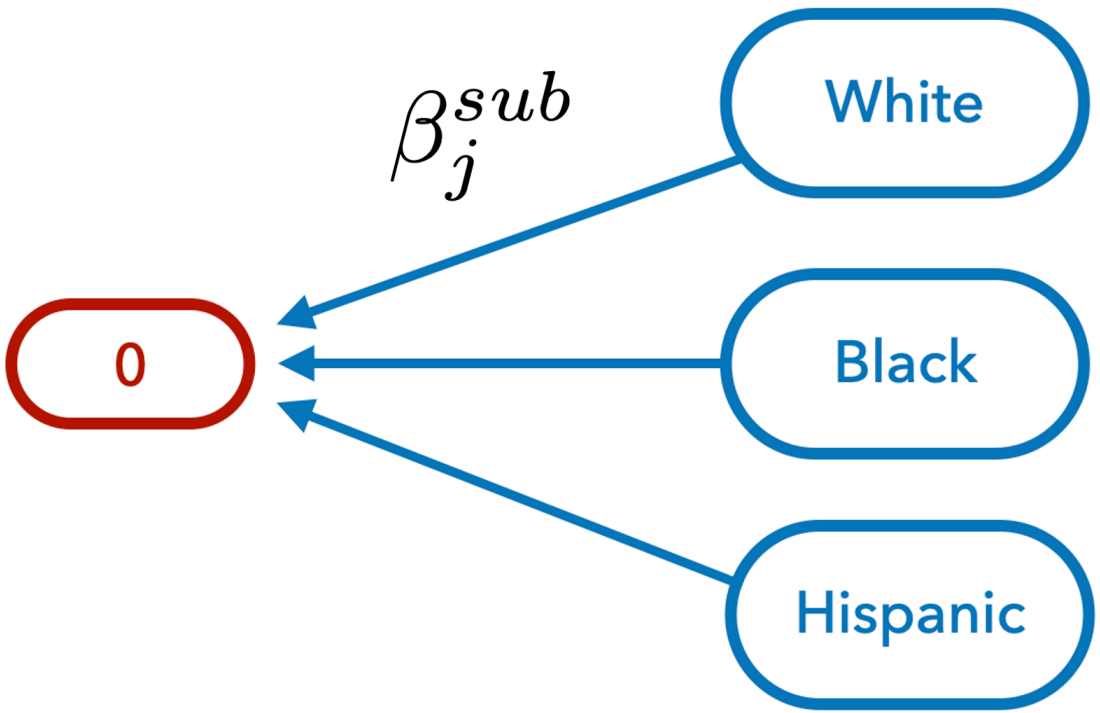
Partially pool the exposure parameters τ_{ijt} across states and across subcategories, with state and subcategory prior distributions centered at zero:

$$
\begin{aligned}
\log(\tau_{ijt}) &\sim N\left(\beta_{ij}^{\text{state,sub}}, \sigma_\tau\right) \\
\beta_{ij}^{\text{state,sub}} &\sim N\left(\beta_i^{\text{state}} + \beta_j^{\text{sub}}, \sigma_\beta\right) \\
\beta_i^{\text{state}} &\sim N\left(0, \sigma_{\text{state}}\right) \\
\beta_j^{\text{sub}} &\sim N\left(0, \sigma_{\text{sub}}\right)
\end{aligned}
$$

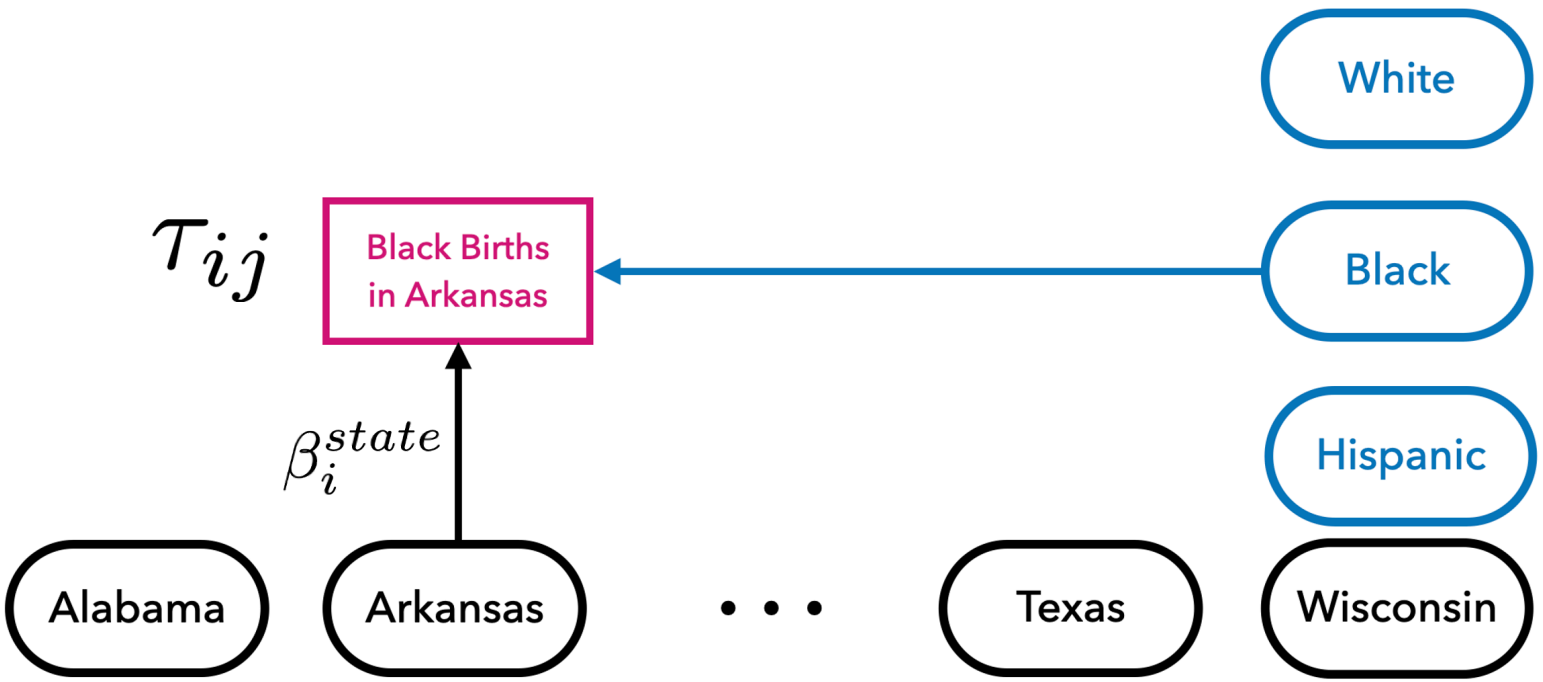
Shrinkage Across States



Shrinkage Across Subcategories



Variation Across Multiple Sources



MCMC Inference

- Model implemented in probabilistic programming library, numpyro
- MCMC inference with Hamiltonian Monte Carlo
- Run multiple chains, check Rhats and effective sample sizes

