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

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Session on Exploring vulnerabilities and family planning

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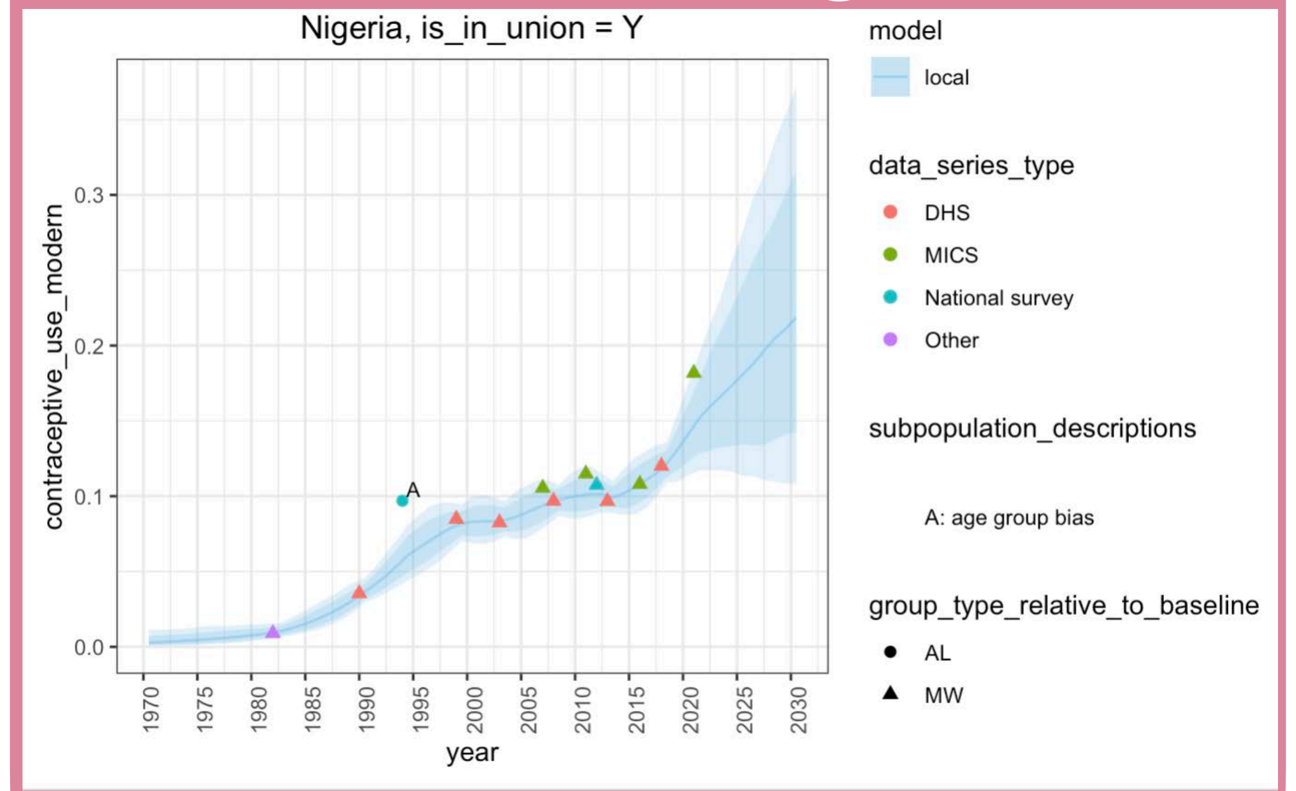

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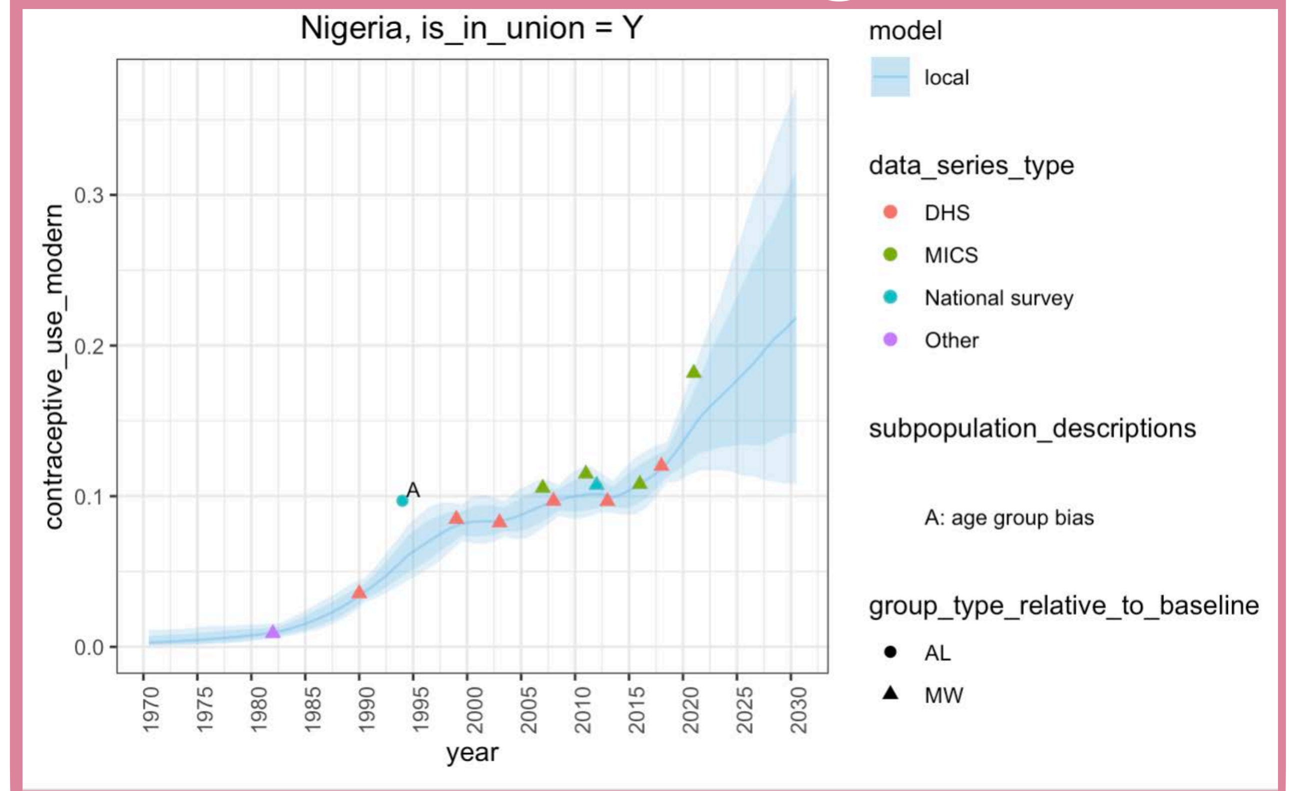

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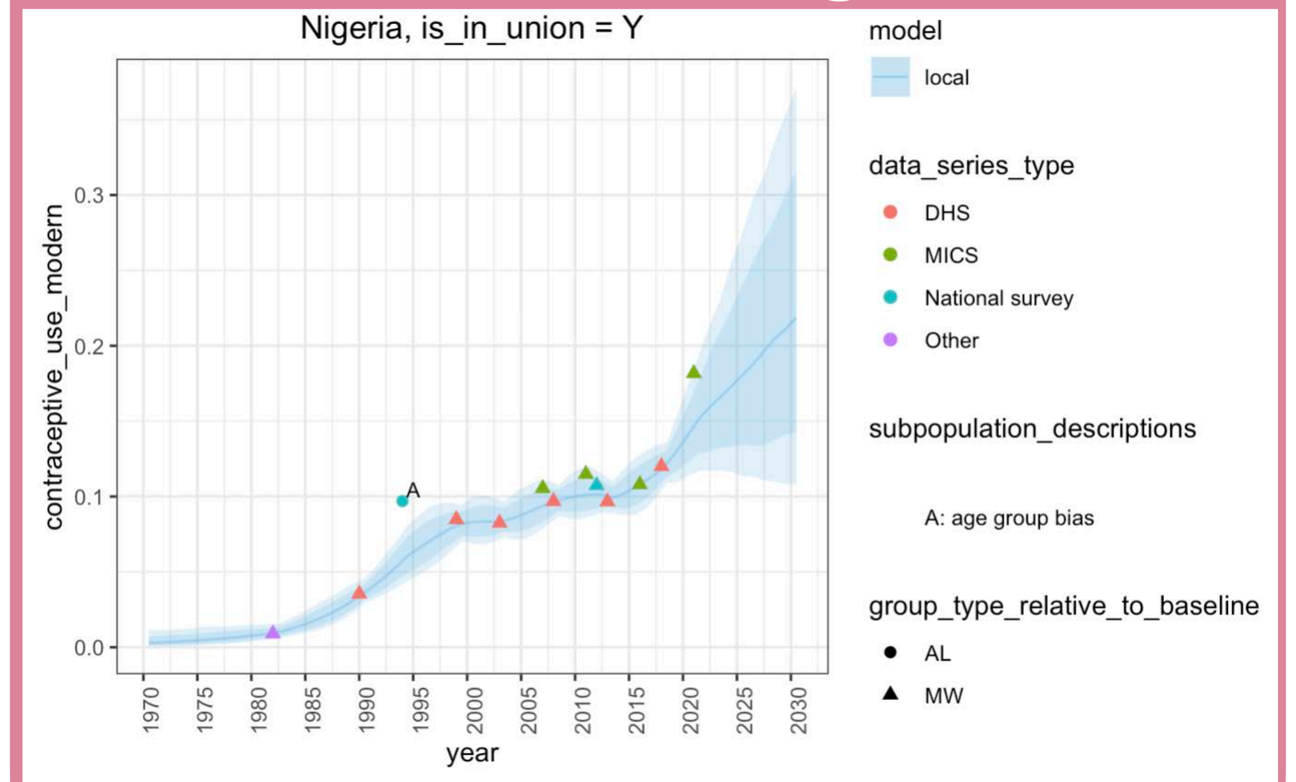

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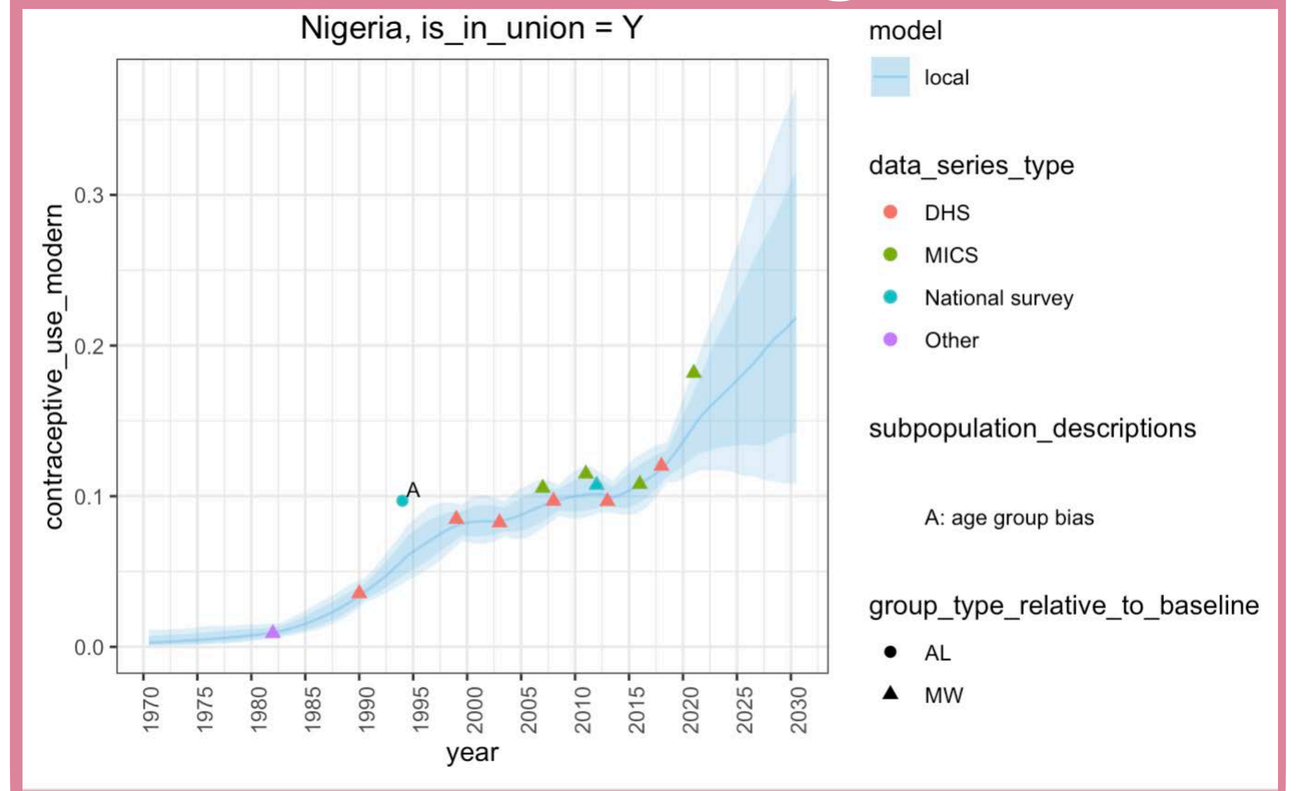

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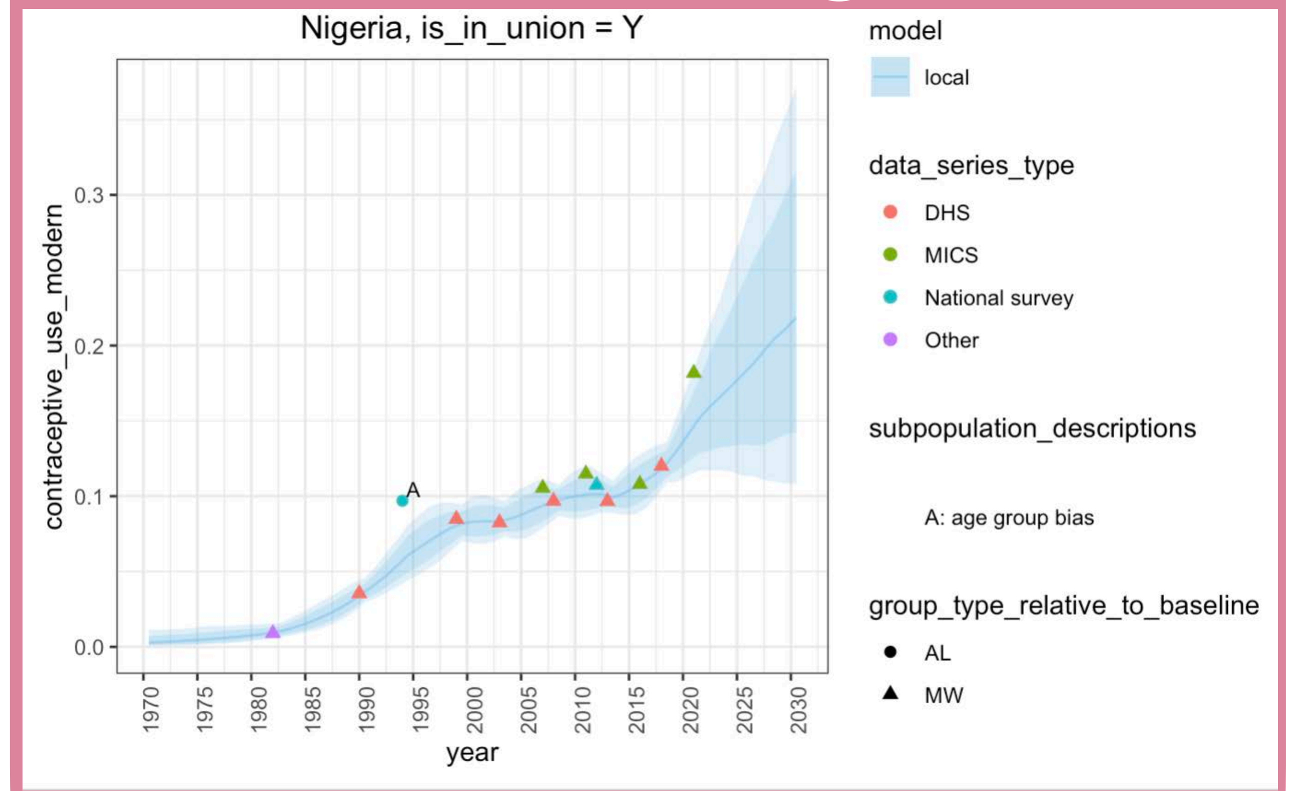

