A Bayesian Model to Estimate Male and Female Fertility Patterns at a Subnational Level

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Importance of measuring male fertility

- ▶ Male fertility measurement is overlooked (Coleman 2000)
- ► Increasing involvement of men in fertility decisions (Lappegård et al. 2011)
- ➤ Trajectories in male fertility can differ systematically from those of women due to:
 - ▶ different reproductive age spans (Schoumaker 2019)
 - unbalanced sex ratios (Dudel & Klüsener 2016)
 - distinct cultural norms (Dudel & Klüsener 2021)

Objectives

- ▶ Goal \rightarrow construction of a Bayesian model to estimate male and female period TFR at a subnational level
 - Essential component of population change
 - Shape local policies
- Data example → US counties during the period 1982-2019
 - ► High heterogeneity in fertility behaviors across time and space
 - High quality data registration systems

Challenges

- Data on births disaggregated by paternal ages are often unavailable
 - Countries with inefficient data registration systems or lacking high quality surveys
 - Small regions with masked ages at childbearing due to privacy concerns
- Even in developed countries, birth registration systems have started recording childbearing ages of men quite recently
- ► The share of births with missing paternal ages is much higher than for maternal ages (Dudel & Klüsener 2016)

Methodological Framework

Build on the Bayesian model by Schmertmann & Hauer (2019)

Idea \rightarrow Estimation of period Total Fertility Rate (TFR) without knowledge of births by maternal ages

Data Requirements

- Counts of children under 5
- Counts of women aged 15-49

Prior requirement

- Child mortality estimates
- Standard age-specific fertility schedules



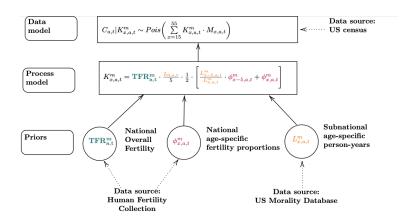
Proposed extension

Extend the previous Bayesian model to estimate male and female fertility at a subnational level

Extensions

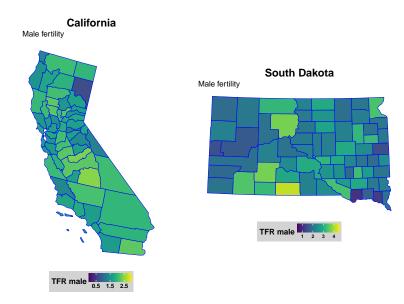
- ► Inclusion of men aged 15-59
- Incorporation of subnational mortality estimates
- ▶ Account for spatial dependencies → information pooling
- ► Account for temporal dependencies → temporal smoothing

Bayesian model summary

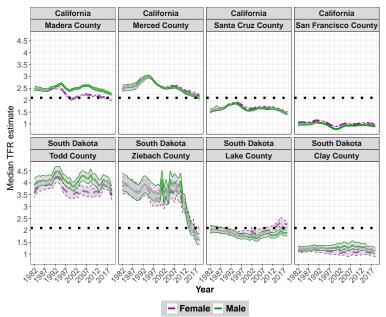


Final Goal \rightarrow Draw samples from the marginal posterior distribution $TFR_{a,t}^s|$ data, other parameters

California and South Dakota in 2015



Male and female TFR in selected counties



Preliminary conclusions

- Using county-level population counts by age and sex allows to derive subnational period TFR estimates without the need of information on parental ages.
- Male and female fertility tend to converge by the end of the considered period
- Country-specific characteristics determine a high spatial heterogeneity and distinct temporal trajectories.

Any Questions??

Looking forward to your feedback!

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Essential Bibliography



Carl P Schmertmann and Mathew E Hauer.

Bayesian estimation of total fertility from a population's age—sex structure. Statistical Modelling, 19(3):225–247, 2019.



David A Coleman.

Male fertility trends in industrial countries: Theories in search of some evidence. International Union for the Scientific Study of Population, 1995.



Christian Dudel and Sebastian Klüsener.

Estimating male fertility in eastern and western germany since 1991: A new lowest low? Demographic Research, 35:1549–1560, 2016.



Bruno Schoumaker.

Male fertility around the world and over time: How different is it from female fertility? Population and Development Review, pages 459–487, 2019.



Christian Dudel, Yen-hsin Alice Cheng, and Sebastian Klüsener.