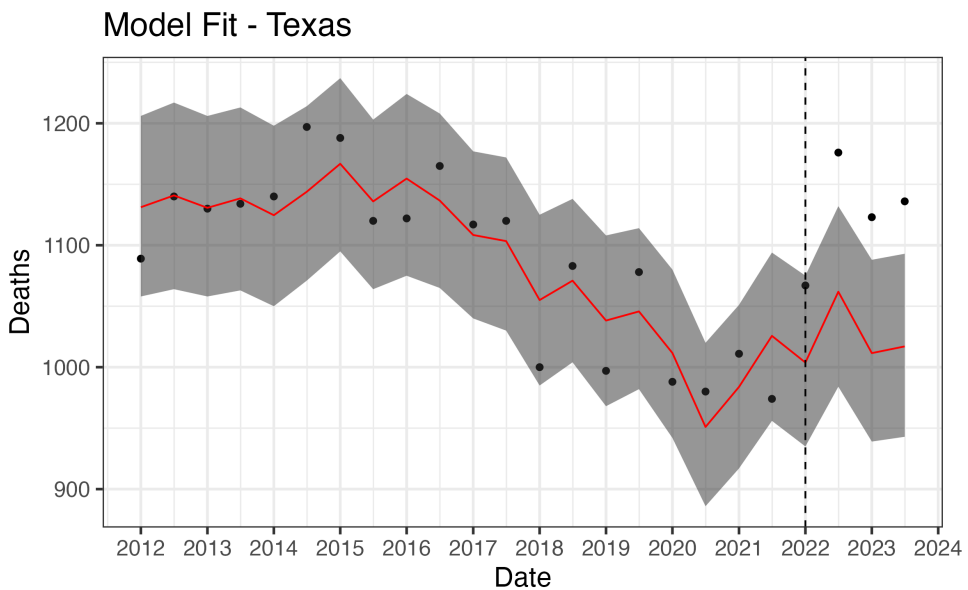
MCMC Inference

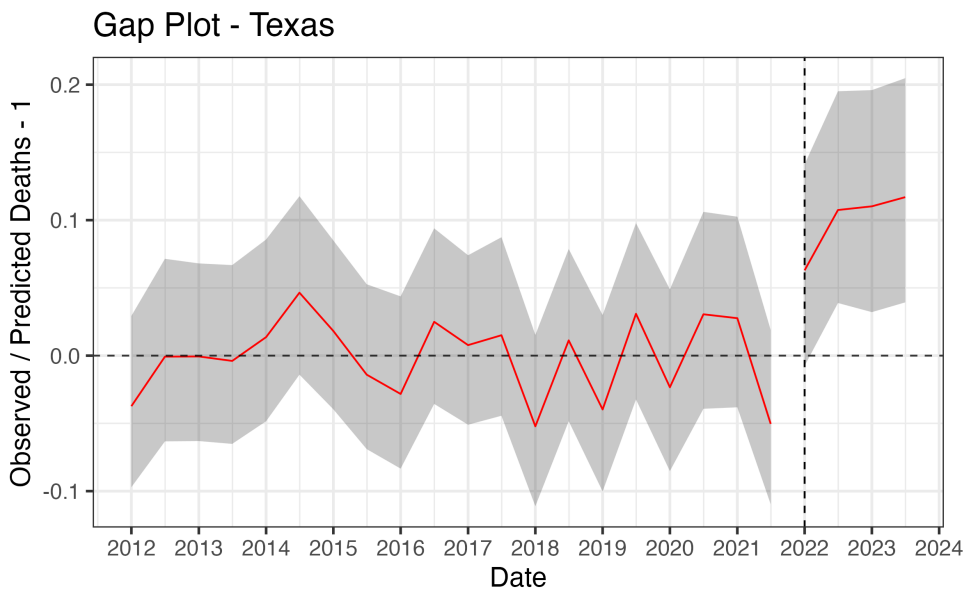
- Fit models for each category
  - Mortality: Total, race/ethnicity, timing of death and type of death
  - Fertility: Total, age, race/ethnicity, education, insurance
- For each, fit models for multiple latent ranks and check fit
- Code available at:
  - github.com/afranks86/dobbs_fertility
  - github.com/afranks86/dobbs_infant_mortality

Model Selection and Checking

- In-sample checks:
  - Question: how well does the model fit the observed data
  - Tool: gap plots and posterior predictive comparisons
  - Used to select latent factor rank
- Out-of-sample checks
  - Question: how well can we forecast
  - Tool: placebo-in-time checks