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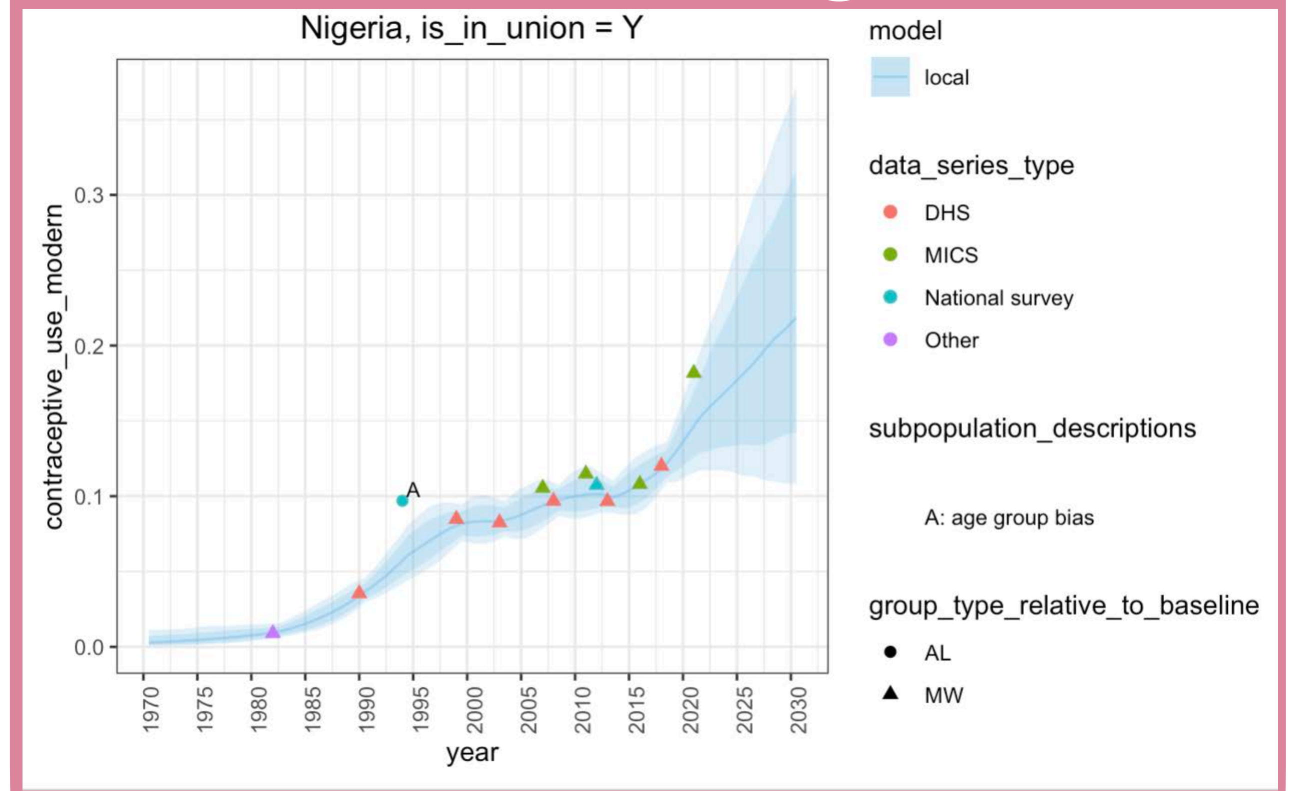

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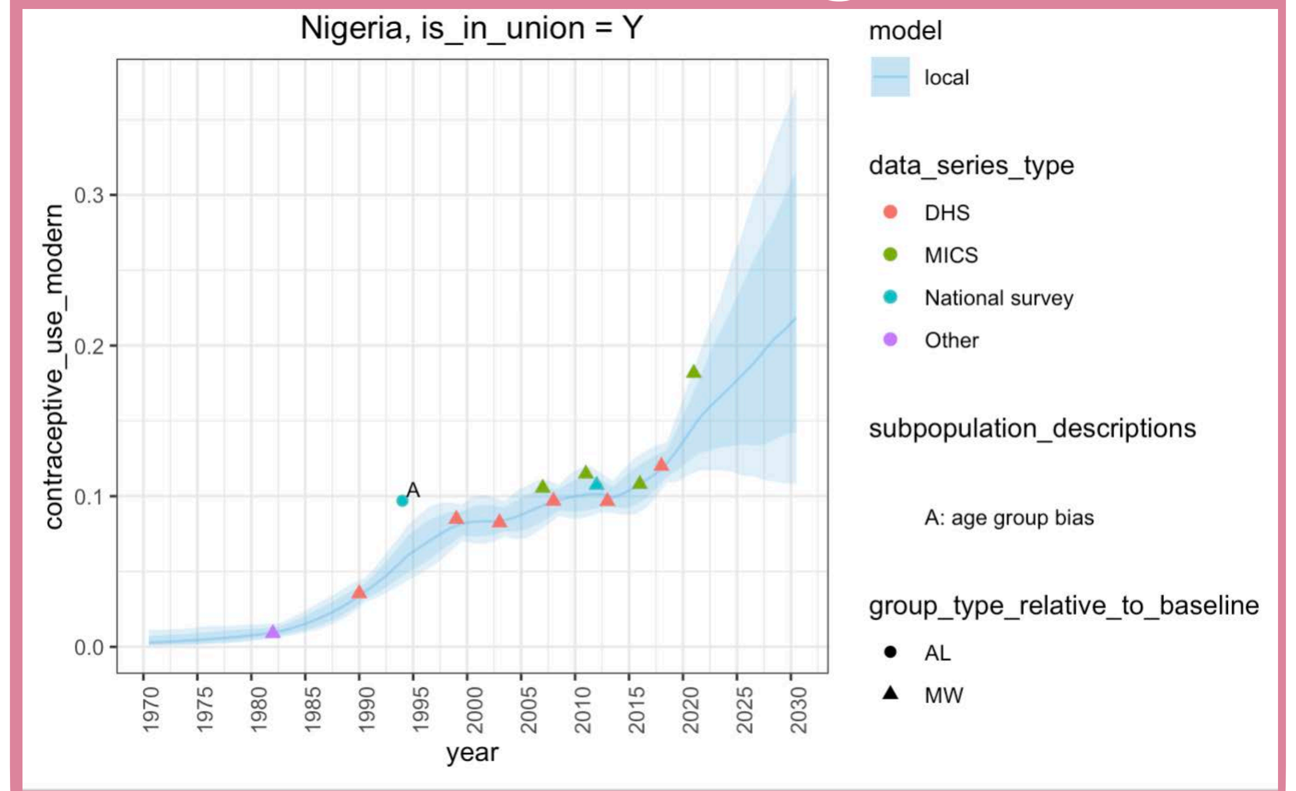

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  - Consider specific population subgroups: unmarried women (Kantorova *et al.*, 2020), subnational estimation

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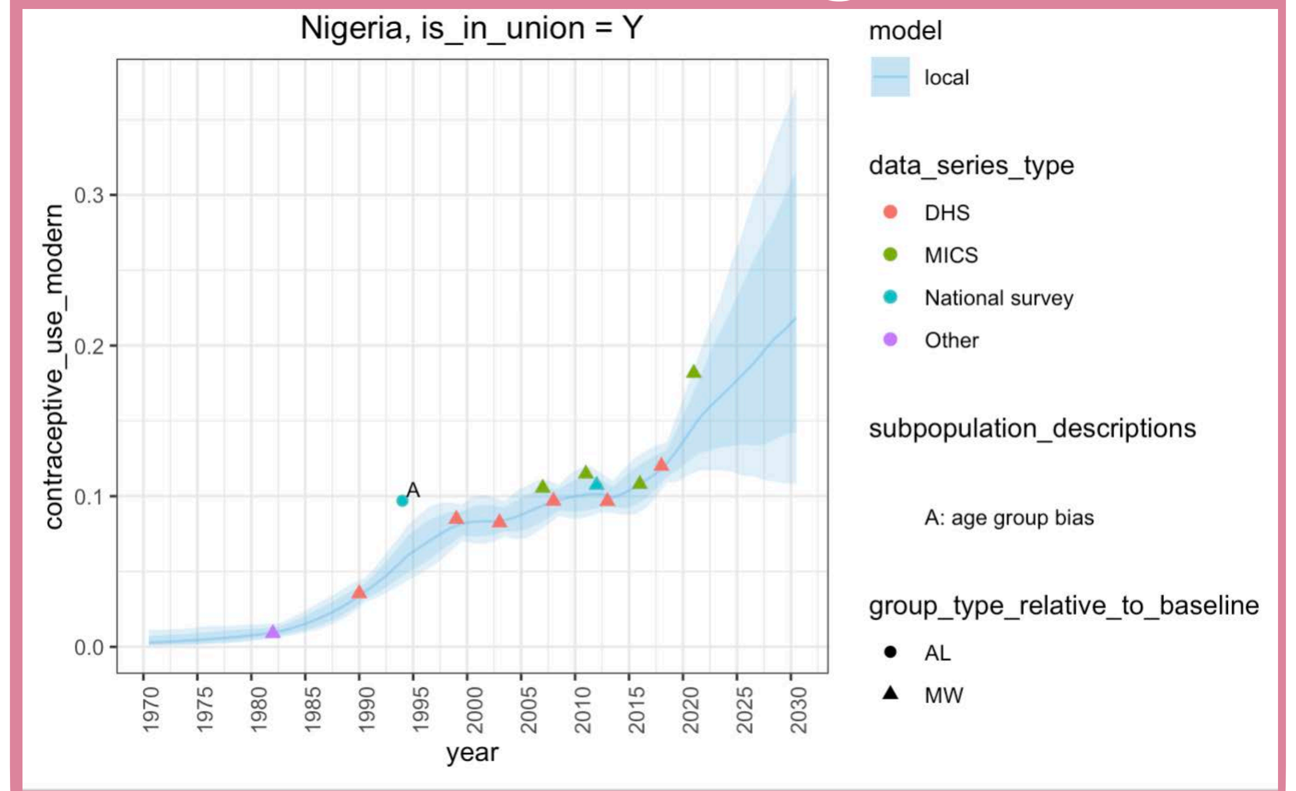

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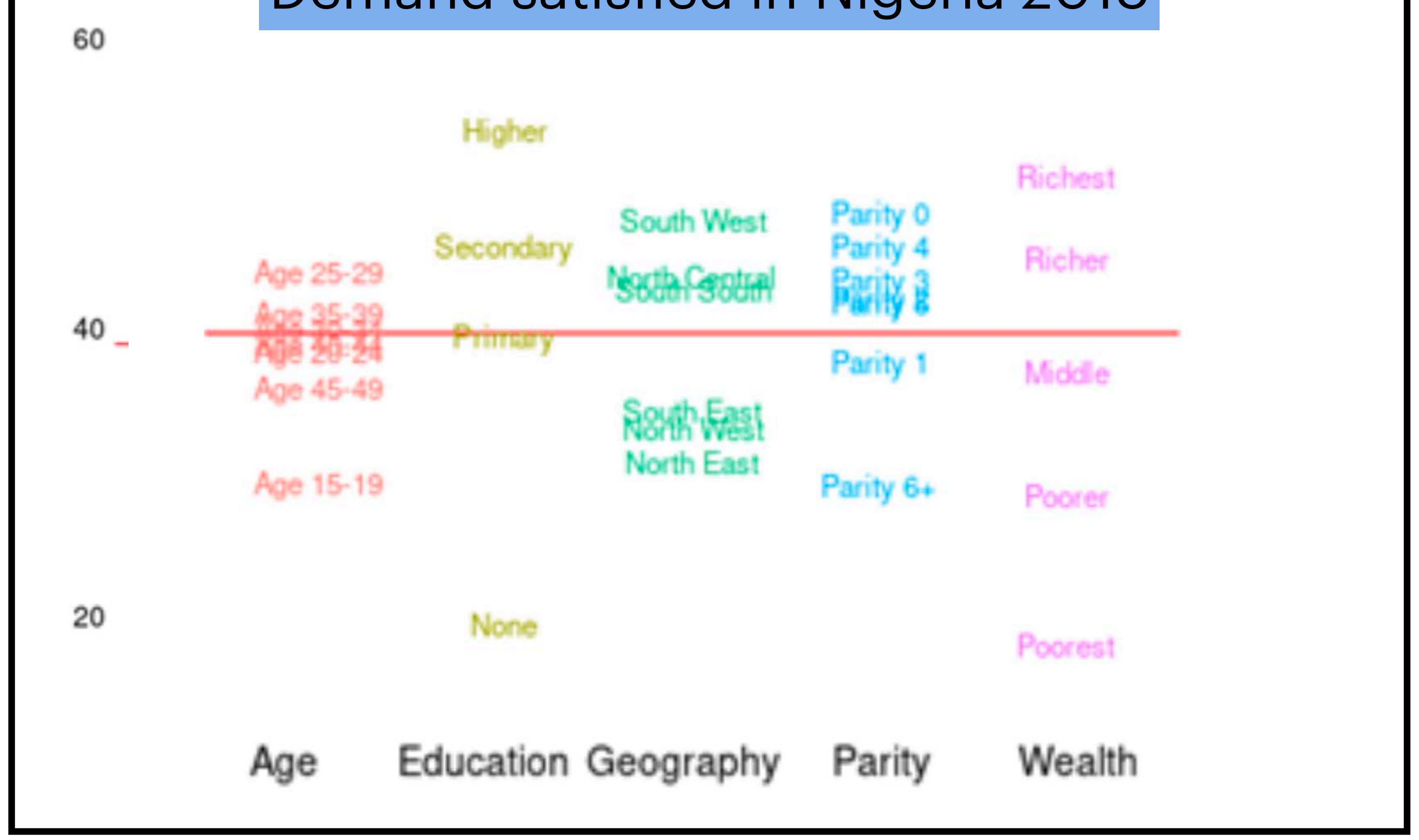

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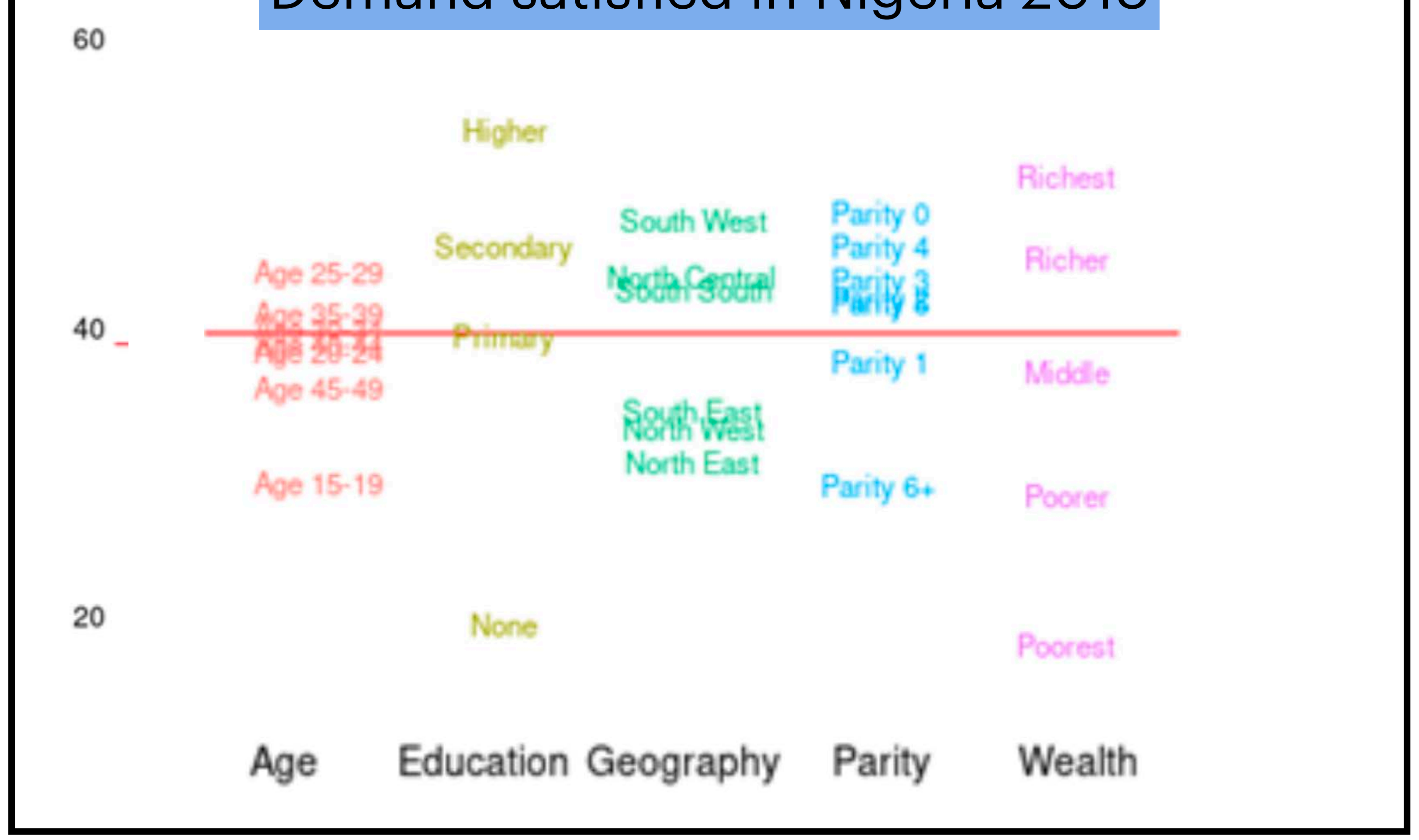
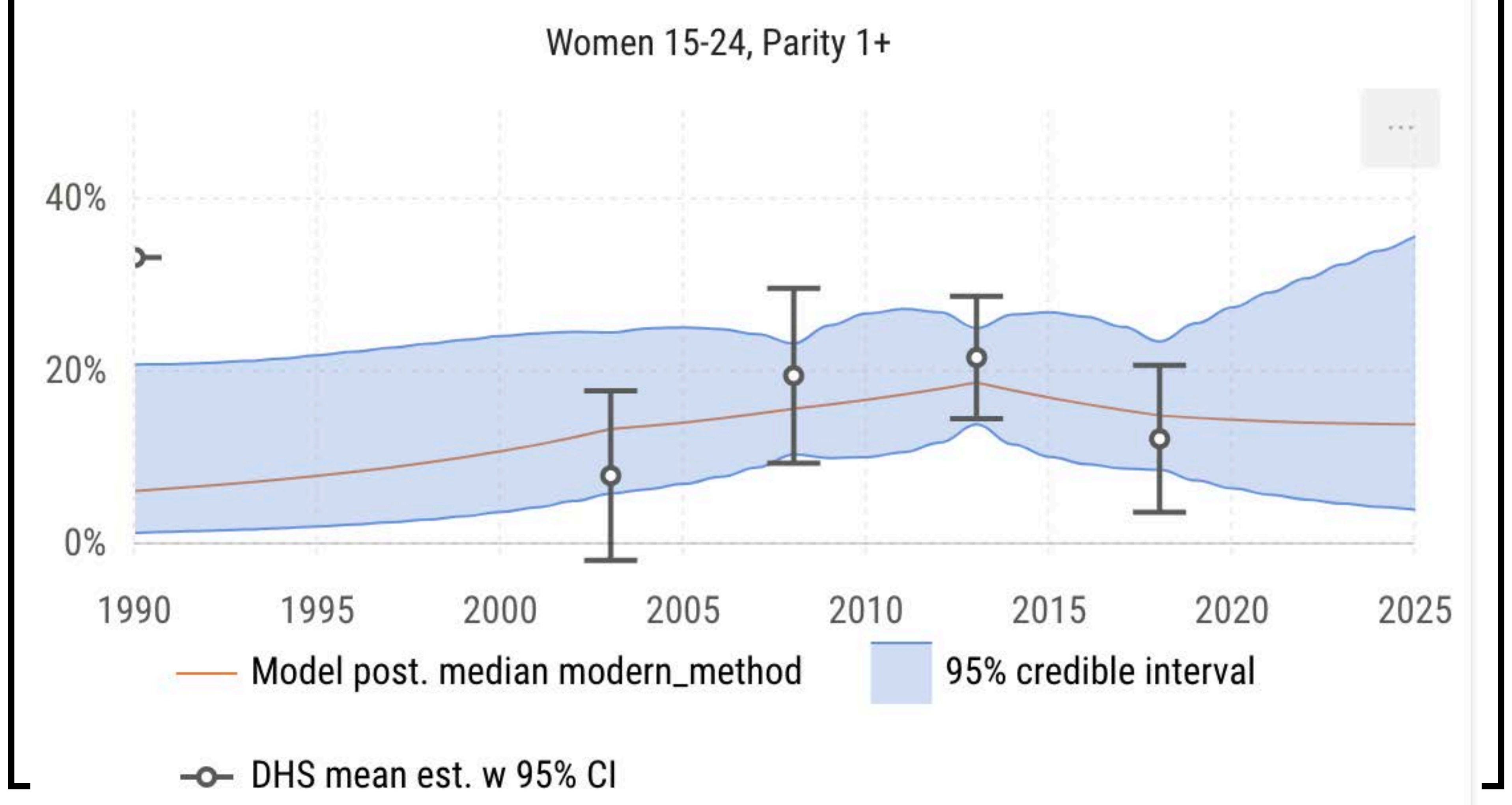


