Measuring inequity in family planning: Towards locally relevant monitoring by local actors

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2023 Annual IDM Symposium - Frontiers in Modeling
Session on Exploring vulnerabilities and family planning
Monitoring family planning indicators using the Family Planning Estimation Model (FPET)
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  Model development:
  - Married and national
Monitoring family planning indicators
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![Graph showing trends](image)
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• Further model updates
• Specific subgroups

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  - Consider specific population subgroups: unmarried women (Kantorova et al., 2020), subnational estimation

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FPET = a tool for local monitoring

![Graph showing trend in family planning indicators over time with markers for specific categories like married and unmarried women, and subnational estimation.](image)
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  • Example: women who are young & parity 1+ & live in Federal Capital Territory & poor & no primary education
  • Important! Existing estimates may mask variation
  • The difficulty: data sparsity & so many groups to consider
Producing model-based estimates of FP indicators for small groups
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- Goal: For some population group $g$, estimate group-specific FP outcome $\mu_g$
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- **Approach:** Bayesian hierarchical sparse regression model
  - Joint work with Jadey Wu, Zhengfan Wang, and Chuchu Wei (UMass Amherst)
Bayesian hierarchical sparse regression model

Data model: \( y_{g,c} \mid \mu_g, \epsilon_c \sim \text{Bin}(n_{g,c}, \text{invlogit}(\logit(\mu_g) + \epsilon_c)) \), where

- \( y_{g,c} \) refers to \# of users among \( n_{g,c} \) women with a demand for FP in group \( g \), cluster \( c \),
- \( \epsilon_c \) refers to a cluster effect to capture across-cluster variability.

Expression for \( \mu_g \):

\[
\logit(\mu_g) = \alpha_{r[g]} + \sum_{d=1}^{D} \sum_{k=1}^{K_d} (\beta_k^{(d)} + \eta_{d,k}^{(d)}\,x_{k,g}^{(d)}) + \sum_{d_1=1}^{D} \sum_{k_1=1}^{K_{d_1}} \sum_{d_2=1}^{D} \sum_{k_2=1}^{K_{d_2}} \beta_{d_1,d_2,k_1,k_2}^{(d_1,d_2)} x_{k_1,g}^{(d_1)} x_{k_2,g}^{(d_2)} + \epsilon_g
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- \( x_{k,g}^{(d)} \) = dummy variables to capture the group-specific category for covariate \( d \), with \( d = 1,...,D \) referring to age, parity, wealth, education, residence. Specifically, \( x_{k,g}^{(d)} = 1 \) if group \( g \) is in category \( k = 1,...,K_d \) for covariate \( d \), 0 otherwise.
- \( r[g] \) refers to the region of group \( g \)
Bayesian hierarchical sparse regression model

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**Output = Estimates for outcome of interest** \( \mu_g \)
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**Account for the survey design and across-cluster variability**

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Account for the survey design and across-cluster variability

Specify subgroup-specific outcomes using
- main effects and 2nd order interaction terms,
- region-specific intercepts and regression coefficients,
- group-specific term \( \epsilon_g \)
Bayesian hierarchical sparse regression model (ctd)

Expression for $\mu_g$:

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Parameters:

- Regional intercepts $\alpha_r$ and regression parameters $\eta_{r,g,k}^{(d)}$ are estimated hierarchically/with spatial structure.

- Regression coefficients for main effects $\beta_{k=1:K_d}^{(d)}$ and interaction terms $\beta_{k_1,k_2=1:K_d}^{(d_1,d_2)}$ and $\eta_{r,1:K_d}^{(d)}$ are estimated using a RW1 set-up:

  - Re-parametrize to sum to zero $\sum_k \beta_k = 0$ and define $\Delta \beta_k = \beta_k - \beta_{k-1}$

  - To encourage shrinkage of irrelevant 1st order differences, we use horseshoe priors (Piironen et al., 2017), e.g., $\Delta \beta_k \mid \tau, \lambda_d \sim N(0, \tau^2 \lambda_k^2)$

- Subgroup effect $\varepsilon_g$ captures unexplained variability across groups and is estimated hierarchically, i.e. $\varepsilon_g \mid \sigma_\varepsilon \sim N(0, \sigma_\varepsilon^2)$
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Capture differences across regions
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Capture differences across regions

Capture relations between outcome and each covariate, and how this relationship varies across levels of other covariates
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- **Goal:** For some population group \( g \), estimate group-specific FP outcome \( \mu_g \)

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  - Estimates for married women in Nigeria in 2018, using DHS data
  - Outcome \( \mu_g \): demand satisfied with modern methods
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- **Approach:** Bayesian hierarchical sparse regression model
  - Assess differentials based on unique combinations of covariates
  - Data model: account for the survey design and across-cluster variability
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- **Computation:**
  - Hamilton Monte Carlo, using Stan/Brms package in R
  - ~5 - 10 minutes to fit model to Nigeria 2018 DHS data
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1. We find substantive differences between subgroups
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Main effects for age:
Demand satisfied increases with age

Interaction effects for being in “richer” group & age:
Among the richer women, younger age groups have lower-than-expected demand satisfied
What do the model-based estimates show? (Ctd)

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Demand satisfied for Federal Capital Territory, for women in richer subgroups, <35 years old
What’s next – using model-based estimates
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   • In parallel work: re-evaluate the impact of interventions using modern methods for causal inference and consider if subgroup characteristics act as effect modifiers

2. Consider summary measures, taking account of subgroup population size and uncertainty, to evaluate process in improving equity
What’s next – using model-based estimates

1. Use findings (average differentials, subgroup estimates) to help target interventions
   • In parallel work: re-evaluate the impact of interventions using modern methods for causal inference and consider if subgroup characteristics act as effect modifiers

2. Consider summary measures, taking account of subgroup population size and uncertainty, to evaluate process in improving equity

3. Consider other outcomes of interest
   • Build off recent work to define alternative measures of FP
   • E.g., better account for sexual activity, different definitions of demand and unmet need, ...
What’s next – the process of producing estimates
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<table>
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<th>How it started</th>
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What’s next – the process of producing estimates

How it started

Model development: Married & National

How it’s going

FPET = a tool for local monitoring

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What’s next?

Locally relevant FP modeling and monitoring by local actors
Locally relevant FP modeling and monitoring by local actors: how?

Model development

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Context-focused model updates & advanced usage

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  - **Tools**: Open-source software tools and training material (e.g., R packages for data processing and model fitting; webinars); we are finalizing FPET-related tools that allow for advanced usage.
Measuring inequity in family planning:
Towards locally relevant monitoring by local actors

• Existing estimates may mask variation in groups defined by different combinations of demographic characteristics.

• We developed a Bayesian hierarchical sparse regression model to produce subgroup estimates. Model-based estimates reveal inequities and can be used to target interventions.

• Consider building a midfield to further increase local FP modeling capacity?

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