Results - Texas





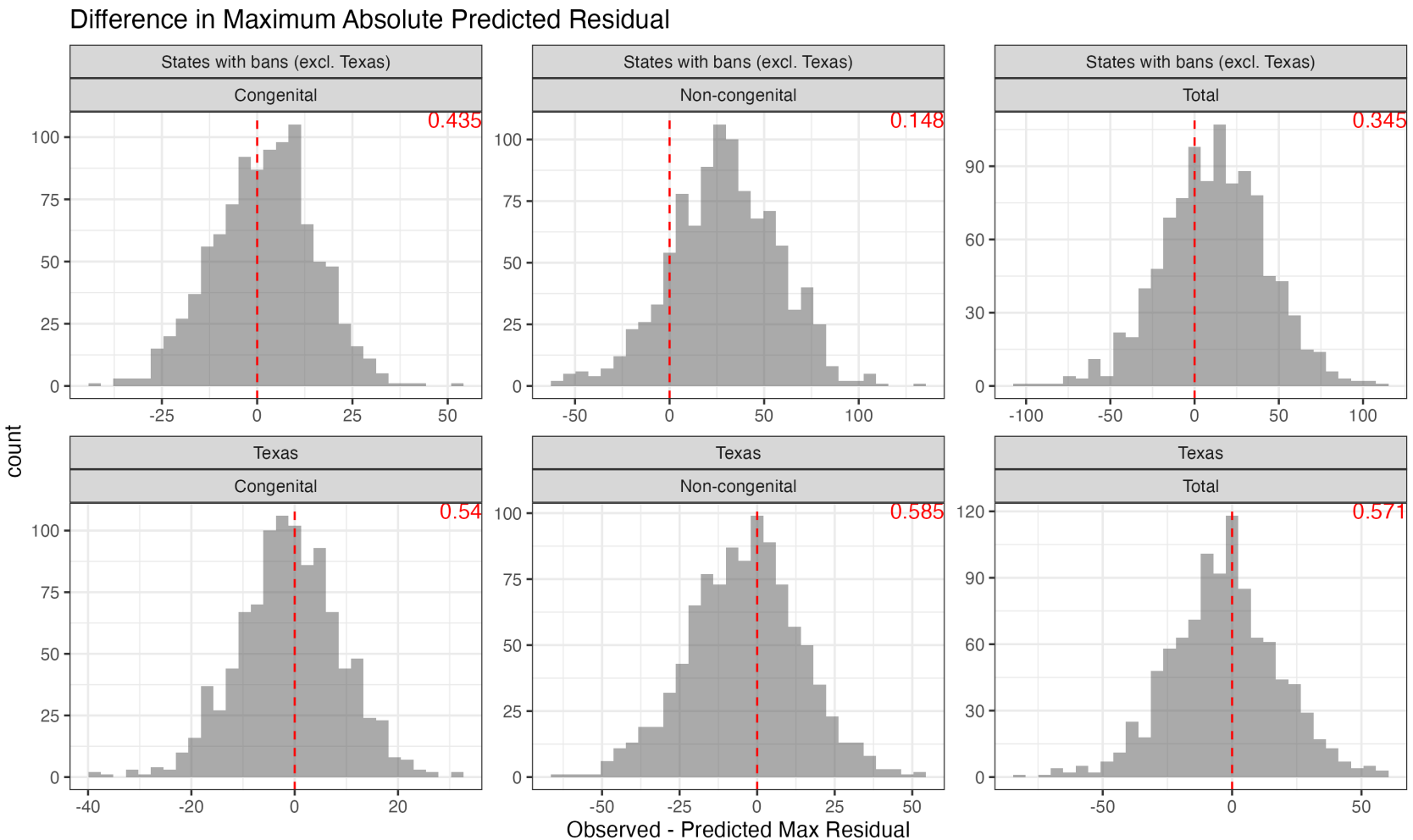
Posterior Predictive Checks

- Posterior predictive checks are used to assess how well a Bayesian model fits observed data
- Unlike classical hypothesis testing, posterior predictive checks focus on practical significance of model inadequacies
- $\mathbb{P}(T^{\text{pred}} > T^{\text{obs}} \mid Y) = \int \mathbb{P}(T^{\text{pred}} > T^{\text{obs}} \mid Y, \theta)\mathbb{P}(\theta \mid Y)d\theta$ should be far from 0 and 1.

Posterior Predictive Checks

- Maximum absolute residual: identify outliers inconsistent with the model: $T_{ij} = \tau_{ij} = \max_t |r_{ijy}|$
- Residual autocorrelation: check for remaining autocorrelation after controlling latent factors (and seasonal trends)
  - Test statistic based on residual autocorrelation at different lags
  - $T_{ij} = cor(r_{ijt}, r_{i,j,t+l})$

PPC: Max Residual



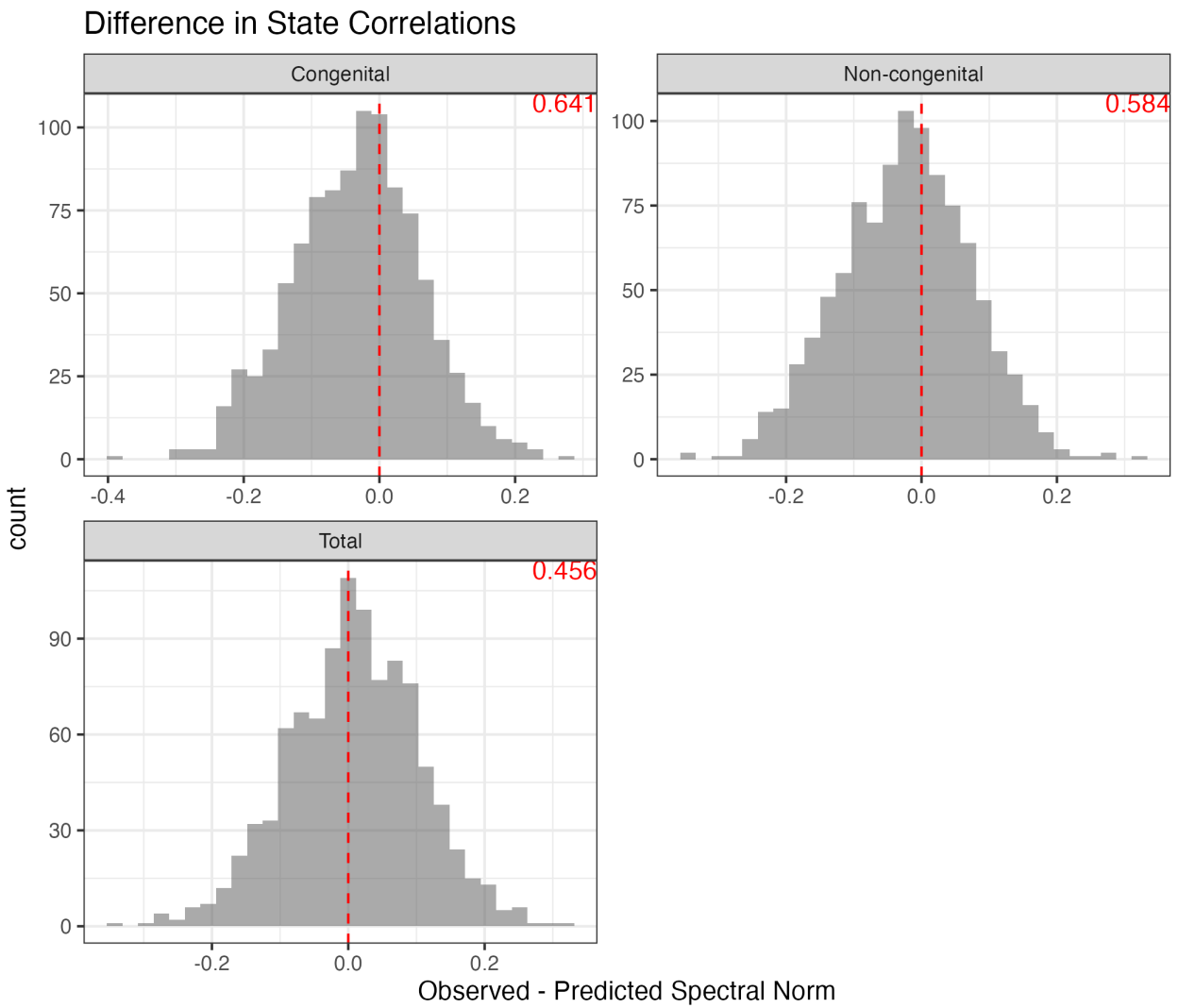
Posterior Predictive Checks

Across-unit correlation: states should be uncorrelated after controlling for latent factors:

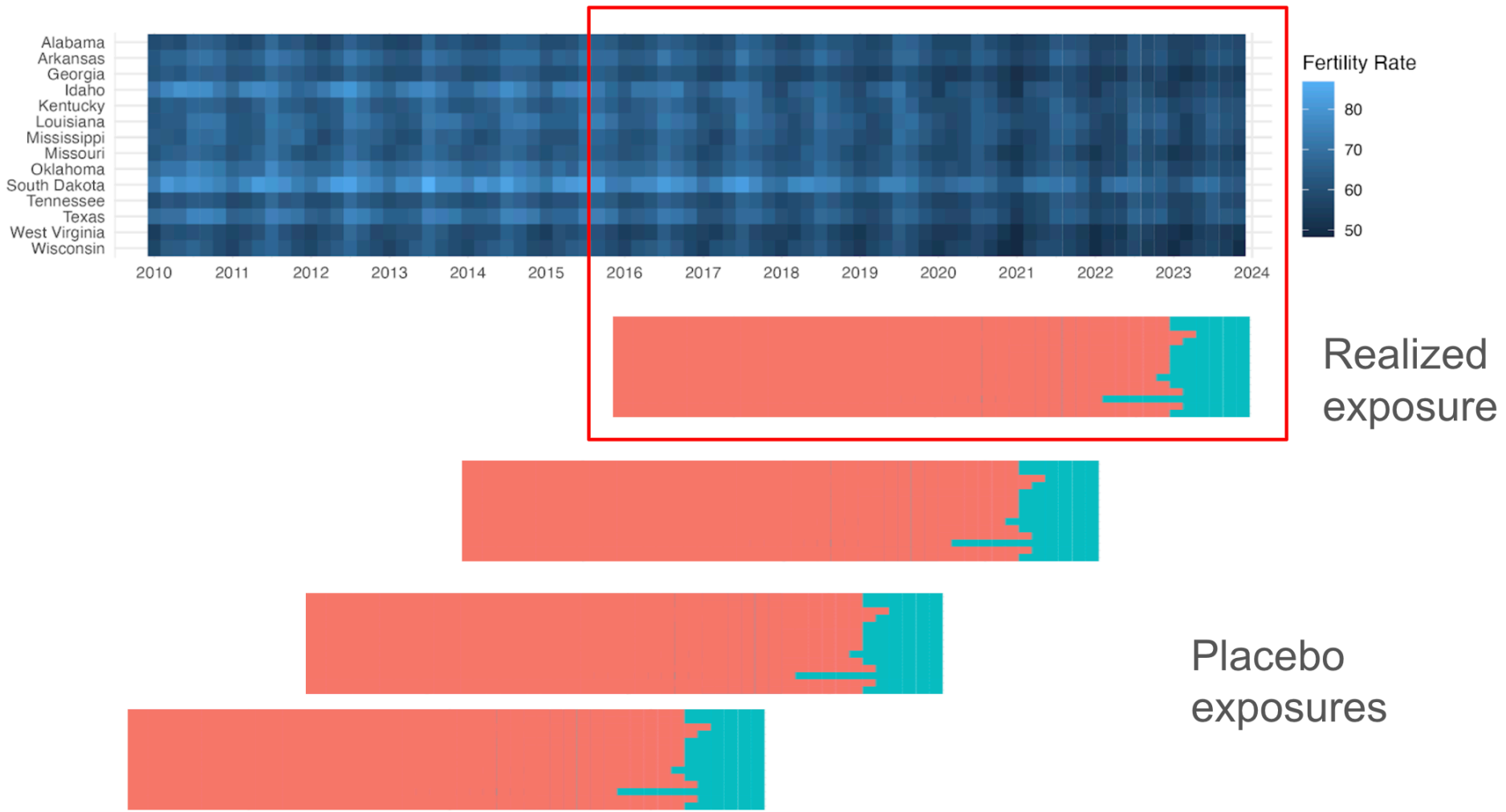
- Test statistic based on eigenspectrum of residual correlation matrix

- Let $\mathcal{C} = (c_{ii'})$ where $c_{ii'} = \text{cor}(r_{i\cdot}, r_{i'\cdot})$
- $T = \sigma_{max}(\mathcal{C})$ where $\sigma_{max}(\mathcal{C})$ is the largest singular of $\mathcal{C}$.
- T should be small for uncorrelated state-residuals