IDM subnational family planning estimation tool
Nigeria Federal Capital Territory, mCPR



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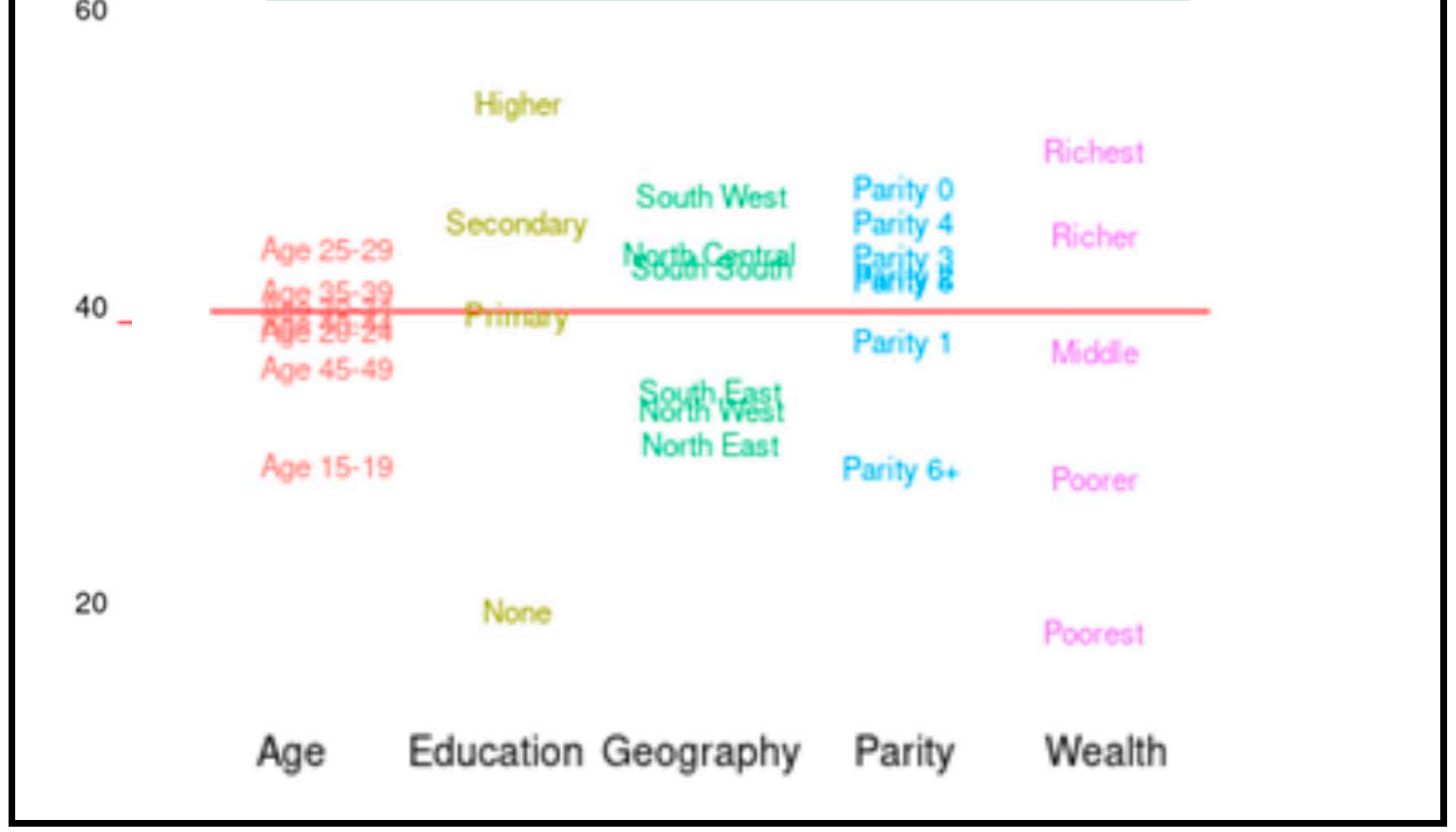

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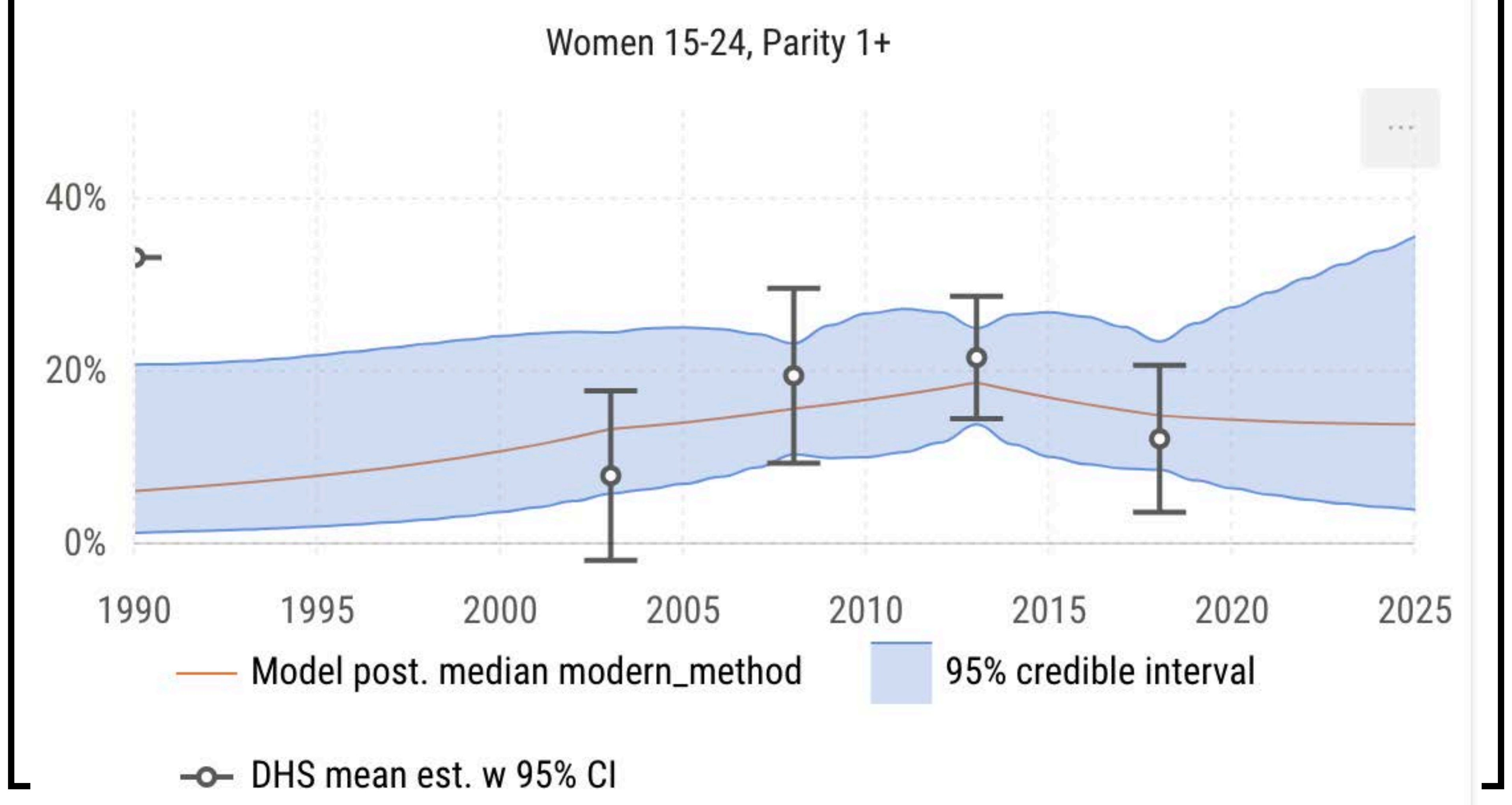

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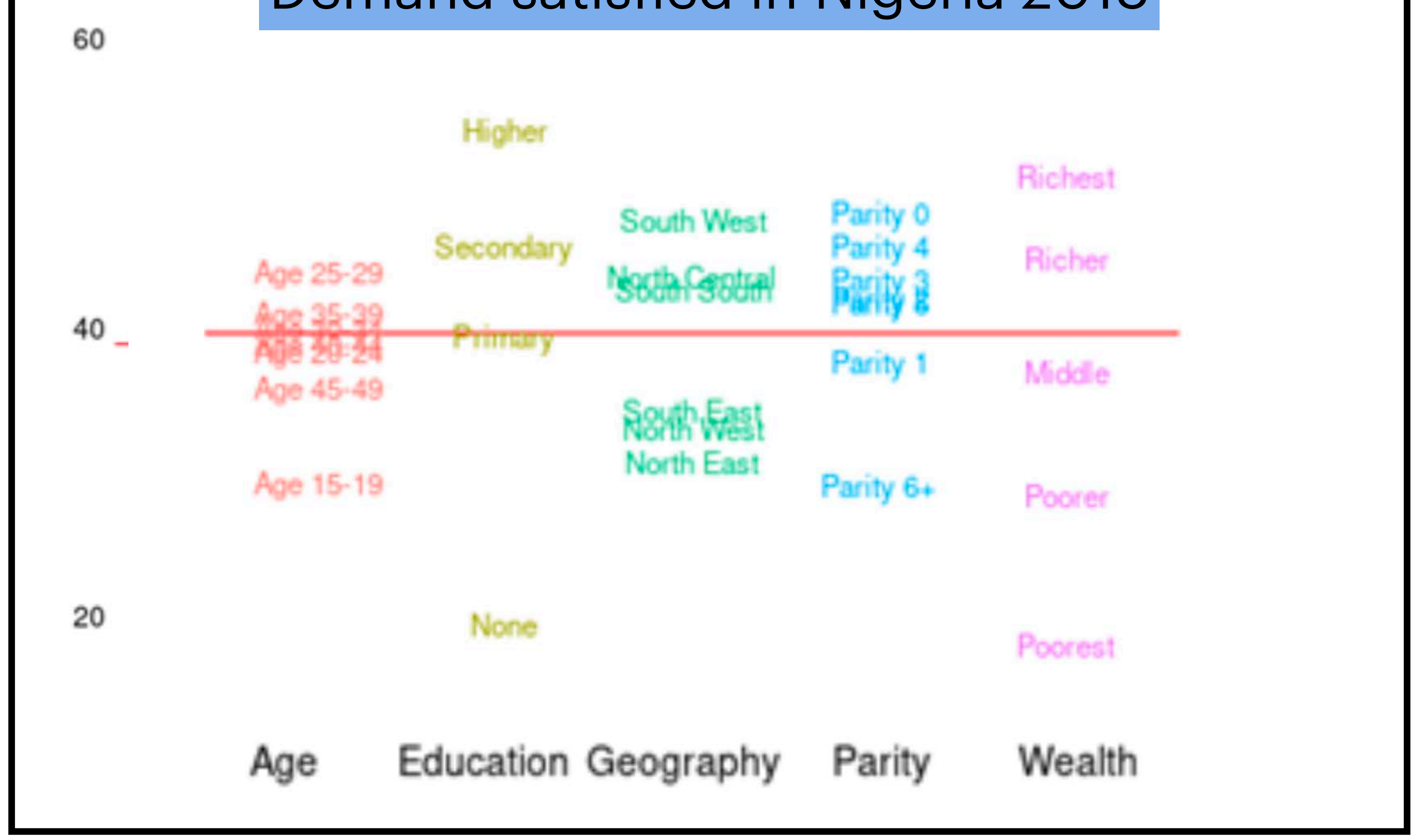

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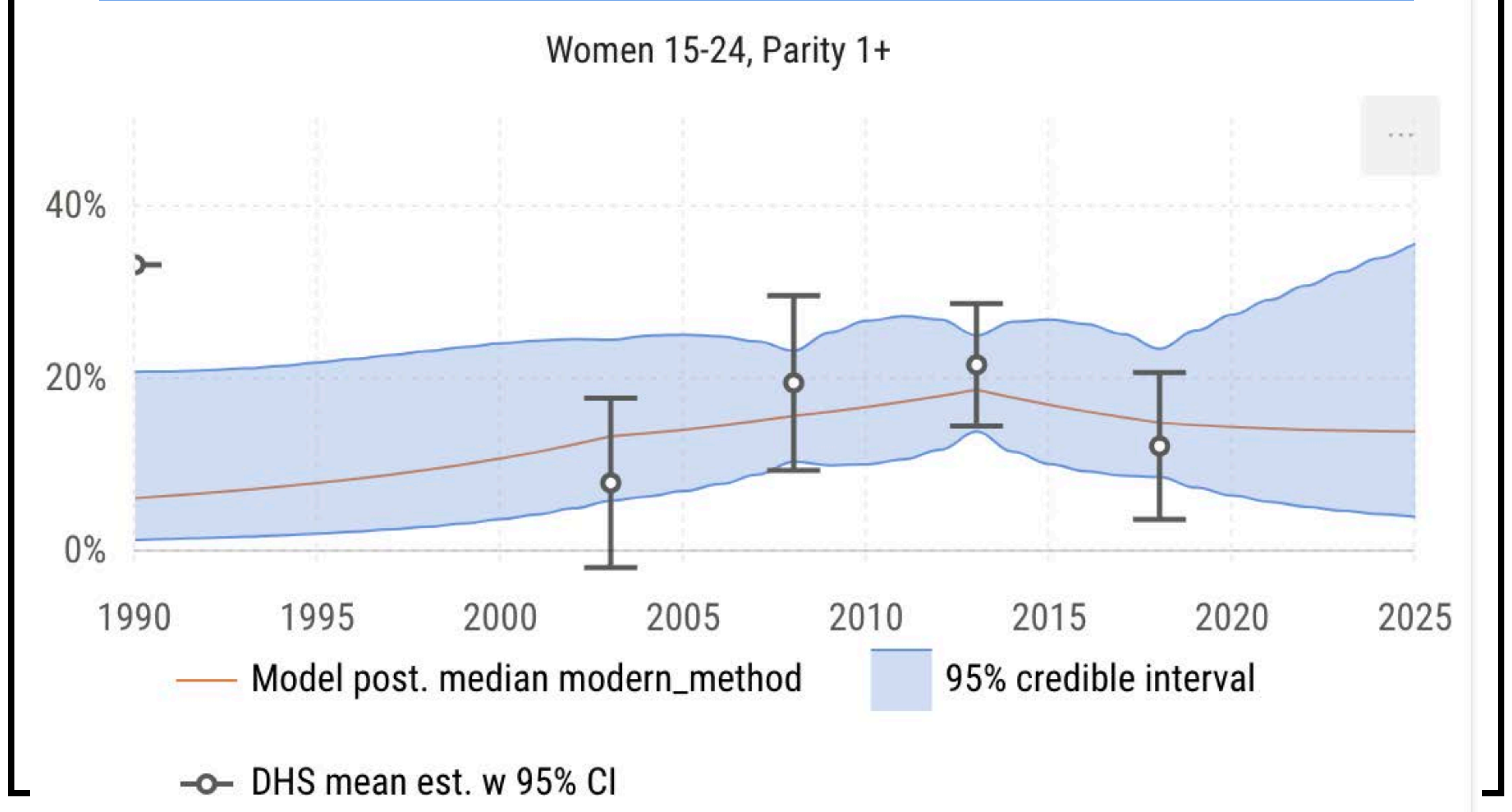