Shifting parental age differences in high-income countries: Insights and implications. *Population and Development Review*, 49(4):879–908, 2023.



Li Zhang.

Male fertility patterns and determinants, volume 27.

Springer Science & Business Media, 2010.

Bayesian model

Data model:

$$C_{a,t}|K^s_{x,a,t} \sim \operatorname{Pois}\bigg(\sum_{x=15}^{\omega^s} K^s_{x,a,t} \cdot E^s_{x,a,t}\bigg)$$

$$K_{x,a,t}^{s} = TFR_{a,t}^{s} \cdot \frac{\tilde{L}_{0,a,t}}{5} \cdot \frac{1}{2} \cdot \left[\frac{\tilde{L}_{x-5,a,t}^{s}}{\tilde{L}_{x,a,t}^{s}} \cdot \phi_{x-5,a,t}^{s} + \phi_{x,a,t}^{s} \right]$$

with $w^F = 45$ and $w^M = 55$

- ▶ Overall fertility $(TFR_{a,t}^s)$
- lacktriangle Age- and sex-specific fertility proportions $(\phi^s_{x,a,t})$
- ▶ Age- and sex-specific person-years $(L_{x,a,t}^s)$

Priors on fertility parameters

Prior on TFR

$$TFR_{a,t}^s \sim \mathcal{N}(TFR_t^{nat,s}, \sigma_{TFR_{a,t}^s}^2)$$

Prior on age-specific fertility patterns

$$\gamma_{x,a,t}^s = m_x^s + y_{1,x}^s \beta_{1,a,t}^s + y_{2,x}^s \beta_{2,a,t}^s$$

$$\gamma_{x,a,t}^s = \log\left(\frac{\phi_{x,a,t}^s}{\phi_{15,a,t}^s}\right)$$

Pooling information over countries

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

Smoothing over time

$$\mu_{\beta_{p,t}^s} \sim \mathcal{N}(2\mu_{\beta_{p,t-1}^s} - \mu_{\beta_{p,t-2}^s}, \sigma_{\mu_{\beta_{p,t}^s}}^2)$$

Priors on mortality and standard deviation parameters

Prior on Person-years

$$\tilde{\underline{L}}_{0,a,t} \sim \mathcal{N}(\hat{L}_{0,a,t}, \hat{\sigma}^2_{\hat{L}_{0,a,t}})$$

$$\underline{\tilde{L}_{x,a,t}^s} \sim \mathcal{N}(\hat{L}_{x,a,t}^s, \hat{\sigma}_{\hat{L}_{0,a,t}}^2)$$

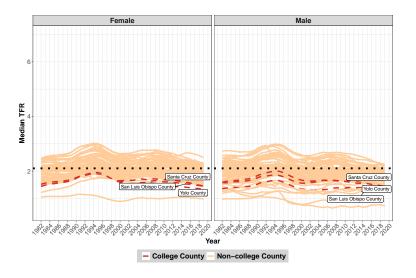
- ullet $ilde{L}^s_{x,a,t}$ from age-, period- and sex-specific subnational life tables
- Variances calculated from the standard errors available from the subnational life tables

Prior on standard deviation parameters

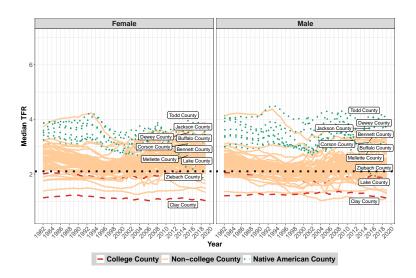
$$\sigma_{\beta_{p,a,t}^s}, \sigma_{TFR_{a,t}^s}, \sigma_{\mu_{\beta_{p,t}^s}} \sim \mathcal{N}^+(0,1)$$

weakly informative priors

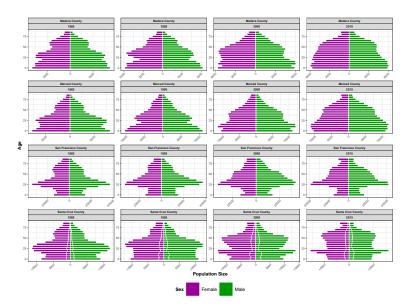
Appendix: California TFR trajectories



Appendix: South Dakota TFR trajectories



Appendix: population pyramids (1)



Appendix: population pyramids (2)