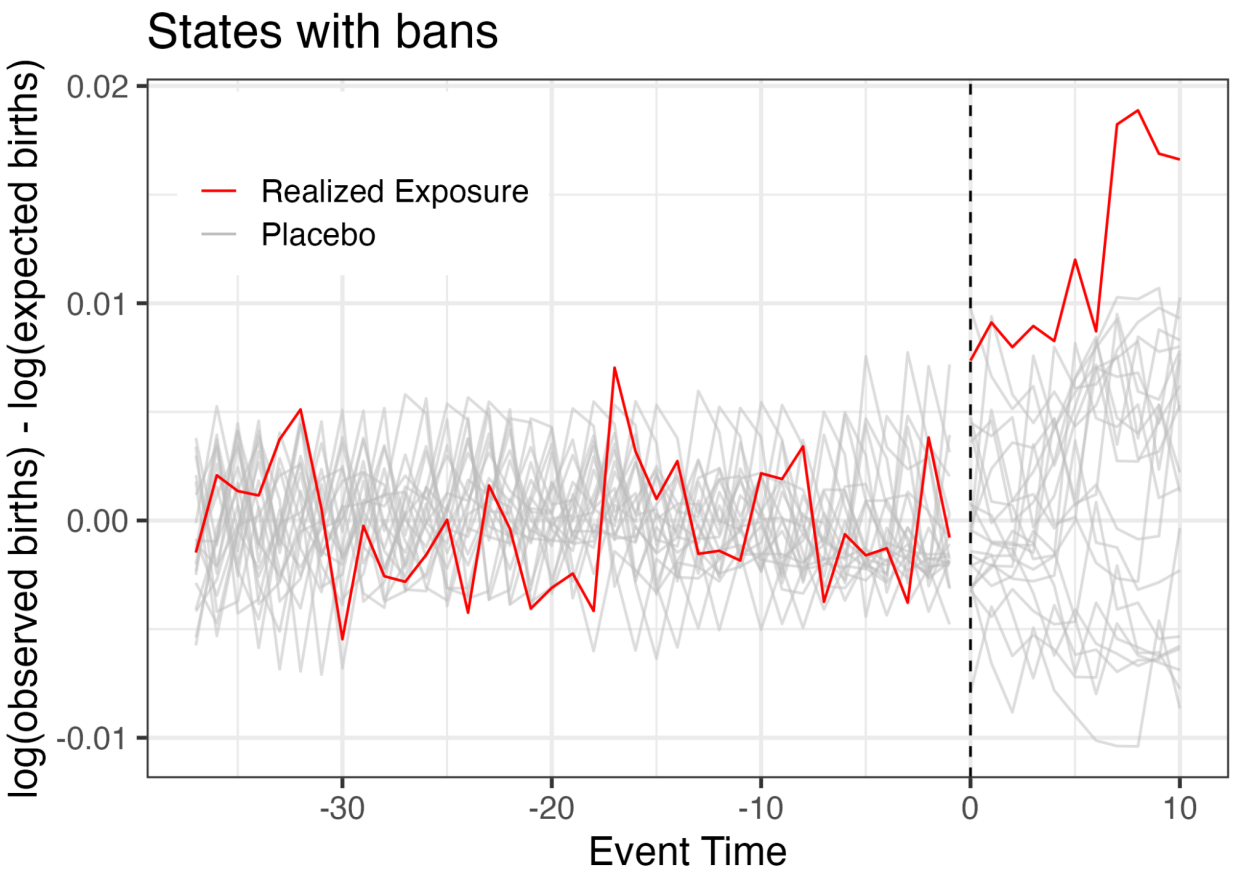
PPC: State Correlations



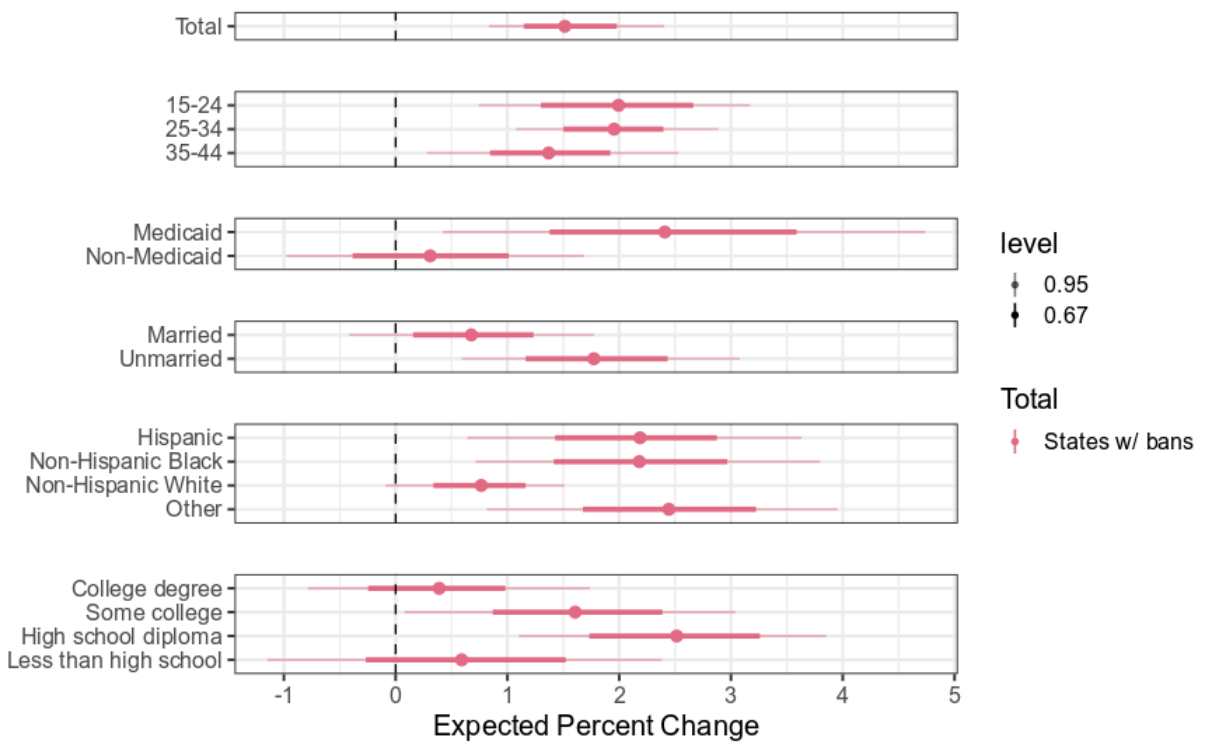
Placebo-in-Time



Placebo-in-Time

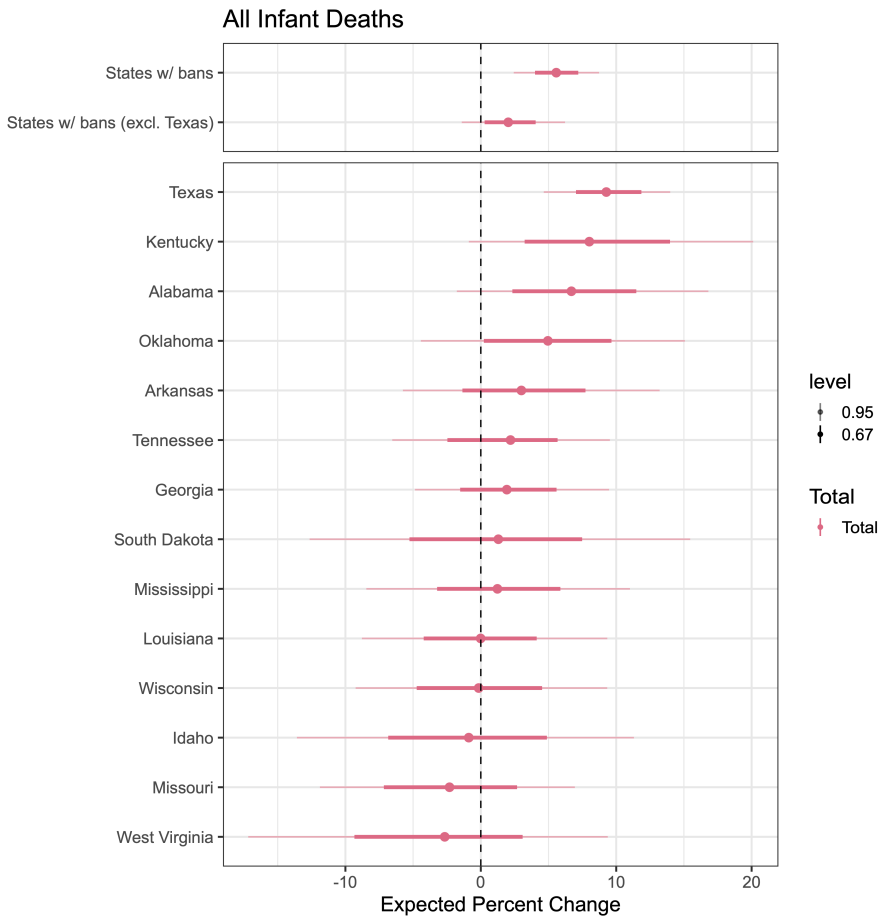


Fertility Impact by Subgroup



+1.7% overall increase

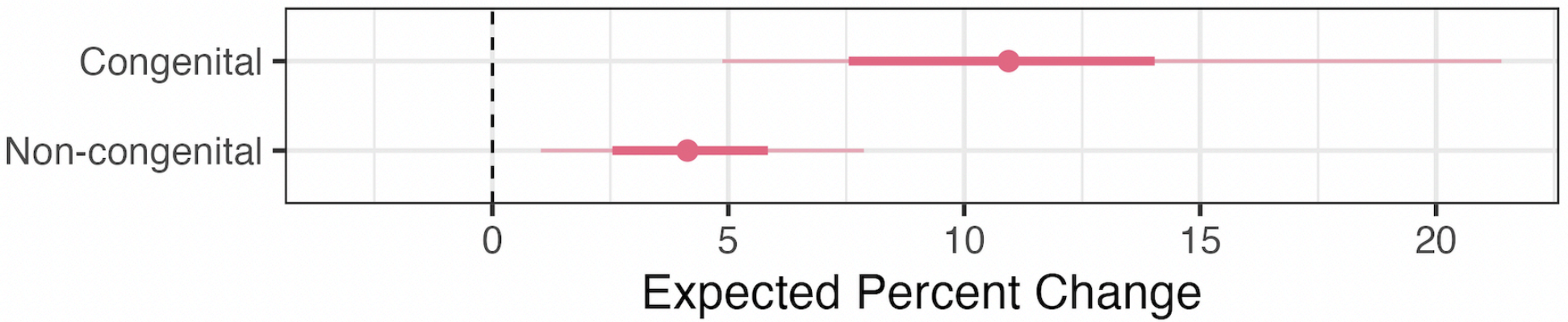
State-Specific Effects on Inf. Mortality



In banned states overall, the infant mortality rate increased by 5.6%

- Kentucky: +7.5%
- Texas: +8.9%

Effect on Infant Mortality by Cause



- +10.9% increase in congenital deaths
- +4.2% increase in non-congenital deaths

- Note: majority of deaths attributable to the bans are non-congenital

Effect on Infant Mortality by Race/Ethnicity

Key Findings

- Strong evidence that birth rates increased above expectation in states that banned abortion (+1.6%)
  - Slightly smaller than prior studies
  - Similar in magnitude of recent population-wide events
  - Largest impacts among those experiencing greatest structural disadvantage (consistent across states)
- Infant mortality increased in states with bans (+5.5%)
  - Outsized influence of Texas
  - Double the impact among non-Hispanic Black infants
  - Larger relative increase among congenital deaths

Implications

- Profound health, social and economic implications of being unable to obtain an abortion (Greene Foster 2020)
- State-specific policies and social contexts may present additional barriers for disadvantaged women
- Bans exacerbate existing health disparities
- Future work: impact of abortion bans on maternal morbidity, high-risk pregnancy care, and birth outcomes (e.g., preterm birth, low birthweight)

Methodological Takeaways

- Missing data and staggered adoption are easier to handle with Bayesian models
- Hierarchical modeling of the treatment effect in panel data is an underexplored strategy for estimating heterogeneous treatment effects