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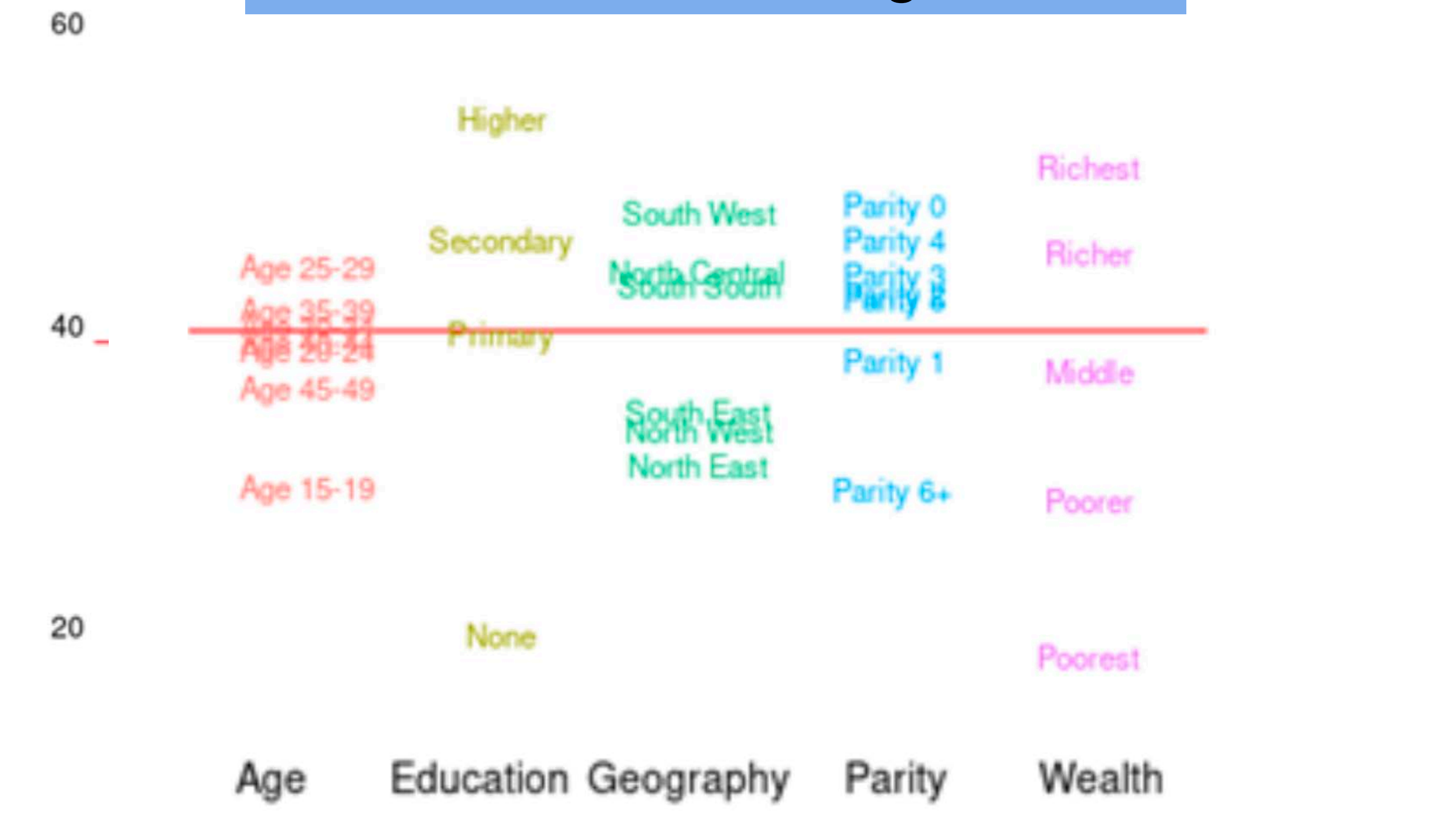

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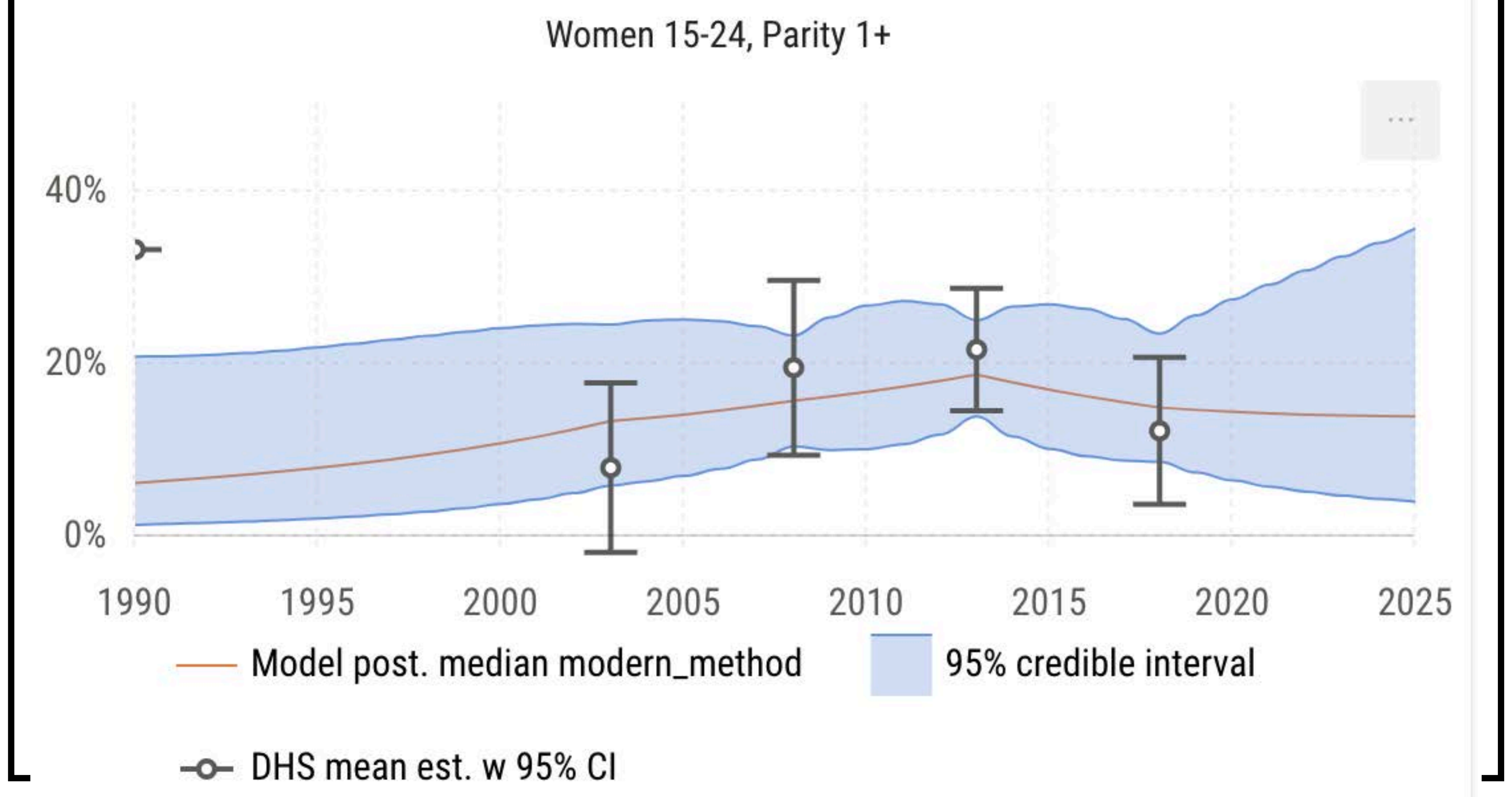

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  - The difficulty: data sparsity & so many groups to consider

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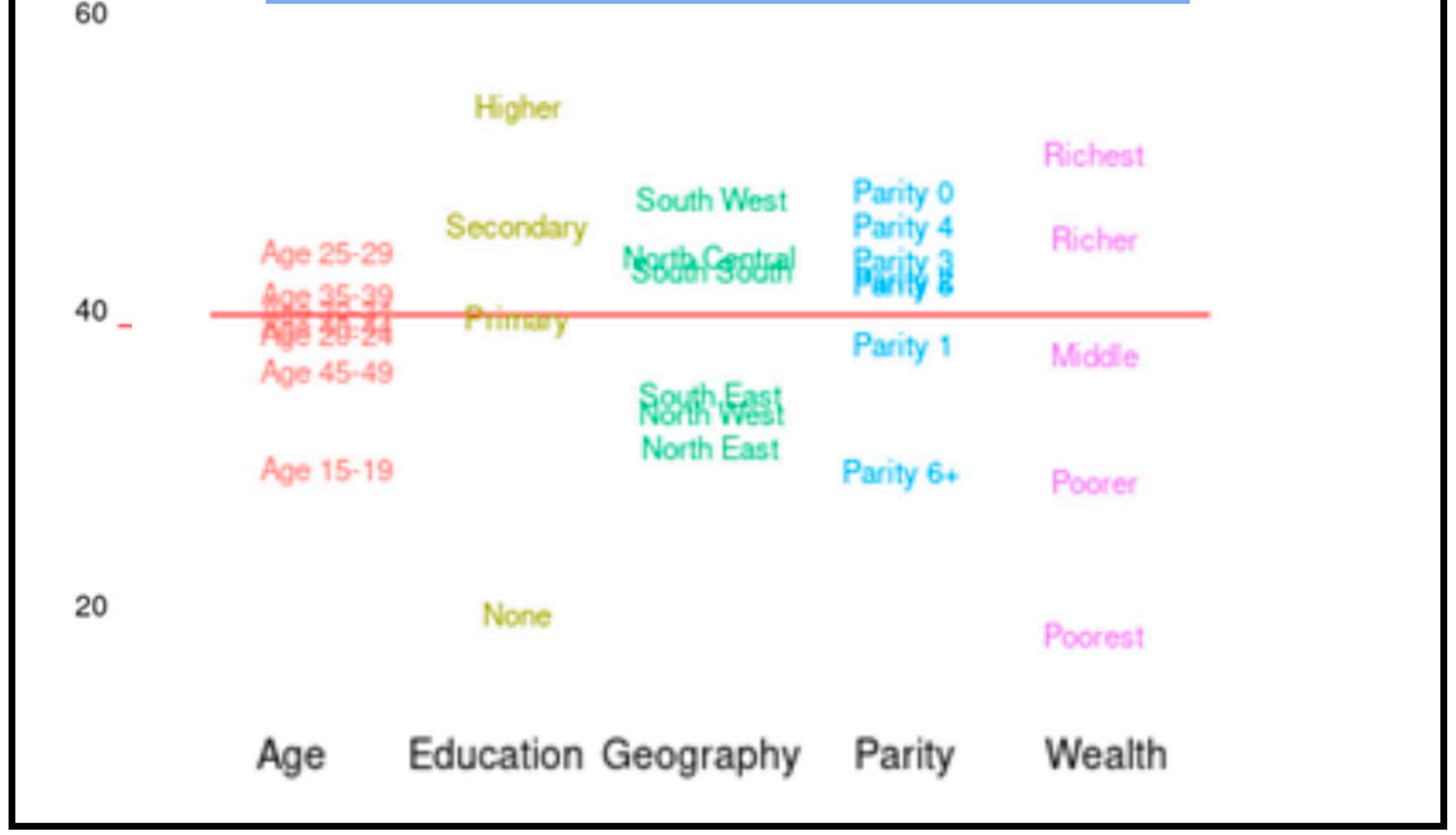

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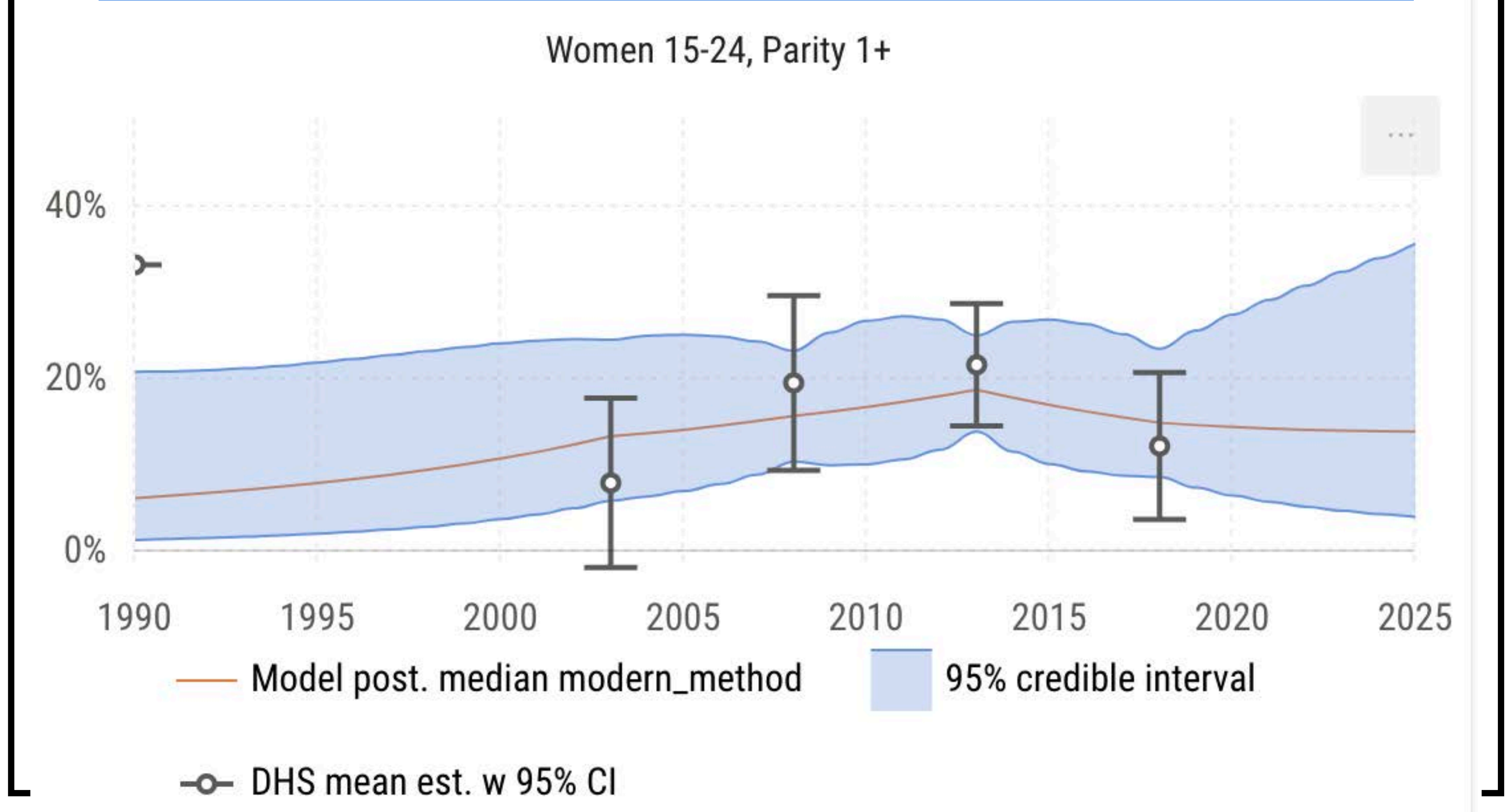

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- *Approach:* Bayesian hierarchical sparse regression model
  - Joint work with Jadey Wu, Zhengfan Wang, and Chuchu Wei (UMass Amherst)

Bayesian hierarchical sparse regression model

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

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

Expression for μ_g:

$$\text{logit}(\mu_g) = \alpha_{r[g]} + \sum_{d=1}^{D} \sum_{k=1}^{K_d} (\beta_k^{(d)} + \eta_{r[g],k}^{(d)}) x_{k,g}^{(d)} + \sum_{d_1=1}^{D} \sum_{k_1 \neq k_1^*} \sum_{d_2 \neq d_1} \sum_{k_2=1}^{K_{d_2}} \beta_{k_1,k_2}^{(d_1,d_2)} x_{k_1,g}^{(d_1)} x_{k_2,g}^{(d_2)} + \varepsilon_g \text{ where}$$

- $x_{k,g}^{(d)}$ = 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.
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Bayesian hierarchical sparse regression model

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Specify subgroup-specific outcomes using

- main effects and 2nd order interaction terms,
- region-specific intercepts and regression coefficients,
- group-specific term ε_g

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Parameters:

- Regional intercepts α_r and regression parameters $\eta_r^{(d)}$ are estimated hierarchically/with spatial structure
- Regression coefficients for main effects $\beta_{k=1:K_d}^{(d)}$ and interaction terms $\beta_{k_1,k_2=1:K_{d_2}}^{(d_1,d_2)}$ 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 ε_g captures unexplained variability across groups and is estimated hierarchically, i.e. $\varepsilon_g \mid \sigma_\varepsilon \sim N(0, \sigma_\varepsilon^2)$

Bayesian hierarchical sparse regression model (ctd)

Capture differences across regions

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Bayesian hierarchical sparse regression model (ctd)

Capture differences across regions

Capture relations between outcome and each covariate, and how this relationship varies across levels of other covariates

Expression for μ_g:

$$\text{logit}(\mu_g) = \alpha_{r[g]} + \sum_{d=1}^{D}\sum_{k=1}^{K_d}(\beta_k^{(d)} + \eta_{r[g],k}^{(d)})x_{k,g}^{(d)} + \sum_{d_1=1}^{D}\sum_{k_1 \neq k_1^*}\sum_{d_2 \neq d_1}\sum_{k_2=1}^{K_{d_2}}\beta_{k_1,k_2}^{(d_1,d_2)}x_{k_1,g}^{(d_1)}x_{k_2,g}^{(d_2)} + \varepsilon_g$$

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Capture differences across subgroups that are not explained by covariates

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Producing model-based estimates of FP indicators for small groups (ctd)

