County-Level Estimates of Mortality and Natality Indicators from the National Vital Statistics System

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County-Level Estimates of Natality and Mortality Indicators

❖ Natality
  • Preterm birth
  • Second and higher order teen birth rates

❖ Mortality
  • Infant mortality
Rationale

Birth or death rates at the county level are often unstable ➔

Rates suppressed for counties with < 20 births/deaths
Outcomes from the National Vital Statistics System

- Percent of infants born before 37 completed weeks gestation
- Aggregated over 3 years

Second and higher order teen births (2007-2016)
- Repeat births to teen mothers
- Number of second or higher order births per 1,000 females 15-19 years
- Annual trends over 10 years
Outcomes from the National Vital Statistics System


• Infant (< 1 year of age) deaths per 1,000 live births
• Aggregated over 3 years
Methods

- Hierarchical Bayesian models
  - Integrated Nested Laplace Approximation (INLA) in R
    - Latent Gaussian models
      - Besag, York, Mollié (BYM) models
        » Spatial random effect, intrinsic conditionally autoregressive structure
        » Non-spatial random effect
    - Fast and flexible
      - Many ‘built-in’ likelihoods and latent models available
        » Temporal random effects, space-time interaction terms
Other Approaches

- CARBayes in R
  - Intrinsic conditionally autoregressive models
  - Not as flexible as INLA
    - Gaussian, binomial, Poisson outcomes
  - MCMC simulations can be slow

- WinBUGS/OpenBUGS
  - Flexible
  - Slow, very computationally intensive
    - Can take *weeks* to run
Preterm birth rates

- Babies born too early have higher rates of death and other adverse health outcomes

INLA Model: Preterm birth rates

- Binomial models with spatially structured random effects:

  \[ Y_i \sim \text{Binomial}(N_i, p_i) \]
  \[ \text{logit}(p_i) = \alpha + u_i + v_i \]

  - \( N_i \) = number of births in county \( i \)
  - \( \alpha \) = intercept
  - \( u_i \) = spatially structured random effect
  - \( v_i \) = non-spatial random effect

- Compared results with:
  - Poisson, zero-inflated Poisson, zero-inflated binomial models (R-INLA)
  - Poisson and binomial models in CARBayes
County-level preterm birth rates, 2013-2015: INLA estimates
County-level preterm birth rates, 2013-2015: INLA estimates: selected states
INLA vs. CARBayes

- Estimates and 95% credible intervals (CIs) very similar:
Second and higher order teen birth rates, 2007-2016

- Having more than one child as a teen is associated with negative health, emotional, social, and financial outcomes
  - Infants more likely to be born too early or too small
  - Limited educational and employment opportunities for the teen

INLA models: Second and higher order teen birth rates, 2007-2016

- Binomial space-time interaction models:

  \[ Y_{it} \sim \text{Binomial}(N_{it}, p_{it}) \]

  \[ \logit(p_{it}) = \alpha + A_i + B_t + C_{it} \]

- \( N_{it} \) = number of births in county \( i \) at time \( t \)
- \( p_{it} \) = probability of teen births in county \( i \) at time \( t \)
- \( \alpha \) = intercept
- \( A_i \) = spatially structured random effect
- \( B_t \) = time term
- \( C_{it} \) = space-time interaction term
Second and higher order teen birth rates
2007

[Map of the United States showing birth rates per 1,000 population across different states, color-coded from light pink to dark red, indicating varying rates.]
Second and higher order teen birth rates 2008

Births per 1,000 population

- 0-2
- 2.01-4
- 4.01-6
- 6.01-8
- 8.01-10
- 10.01-12
- 12.01-14
- >14
Second and higher order teen birth rates 2009

Births per 1,000 population

- 0-2
- 2.01-4
- 4.01-6
- 6.01-8
- 8.01-10
- 10.01-12
- 12.01-14
- >14
Second and higher order teen birth rates 2010
Second and higher order teen birth rates
2011

Births per 1,000 population

- 0-2
- 2.01-4
- 4.01-6
- 6.01-8
- 8.01-10
- 10.01-12
- 12.01-14
- >14
Second and higher order teen birth rates 2012

Births per 1,000 population

- 0-2
- 2.01-4
- 4.01-6
- 6.01-8
- 8.01-10
- 10.01-12
- 12.01-14
- >14
Second and higher order teen birth rates
2013

Births per 1,000 population
Second and higher order teen birth rates 2014

Births per 1,000 population

0-2
2.01-4
4.01-6
6.01-8
8.01-10
10.01-12
12.01-14
>14
Second and higher order teen birth rates
2015
Second and higher order teen birth rates
2016

Births per 1,000 population
Infant Mortality Rates

- Considered a key marker of the overall health of a society
  - The United States has a higher infant mortality rate than similarly developed nations

- In 2015, 27 states met the Healthy People 2020 target of 6.0 infant deaths per 1,000 live births
  - Infant mortality rates higher in southern states

- Zero-inflated Poisson models with spatially structured random effects

\[
\text{Prob}(y | \ldots) \sim \begin{cases} 
0, & \text{with probability } p \\
\text{Poisson}(y), & \text{with probability } (1-p)
\end{cases}
\]

\[
\log(y_i) = \alpha + u_i + v_i + \log(E_i)
\]

- \(E_i\) = exposure, number of births in county \(i\)
- \(\alpha\) = intercept
- \(u_i\) = spatially structured random effect
- \(v_i\) = non-spatial random effect

- Compared results with:
  - Poisson, binomial, zero-inflated binomial models (R-INLA)
  - Poisson and binomial models in CARBayes
Infant deaths per 1,000 live births, 2013-2015: INLA estimates
Infant deaths per 1,000 live births, 2013-2015: CARBayes estimates
Discussion

- Birth or death rates at the county level are often unstable, suppressed for small areas.
- Aggregating over several years or larger geographic regions can mask patterns and trends:
  - Variation within states or over time
  - Areas of high or low values that cross state boundaries

![Preterm birth map](#)

![Infant mortality map](#)

Deaths per 1,000 births

Preterm births

Percent of births preterm
Limitations and Strengths

- Model-based estimates might smooth away important effects
- People trust direct estimates (*real data*) more
  - “Black box” models, assumptions

- Various model-based approaches produce rather consistent results
  - For a variety of birth and death outcomes examined
    - INLA, CARBayes, WinBUGS/OpenBUGS
    - Different likelihoods and models with/without covariates
  - The overall patterns are very similar
Conclusions

- Model-based approaches can be used to generate county-level estimates of birth and death rates
  - Examine variation across the entire U.S.
  - Pick up on important spatial or temporal 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
Questions?

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INLA Models

- **Preterm birth**
  
  ```
  > numerator ~ 1 + f(region, model="bym", graph="map")
  > inla(formula,family="binomial",Ntrials=denominator, data=data,
  >       control.compute=list(dic=TRUE, cpo=TRUE, waic=T))
  ```

- **Teen birth rates**
  
  ```
  > numerator ~ 1 + year + f(region, model="bym", graph="map") +
  >     f(interaction, model="rwl")
  > inla(formula,family="binomial",Ntrials=denominator, data=data,
  >       control.compute=list(dic=TRUE, cpo=TRUE, waic=T))
  ```

- **Infant mortality**
  
  ```
  > numerator ~ 1 + f(region, model="bym", graph="map")
  > inla(formula, family="zeroinflatedpoisson1", E=denominator,
  >       data=data, control.compute=list(dic=TRUE, cpo=TRUE, waic=T))
  ```
Helpful References

- [http://www.r-inla.org/](http://www.r-inla.org/)