- Choice of temporal aggregation is important and tied to the amount of missingness
- More work needed to understand how and when to disaggregate when inferring total effects

Publications


New Online Views 21,377 | Citations 6 | Altmetric 1254

Original Investigation

February 13, 2025

US Abortion Bans and Infant Mortality

Alison Gemmill, PhD[1]; Alexander M. Franks, PhD[2]; Selena Anjur-Dietrich, PhD[1]; et al

» Author Affiliations

JAMA. Published online February 13, 2025. doi:10.1001/jama.2024.28517


New Online Views 7,229 | Citations 4 | Altmetric 705

Original Investigation

February 13, 2025

US Abortion Bans and Fertility

Suzanne O. Bell, PhD[1]; Alexander M. Franks, PhD[2]; David Arbour, PhD[3]; et al

» Author Affiliations

JAMA. Published online February 13, 2025. doi:10.1001/jama.2024.28527

Papers published in JAMA. See Gemmill et al. (2025) and Bell et al. (2025). Supplementary materials contain modeling details.

Thank you!

Bell, Suzanne O, Alexander M Franks, David Arbour, Selena Anjur-Dietrich, Elizabeth A Stuart, Eli Ben-Michael, Avi Feller, and Alison Gemmill. 2025. “US Abortion Bans and Fertility.” *JAMA*.

Caraher, Raymond. 2024. “Do Abortion Bans Affect Reproductive and Infant Health? Evidence from Texas’s 2021 Ban and Its Impact on Health Disparities.” *Political Economy Research Institute Working Paper No* 606.

Dench, Daniel, Mayra Pineda-Torres, and Caitlin Myers. 2024. “The Effects of Post-Dobbs Abortion Bans on Fertility.” *Journal of Public Economics* 234: 105124.

Gemmill, Alison, Alexander M. Franks, Selena Anjur-Dietrich, Amy Ozinsky, David Arbour, Elizabeth A. Stuart, Eli Ben-Michael, Avi Feller, and Suzanne O. Bell. 2025. “US Abortion Bans and Infant Mortality.” *JAMA* 333 (15): 1315–23. https://doi.org/10.1001/jama.2024.28517.