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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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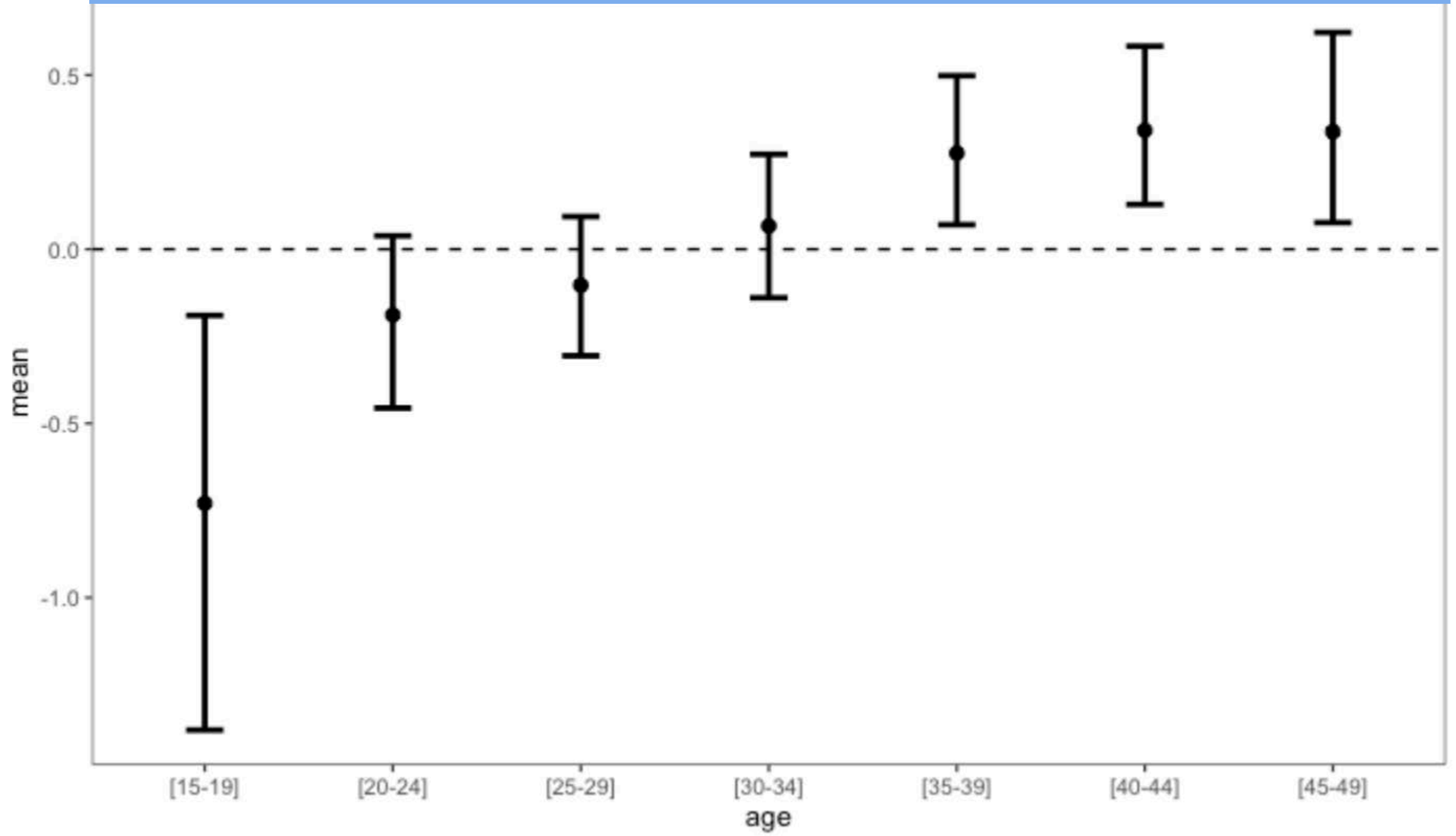
Main effects for age:
Demand satisfied increases with age



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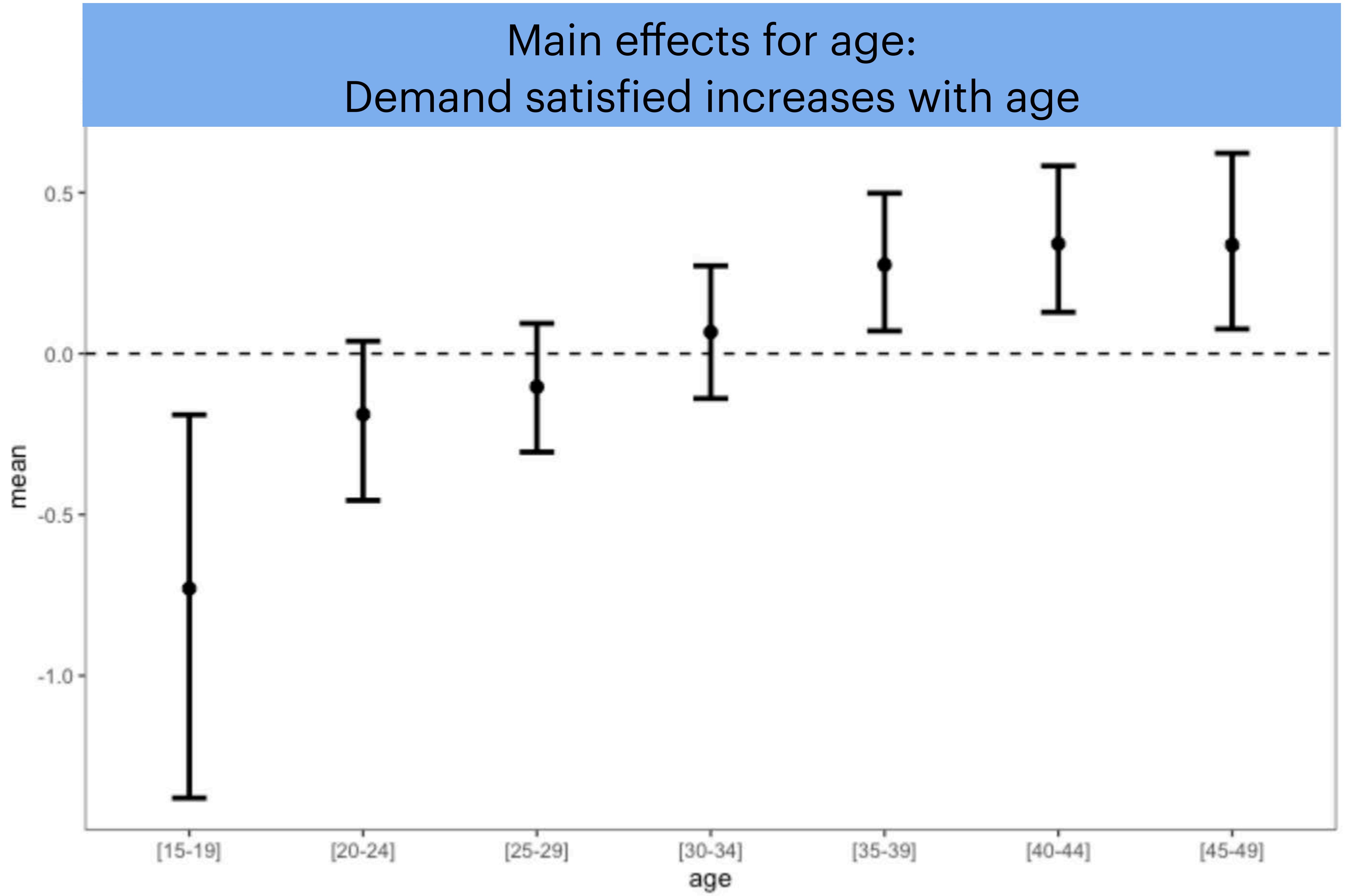

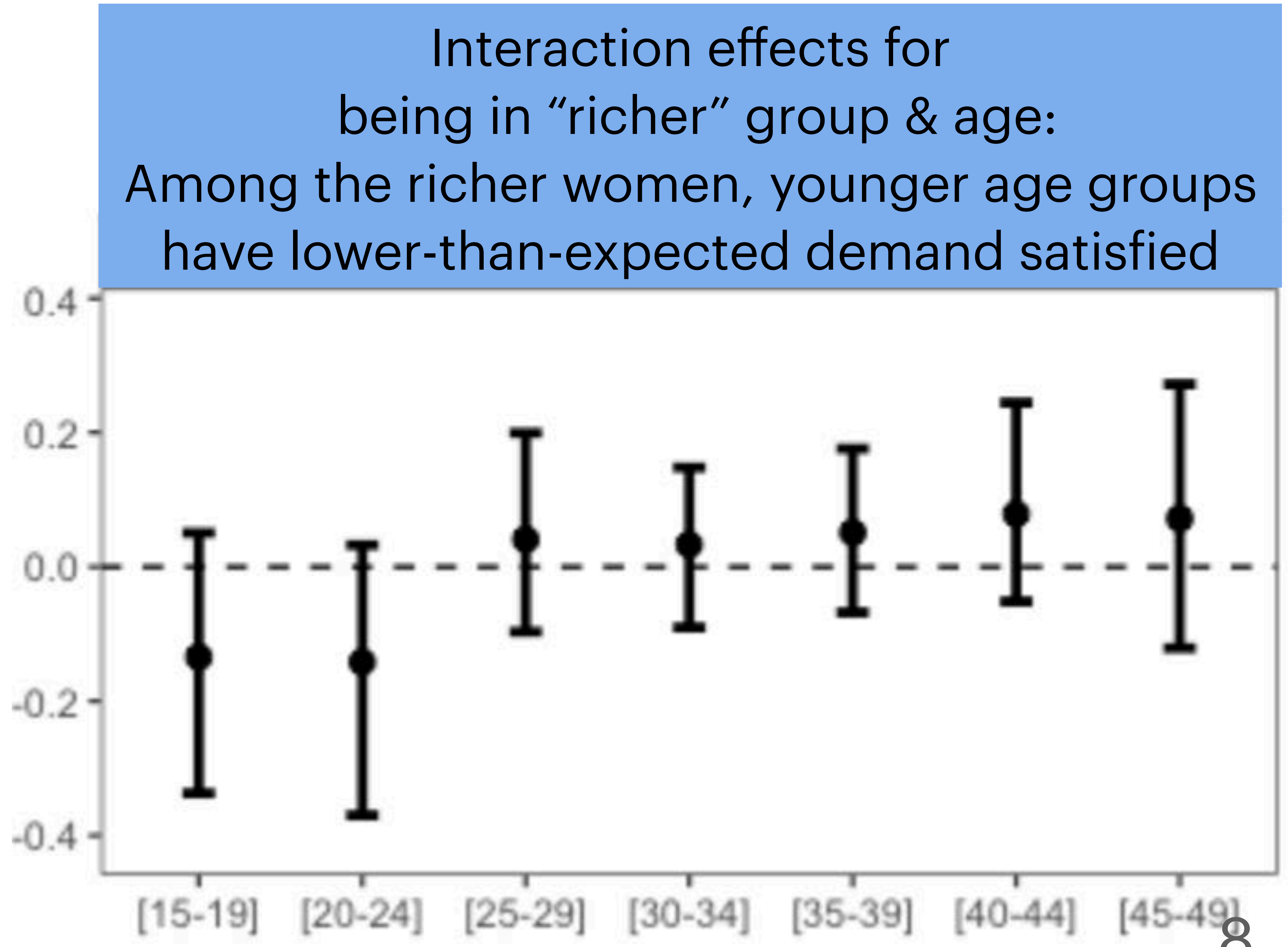

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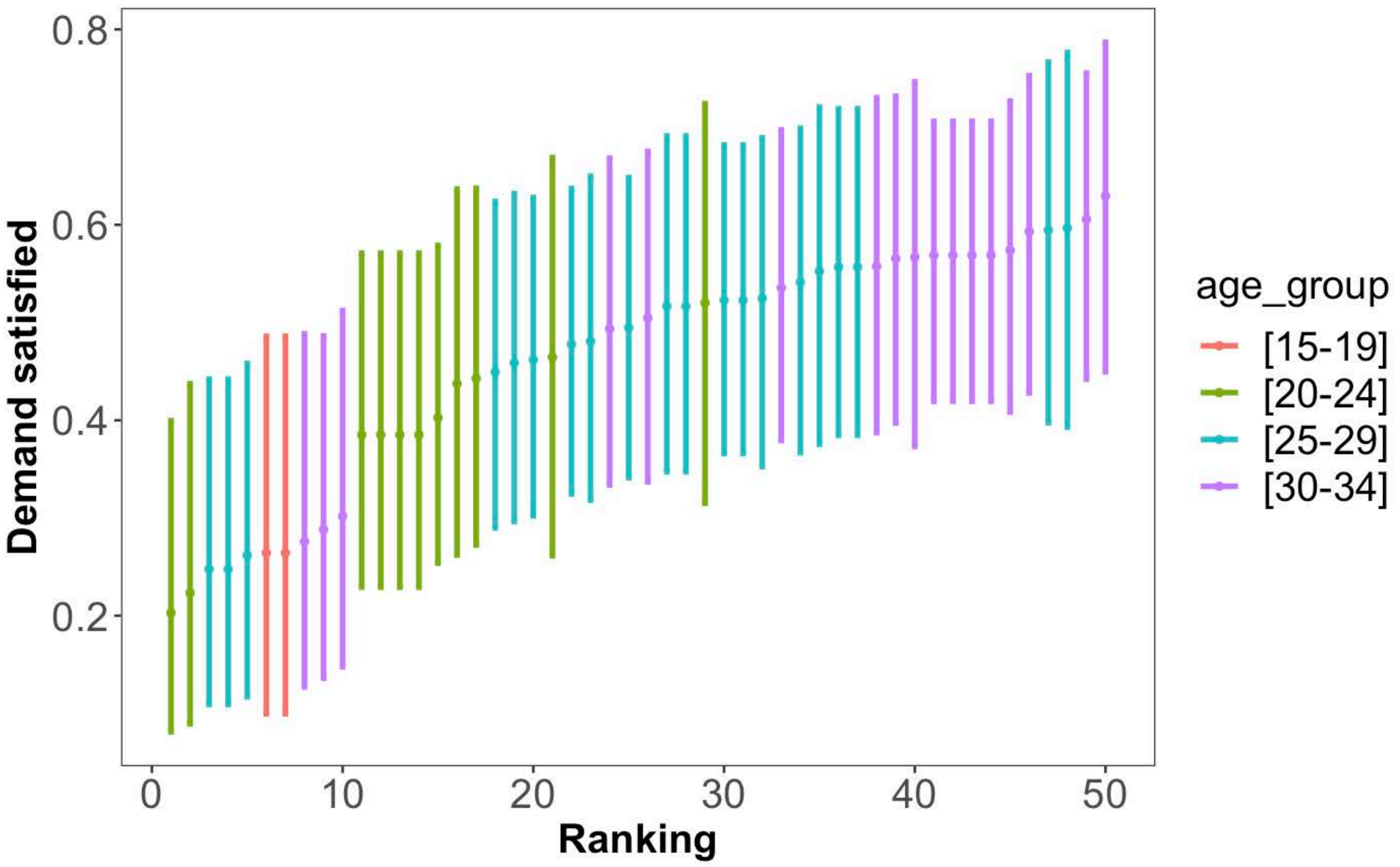
Demand satisfied for Federal Capital Territory, for women in richer subgroups, <35 years old



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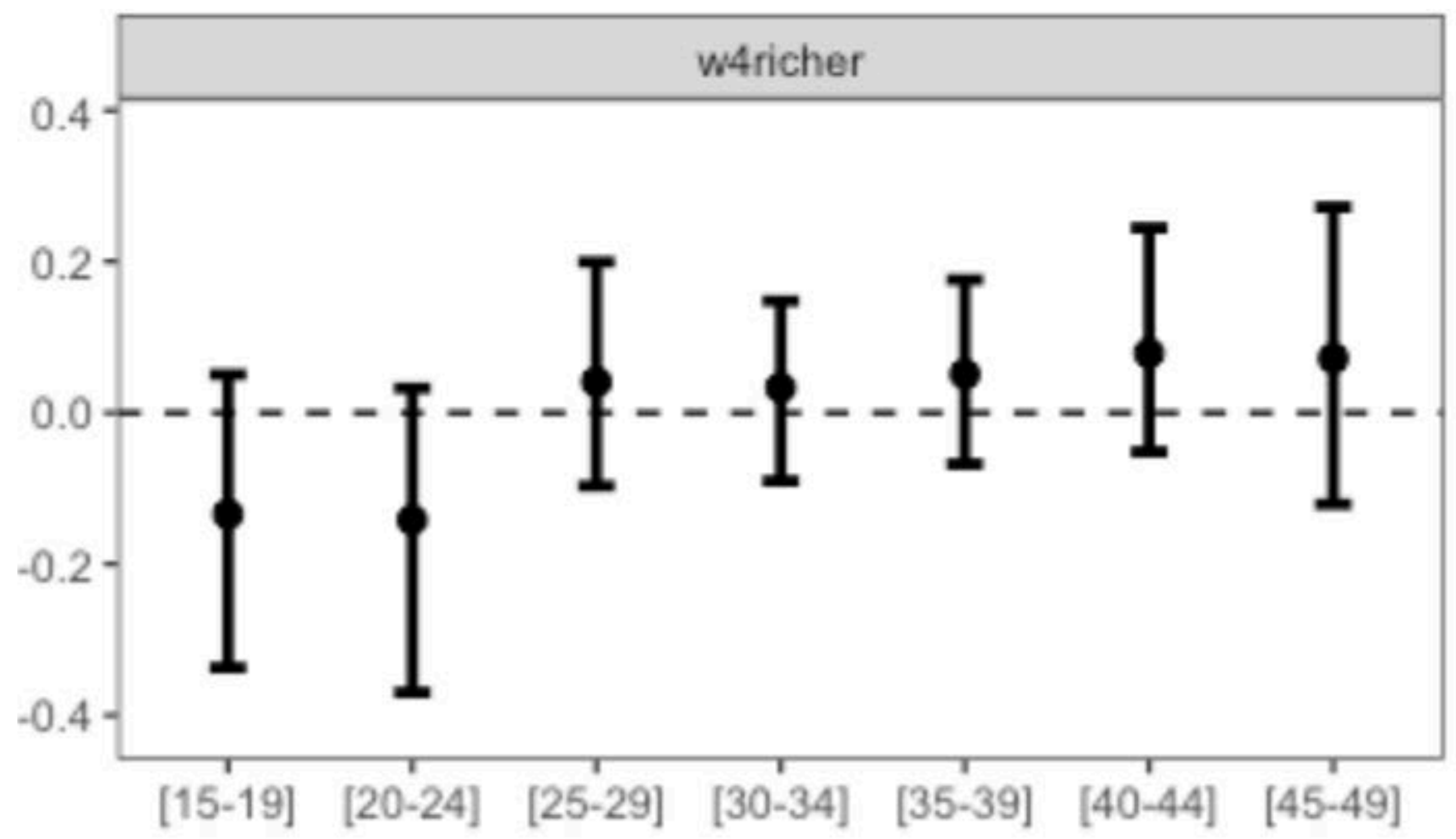