Gemmill, Alison, Claire E Margerison, Elizabeth A Stuart, and Suzanne O Bell. 2024. “Infant Deaths After Texas’ 2021 Ban on Abortion in Early Pregnancy.” *JAMA Pediatrics* 178 (8): 784–91.

Sun, Liyang, Eli Ben-Michael, and Avi Feller. 2024. “Temporal Aggregation for the Synthetic Control Method.” In *AEA Papers and Proceedings*, 114:614–17. American

Additional Slides

Fertility Data

- Bimonthly (e.g., January-February) counts of **live births** for 50 states and DC from birth certificates for 2014-2023
  - Compiled by the National Center for Health Statistics (NCHS)
  - 2023 provisional data
- Denominators (women 15-44) by state-year for 2014-2022 (imputed 2023)
  - Census: total counts and by age, race/ethnicity
  - American Community Survey: proportion by education, marital status, insurance (indirectly)

Fertility Approach

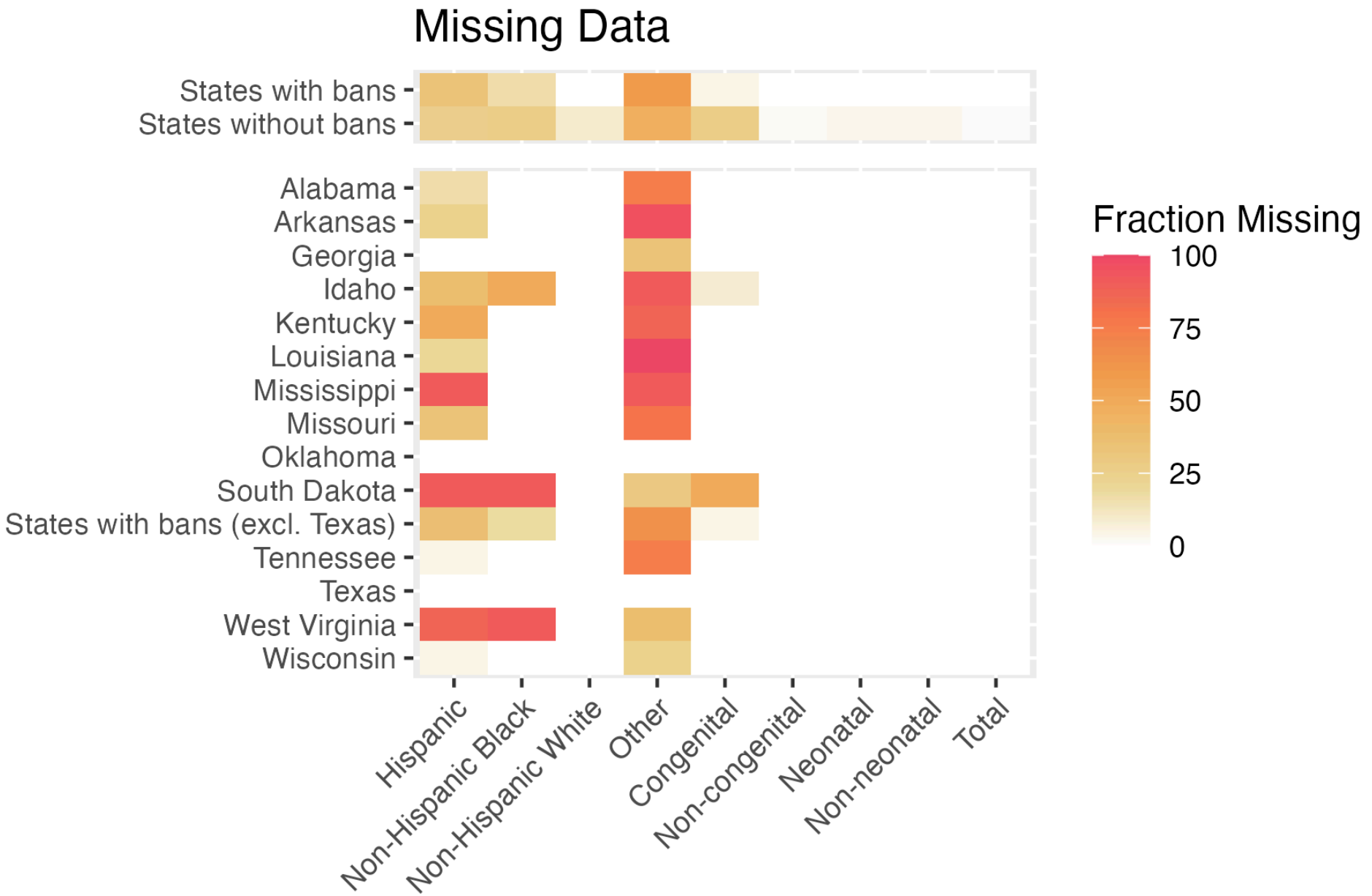
- Outcome: fertility rate (births per 1,000 per year)
- Exposure: 6-week or complete abortion ban (14 states[1]), staggered adoption
- Pre-policy period: January 2014 through ~December 2022
- Treated period: ~January 2023 through December 2023

- Subgroups
  - Age: 15-24, 25-34, 35-44
  - Race/ethnicity: non-Hispanic White, non-Hispanic Black, Hispanic, and Other
  - Marital status: married, not married
  - Educational attainment: <high school, high school degree, some college, college degree+
  - Insurance payer for the delivery: Medicaid, non-Medicaid

Infant Mortality Data

- Biannual (e.g., January-June) counts of **infant deaths (< 1 year)** for 50 states and DC from death certificates for 2012-2023
  - 2023 provisional data
  - Impute suppressed data
- Denominators (live births) by state-biannual period for 2012-2023 from birth certificates