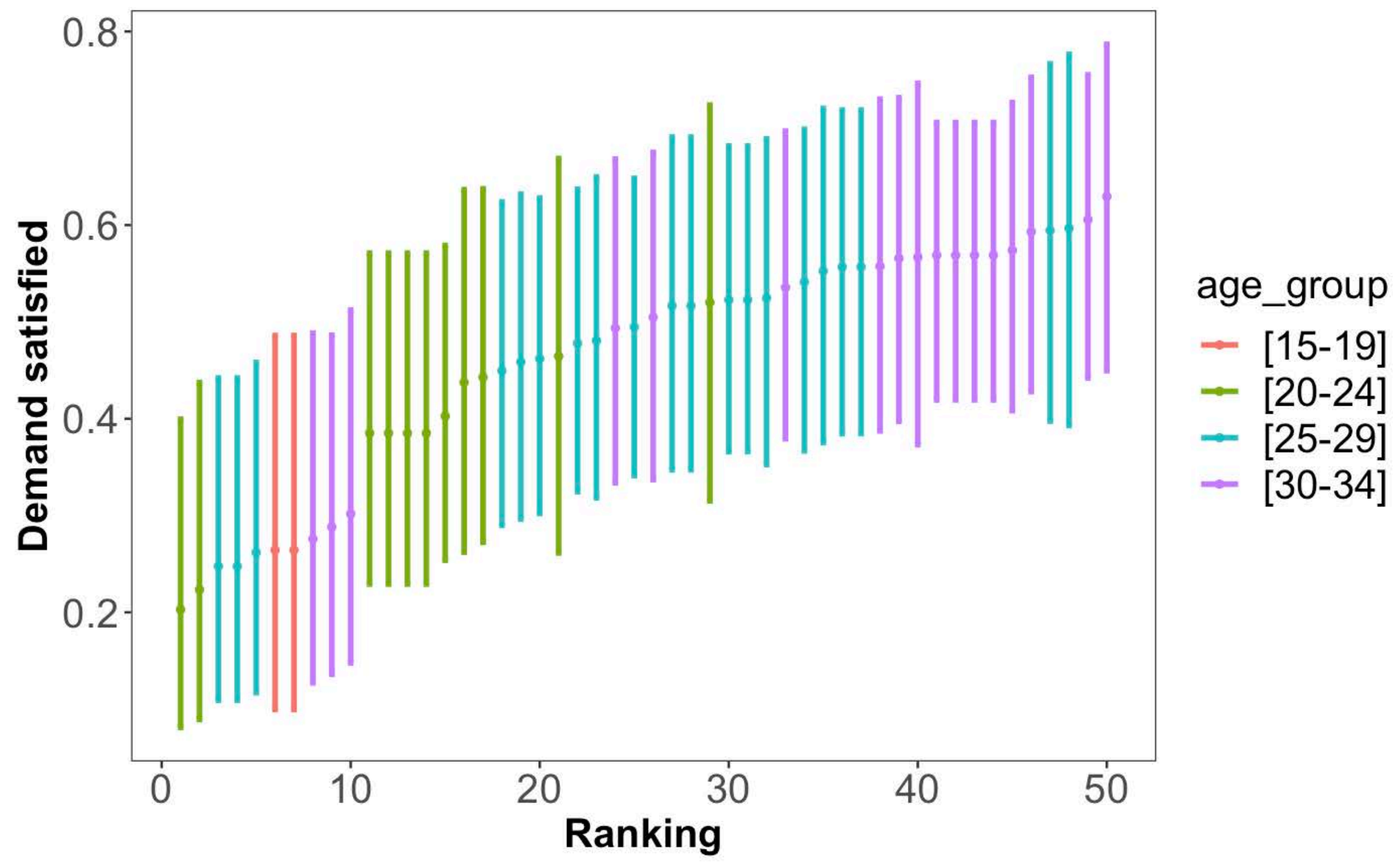

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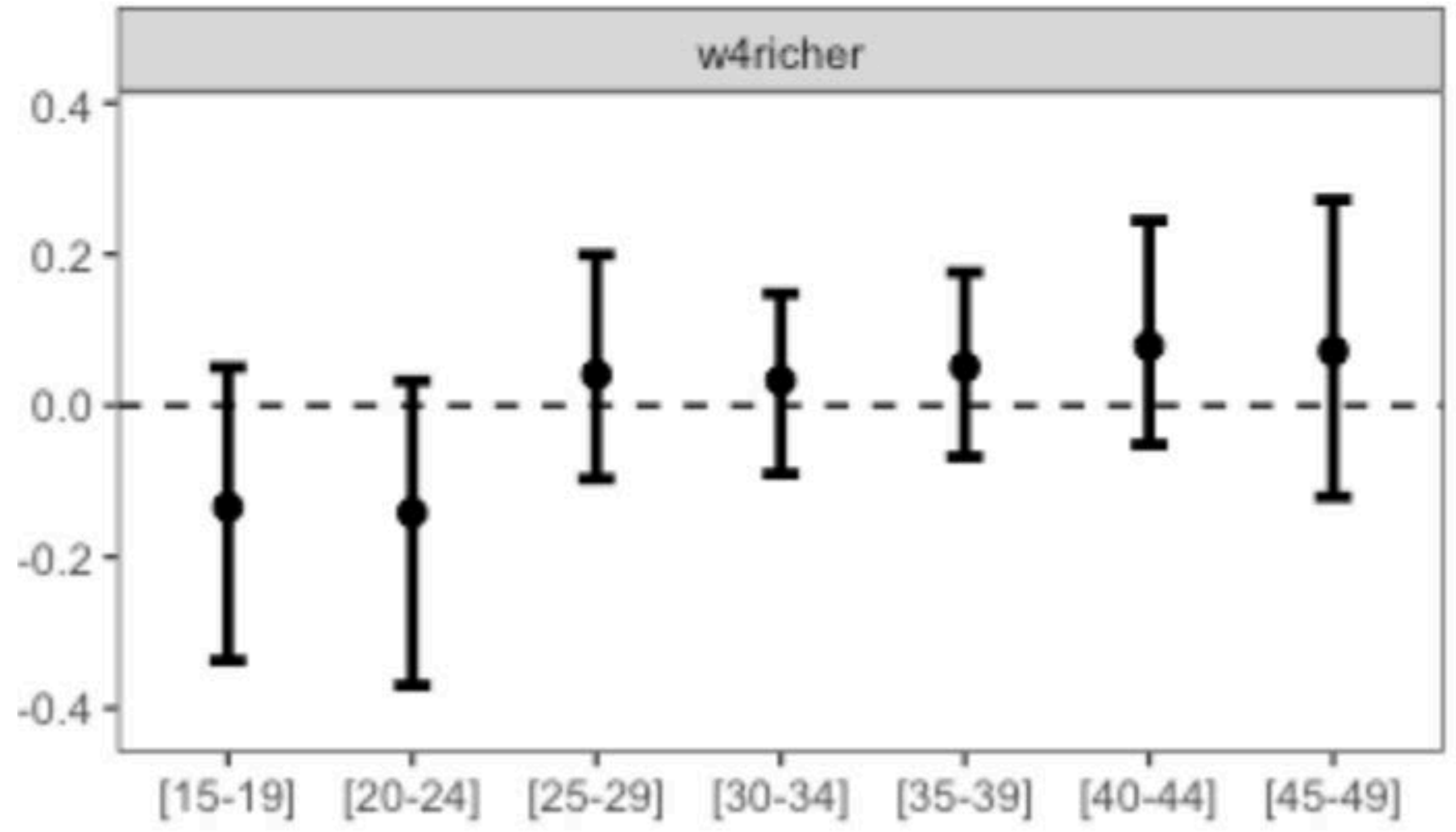

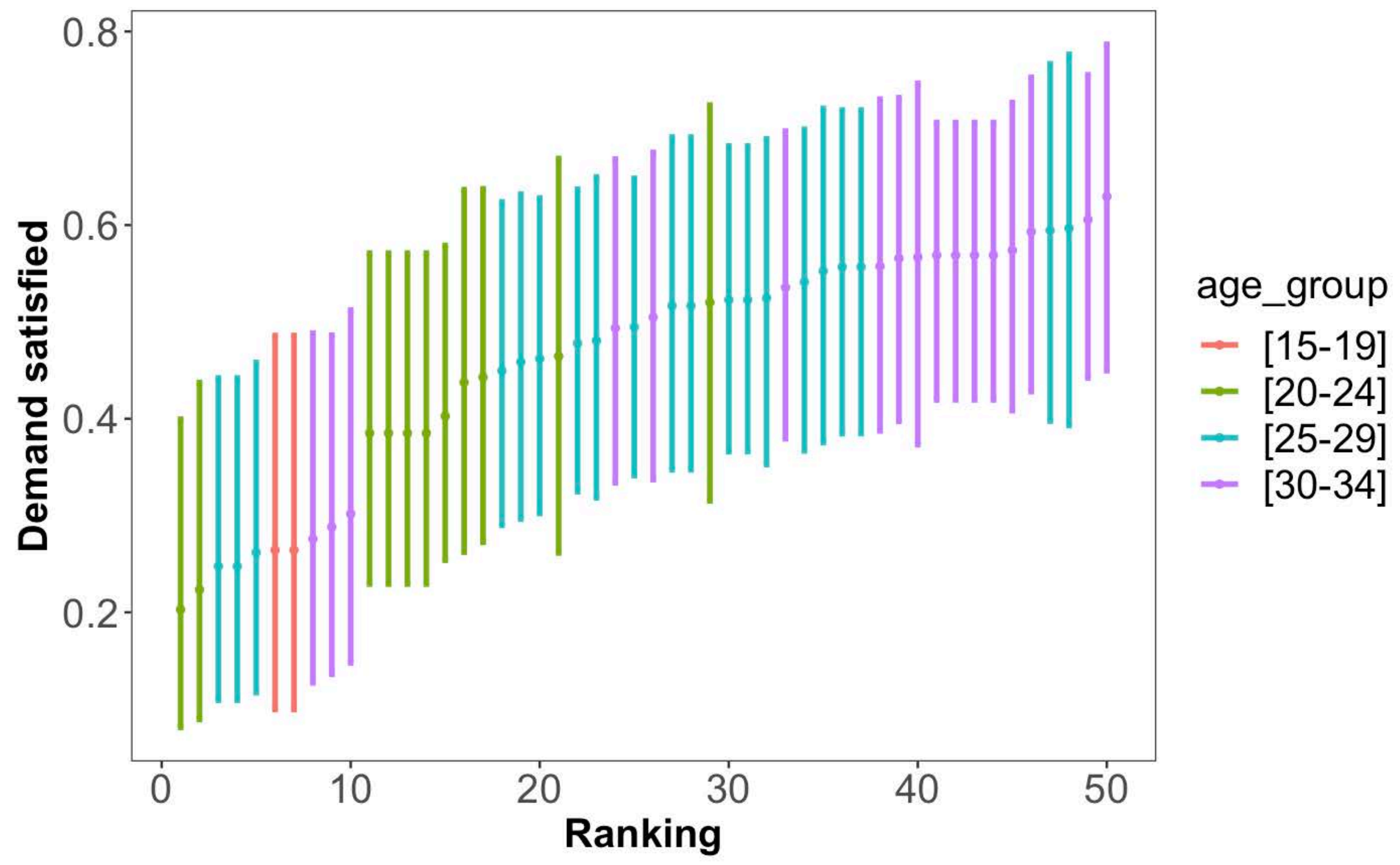

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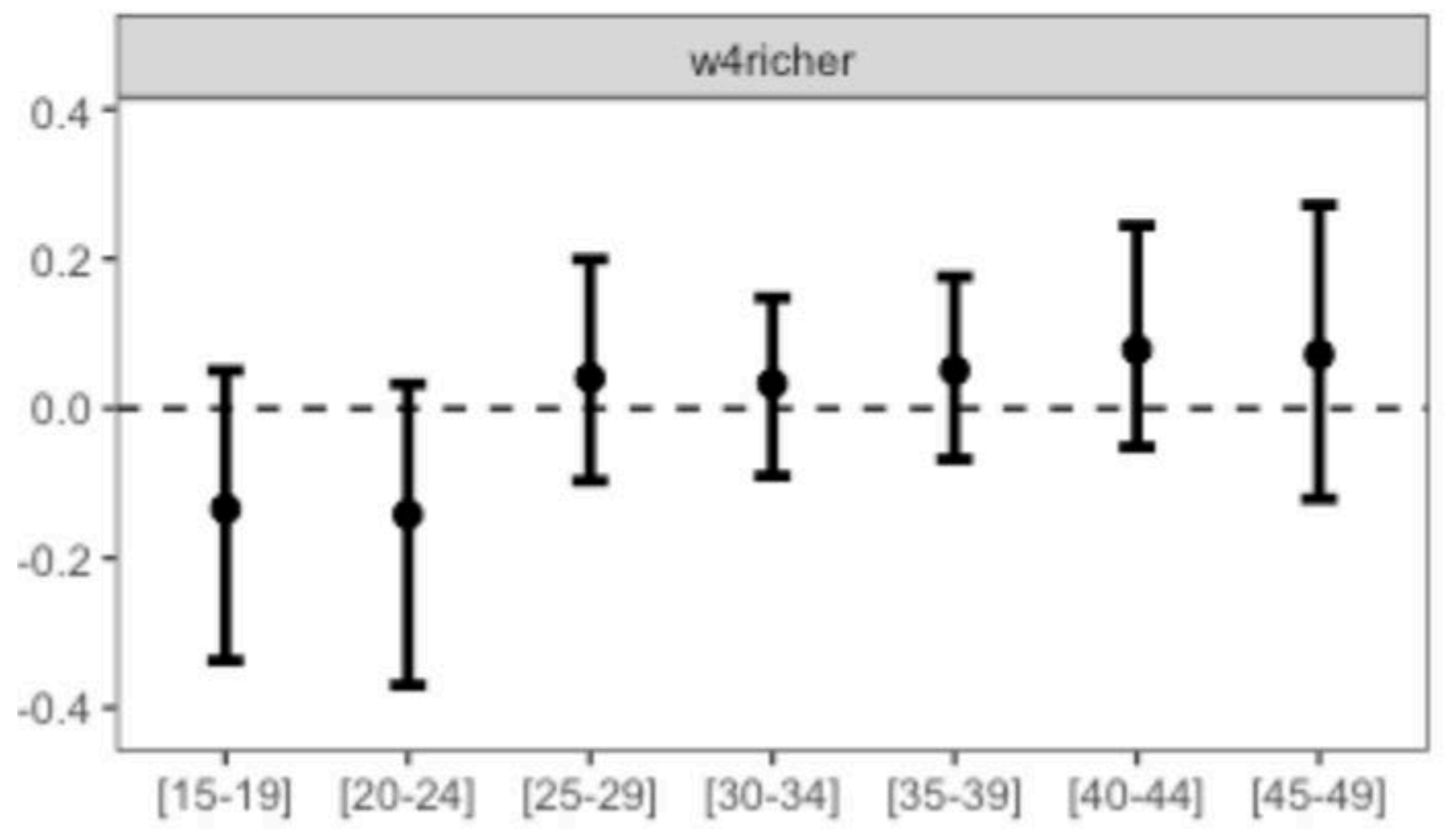
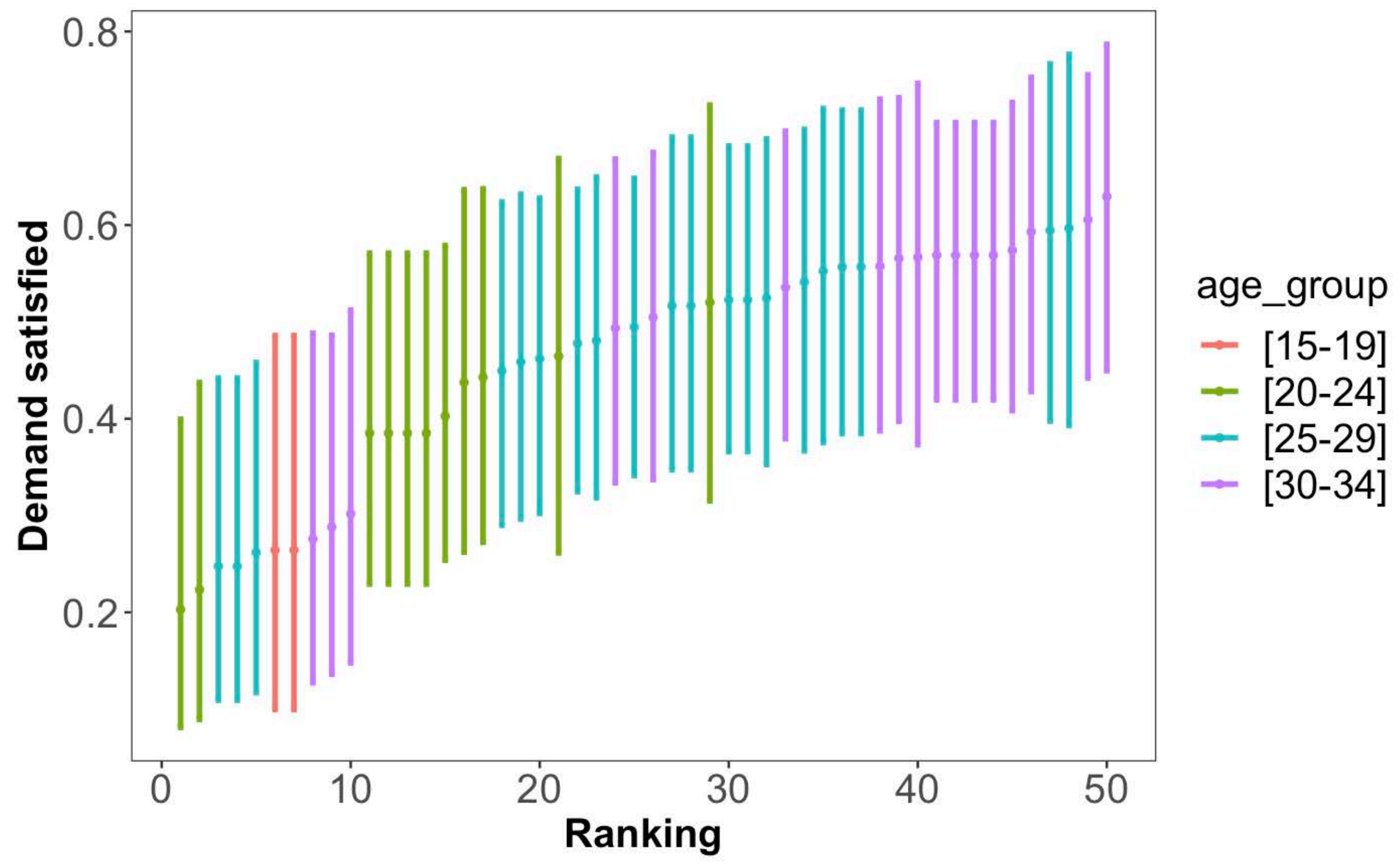
3. Consider other outcomes of interest
   - Build off recent work to define alternative measures of FP
   - E.g., better account for sexual activity, different definitions of demand and unmet need, …





What's next – the process of producing estimates

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How it started	How it's going	What's next?

What's next – the process of producing estimates

How it started

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What's next?

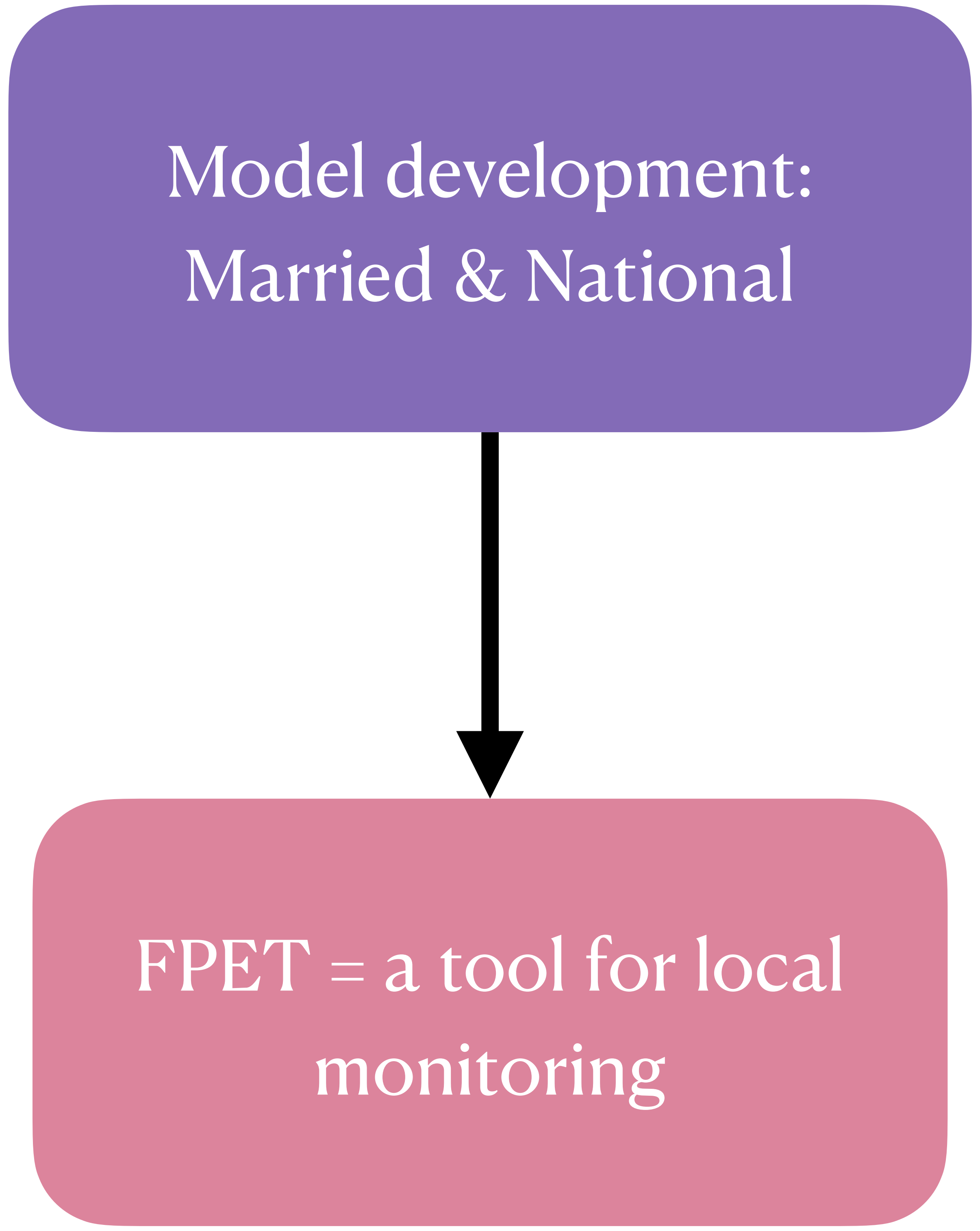
Model development: Married & National

↓

FPET = a tool for local monitoring

What's next – the process of producing estimates

How it started



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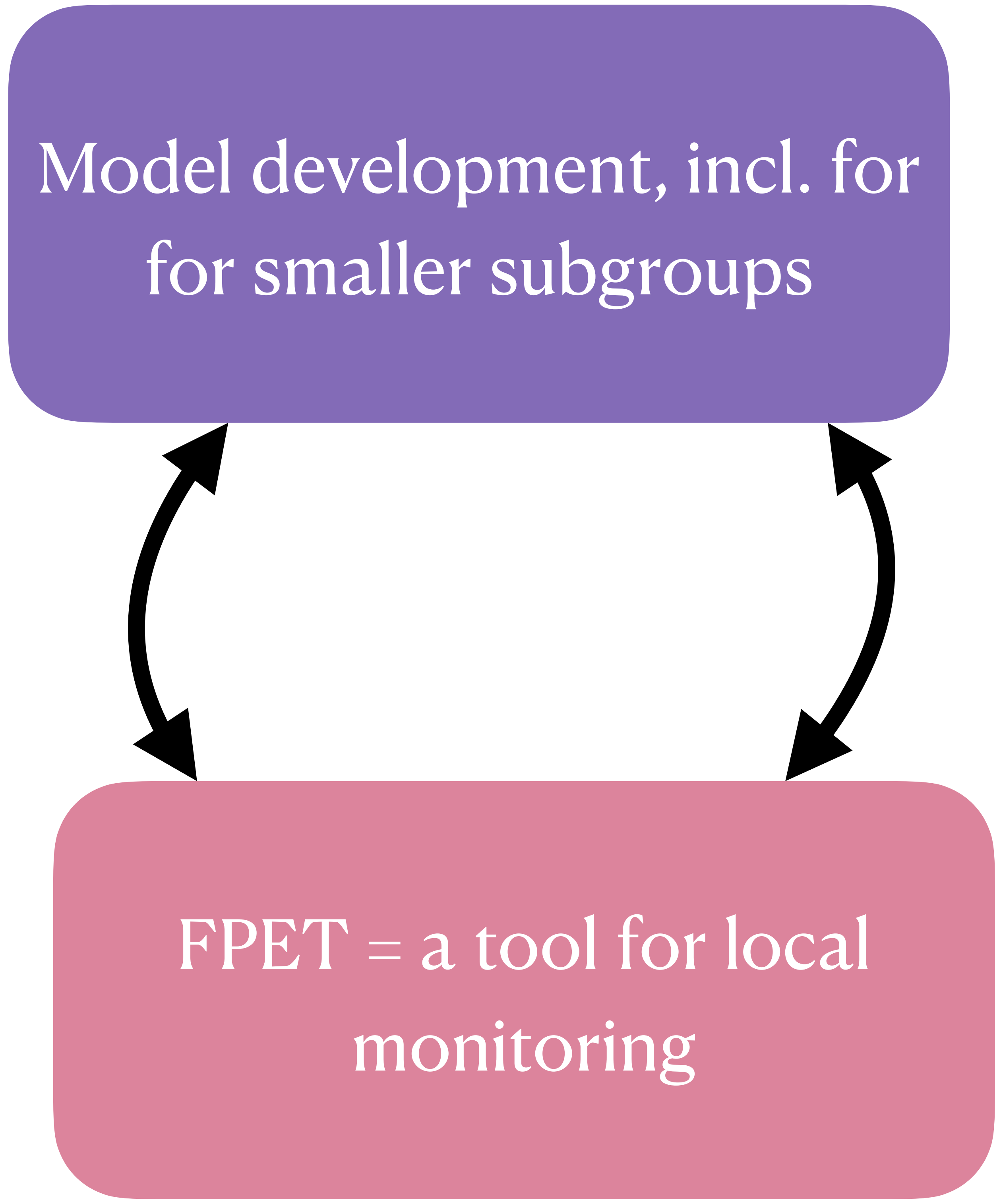

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What's next – the process of producing estimates

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FPET = a tool for local monitoring

How it's going

Model development, incl. for for smaller subgroups

FPET = a tool for local monitoring

What's next?

Locally relevant FP modeling and monitoring **by local actors**

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

Model development

FPET = a tool for local monitoring

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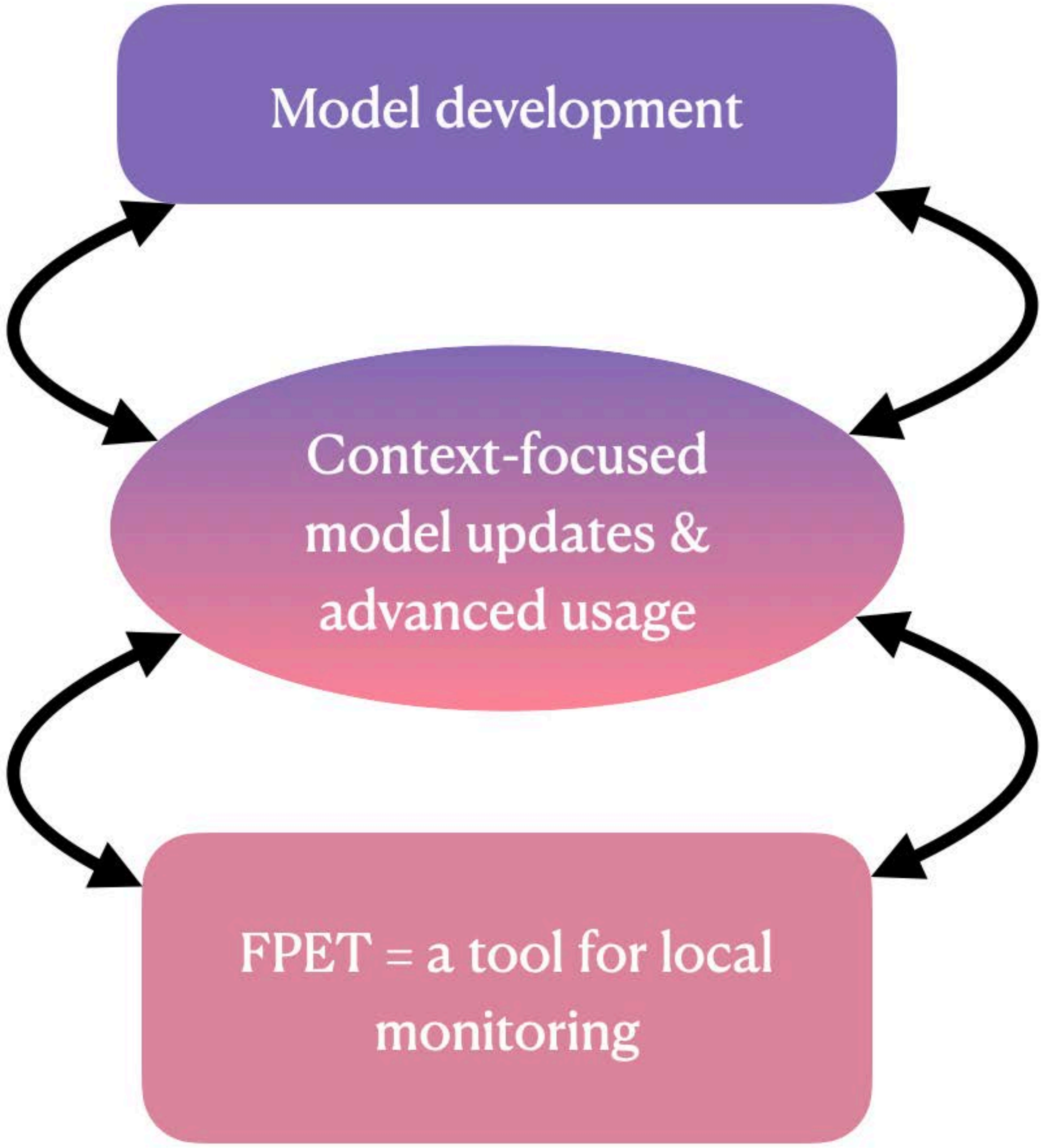

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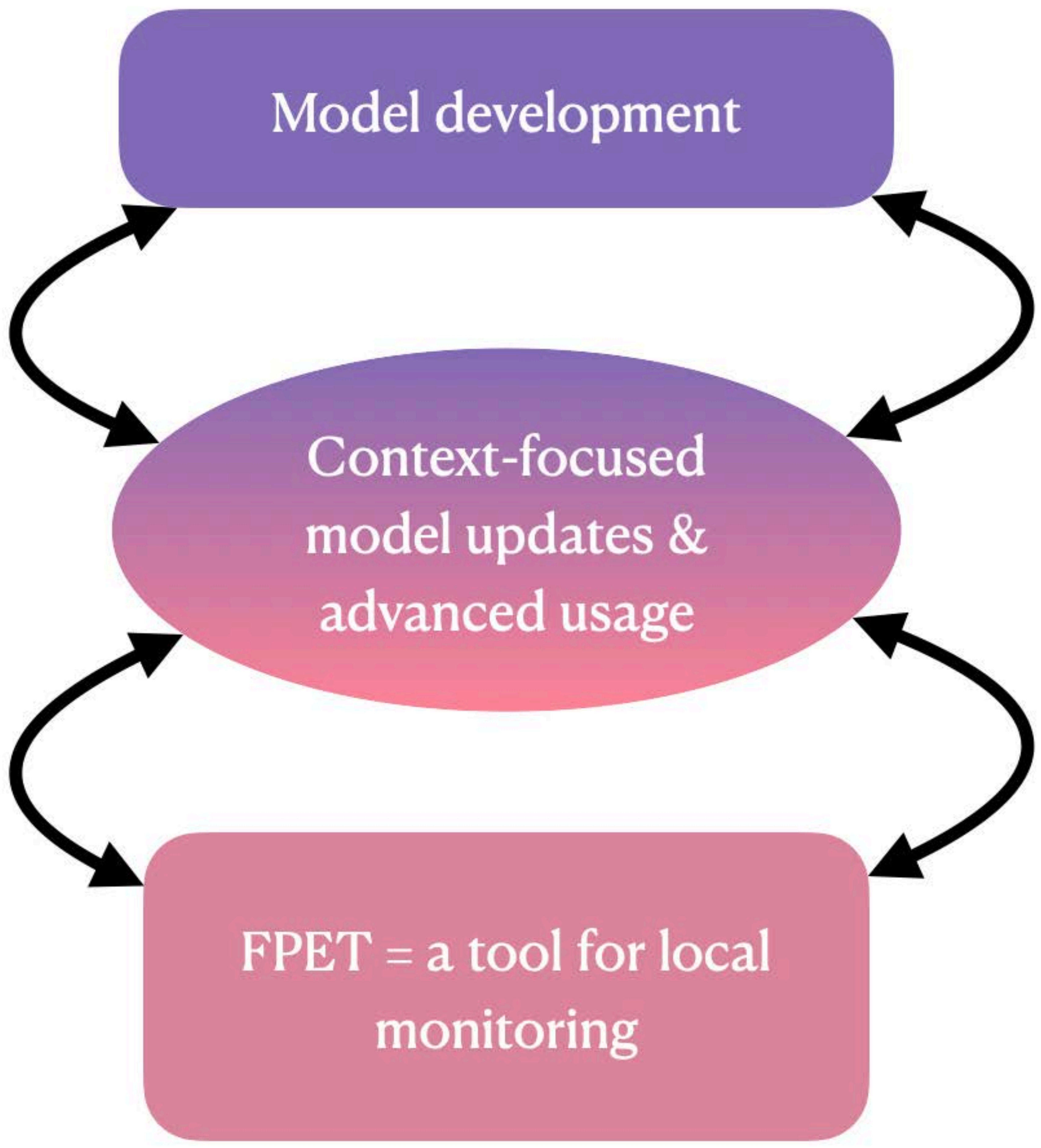