Missing Data

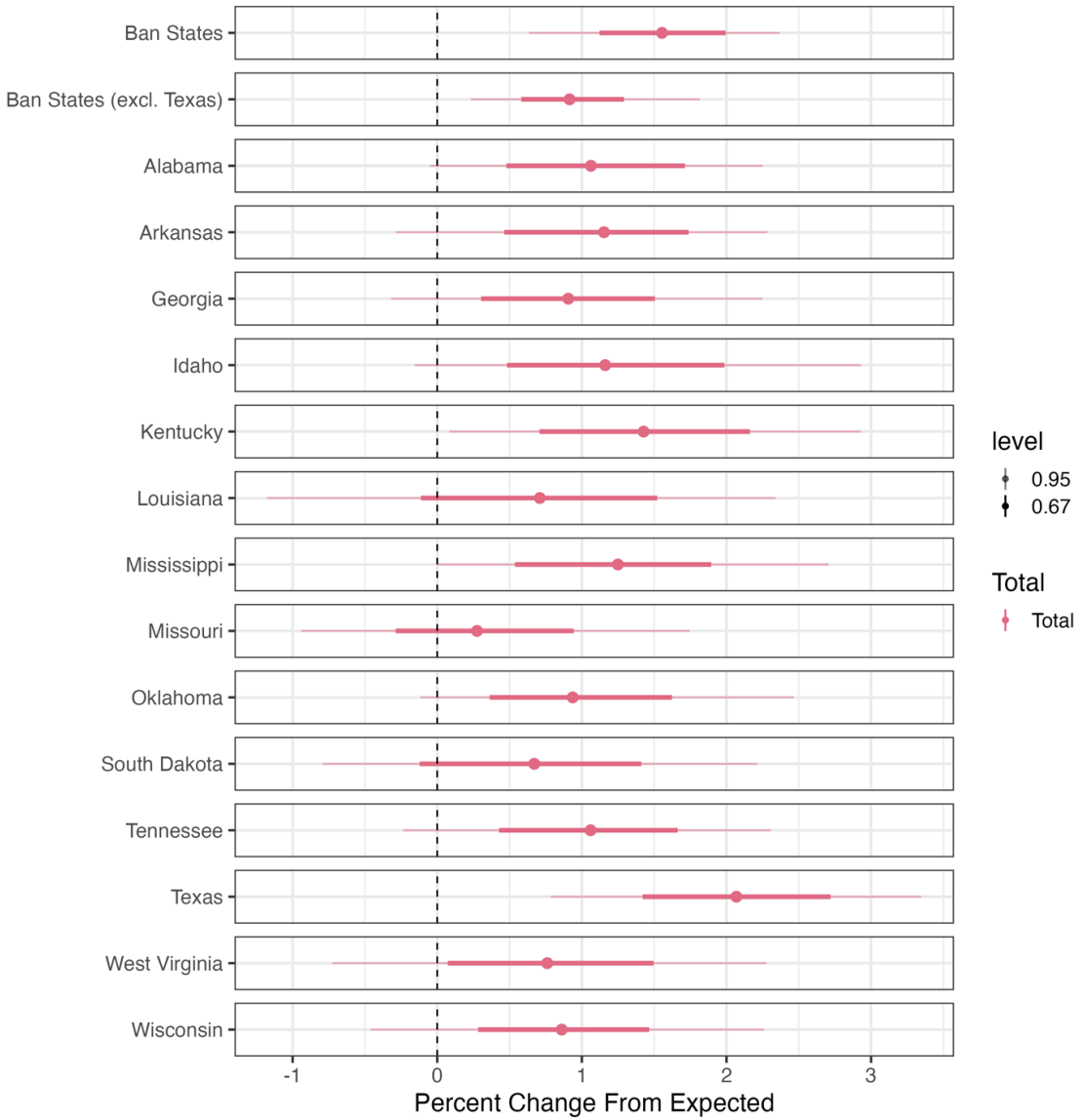


Note: missingness depends on level of temporal aggregation

Median Infant Deaths per Half-Year

	Type		Timing		Race				
	Congenital	Noncongenital	Neonatal	Nonneonatal	Non-Hispanic White	Non-Hispanic Black	Hispanic	Other	Total
States with bans									
Alabama	45	180	134	96	100	106	14	<10	225
Arkansas	32	110	87	59	86	43	11	<10	144
Georgia	76	372	294	157	146	243	45	11	446
Idaho	15	42	36	19	42	<10	10	<10	54
Kentucky	41	127	106	70	123	28	<10	<10	171
Louisiana	42	196	134	98	80	132	13	<10	237
Mississippi	32	129	96	64	60	94	<10	<10	162
Missouri	46	180	140	86	142	64	12	<10	228
Oklahoma	39	142	109	70	85	32	28	34	182
South Dakota	<10	30	23	16	21	<10	<10	12	38
Tennessee	60	217	167	108	150	96	23	<10	279
Texas	262	850	736	376	310	260	486	36	1120
West Virginia	15	50	42	25	57	<10	<10	<10	66
Wisconsin	40	154	132	62	105	51	21	14	187

State-Specific Effects on Fertility Rate



- Range: 0.6% - 2.1%
- Overall: +1.7%
- Non-Texas: +0.9%

Likelihood - Infant Mortality

Let M_{ijt} denote the indicator for suppressed counts, with $M_{ijt} = 1$ if $0 < Y_{ijt}^{\text{obs}} < 10$ and $M_{ijt} = 0$ otherwise. % If we let $B_{ijt}^{obs} = B_{ijt}(G_i)^{D_{ijt}} B_{ijt}(\infty)^{(1-D_{ijt})}$ then, The observed data likelihood can then be written as:

$$\begin{aligned}\mathbb{P}(\mathbf{Y}^{obs}, \mathbf{M} \mid \mathbf{B}^{obs}, \mathbf{D}, \rho, \tau) = \prod_{ijt} \Big[&((1 - P_{\text{miss}}(\rho_{ijt} B_{ijt}^{obs}))\text{Pois}(Y_{ijt}; \rho_{ijt} B_{ijt}^{obs}))^{(1-M_{ijt})(1-D_{ij} \\ &((1 - P_{\text{miss}}(\tau_{ijt}\rho_{ijt} B_{ijt}^{obs}))\ \text{Pois}(Y_{ijt}; \tau_{ijt}\rho_{ijt} B_{ijt}^{obs}))^{(1-M_{ijt})D_{ijt}} \\ &(P_{\text{miss}}(\rho_{ijt} B_{ijt}^{obs})^{M_{ijt}(1-D_{itj})} (P_{\text{miss}}(\tau_{ijt}\rho_{ijt} B_{ijt}^{obs})^{M_{ijt}D_{itj}}) \Big].\end{aligned}$$

where $\text{Pois}(Y_{ijt}; \rho_{ijt} B_{ijt}^{obs})$ is the poisson PMF with mean $\rho_{ijt} B_{ijt}^{obs}$ evaluated at Y_{ijt}; and

$$P_{\text{miss}}(\rho_{ijt} B_{ijt}^{obs}) = (F(9; \rho_{ijt} B_{ijt}^{obs}) - F(0; \rho_{ijt} B_{ijt}^{obs})),$$

where $F(a; \mu)$ is the CDF of a Poisson with mean μ evaluated at a so that $P_{\text{miss}}(\mu_{ijt}) = F(9; \mu) - F(0; \mu)$ is the probability of observing a missing count between 1 and 9, inclusive.