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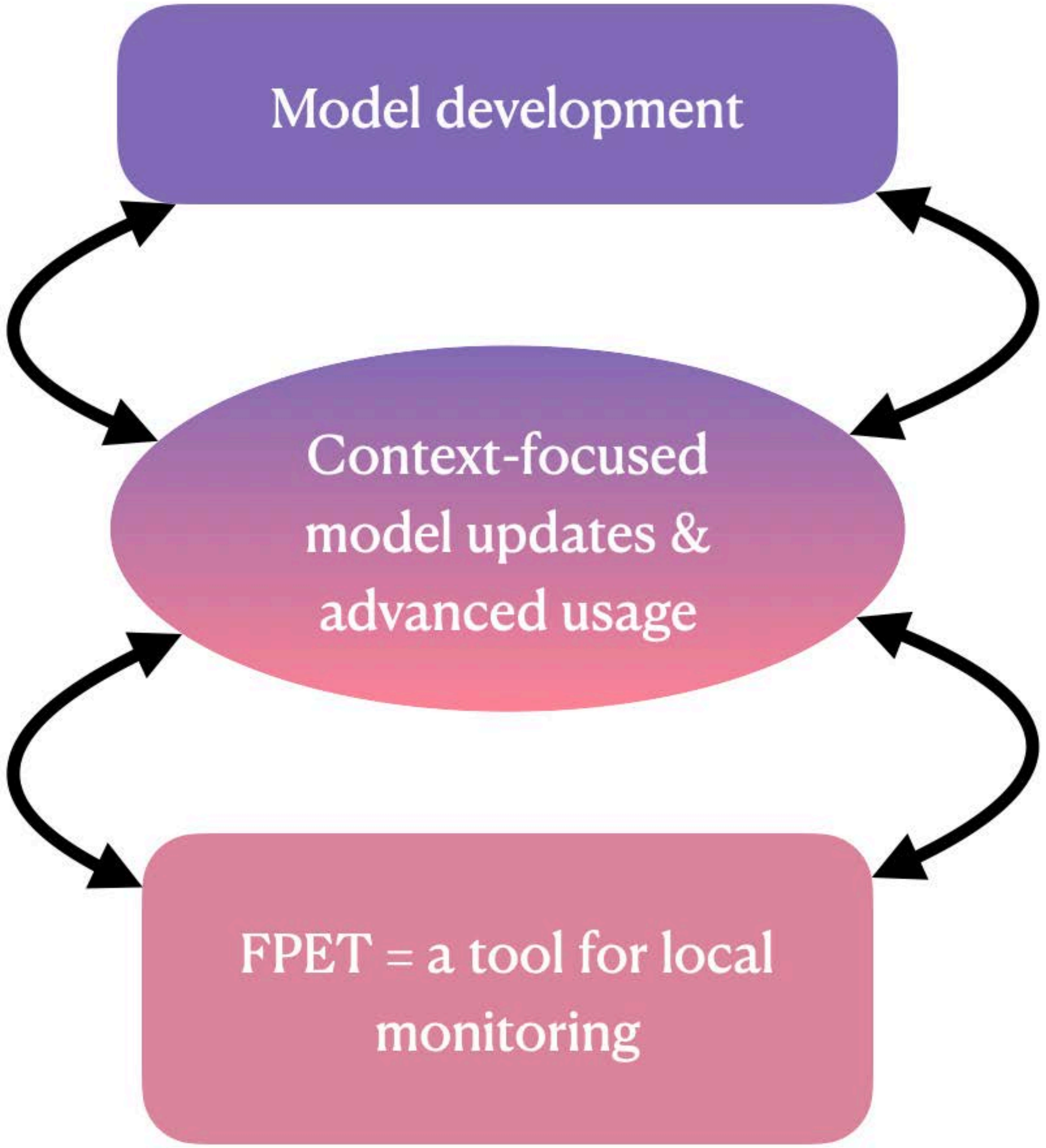

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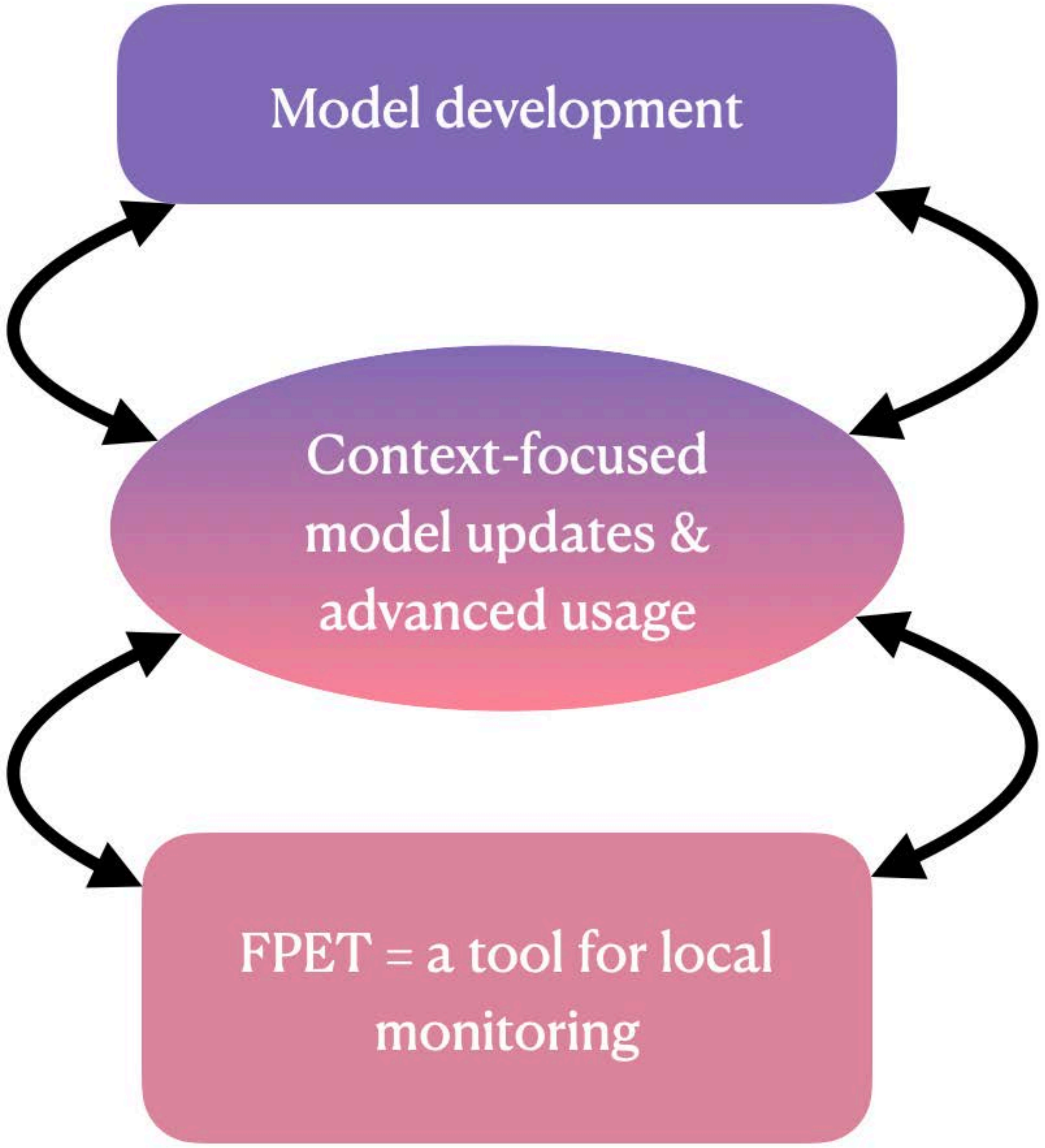

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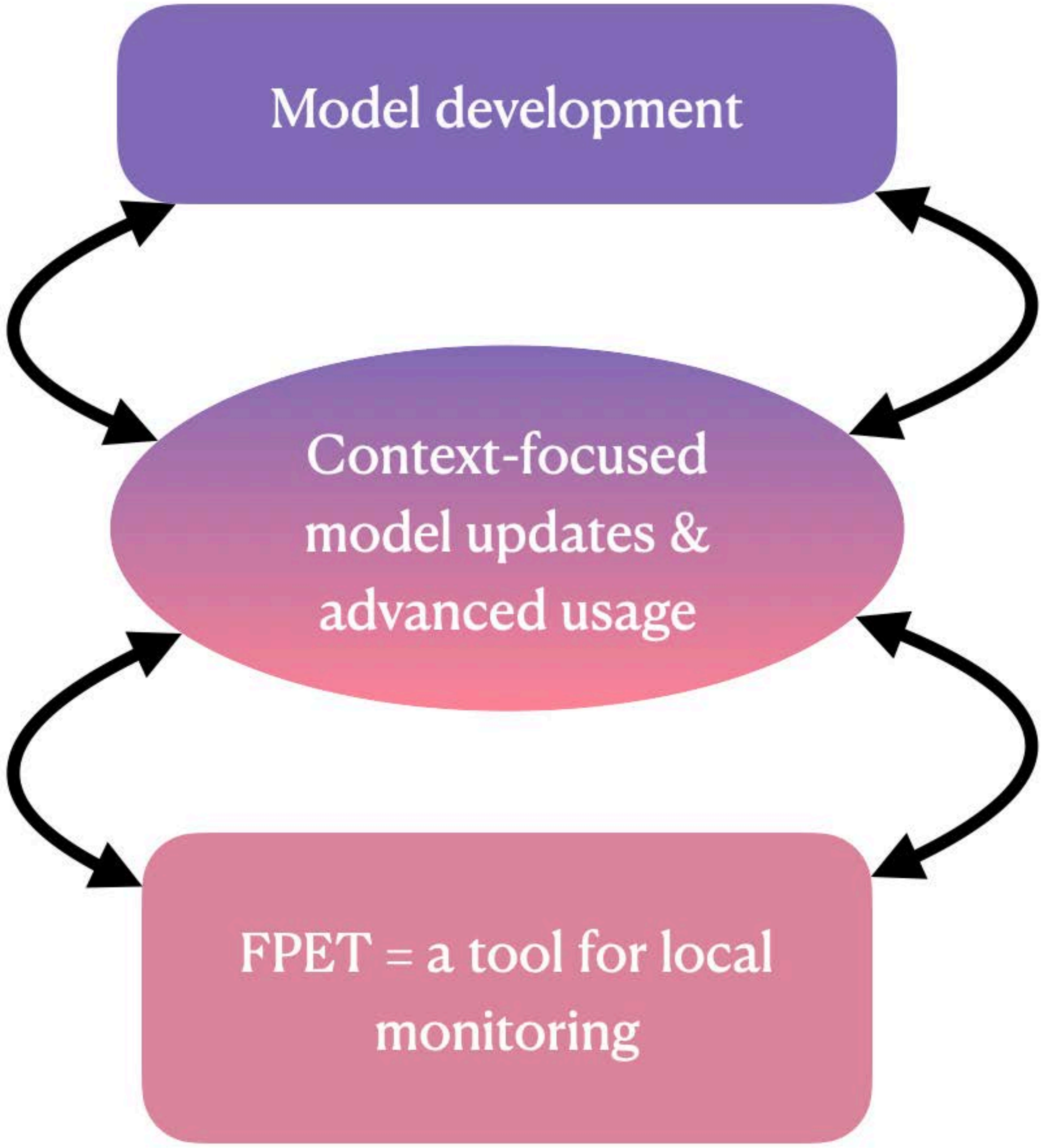

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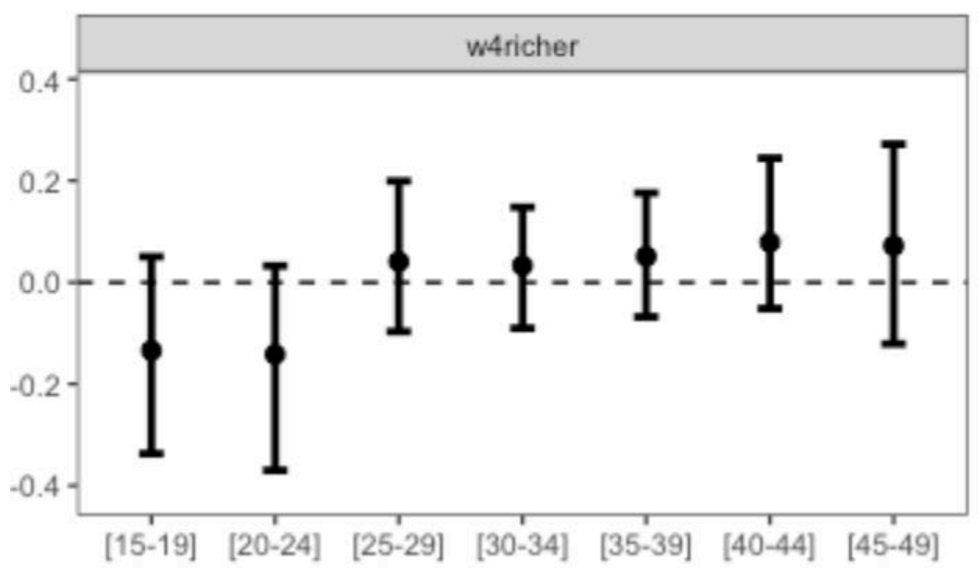
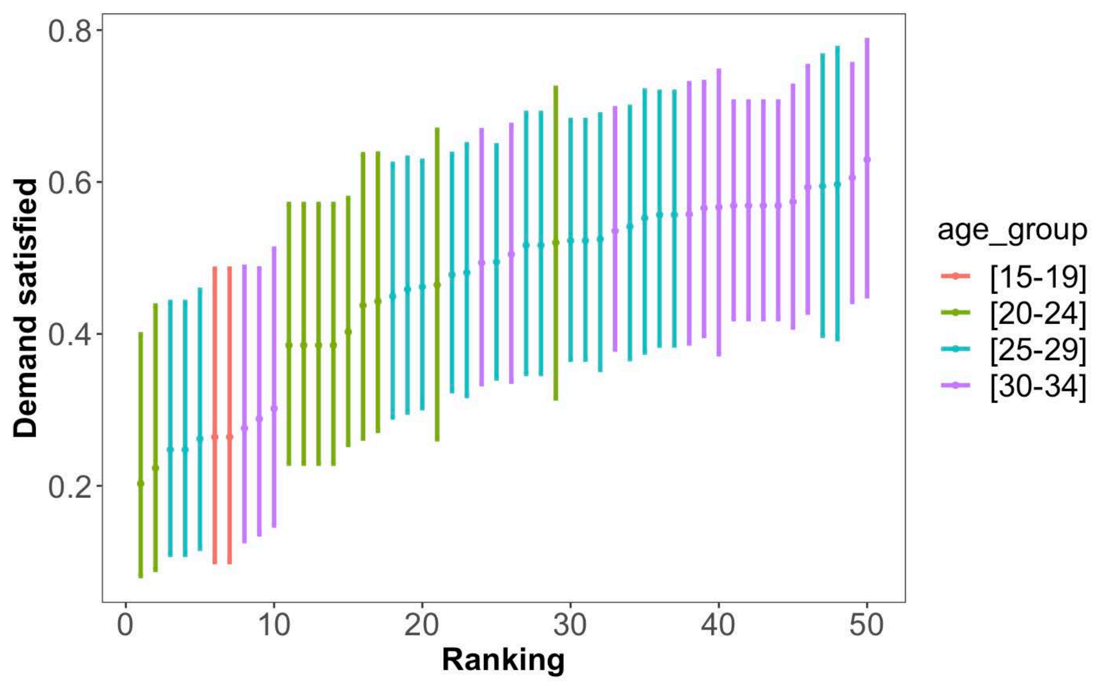
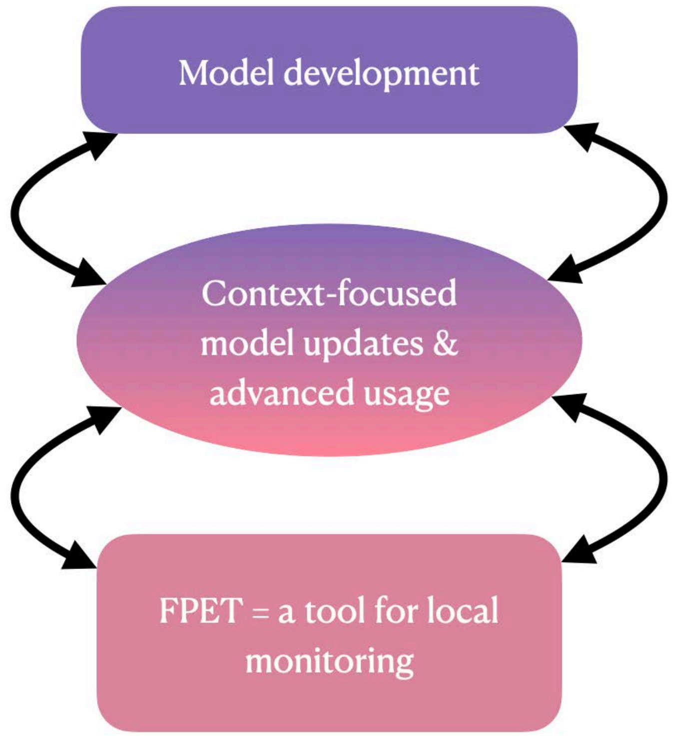
  - *Tools:* Open-source software tools and training material (e.g., R packages for data processing and model fitting; webinars); we are finalizing FPET-related tools that allow for advanced usage.

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?







Contact: Leontine Alkema (lalkema@umass.edu, leontinealkema.github.io/alkema_lab/)