Simulating outcomes: a Bayesian approach to estimating longitudinal survey parameters

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Summary

Presentation outline

- Case study background
  - Introduction of High School Longitudinal Study of 2009 (HSLS:09)
  - Calibration subsample
  - Phases
  - Subgroups
  - Modeling
  - Adaptive components
- Simulation case study
  - Goals
  - Approach
  - Priors
  - Posterior results
- Discussion
- Next steps

Case study background

High School Longitudinal Study of 2009 (HSLS:09)

- U.S. Department of Education, National Center for Education Statistics
- Nationally representative, longitudinal study of 23,000+ 9th graders in 2009
- Study design:
  - Base year (2009)
  - First follow-up (2012)
  - 2013 Update (2013)
  - **Second follow-up (2016)**

HSLS:09 second follow-up summary

- **Calibration** subsample and **main** sample
- Several distinct **phases** of data collection with corresponding interventions
- 3 study **subgroups** of interest
- **Response propensity model** to maximize efficient allocation of project resources
- Model to predict likelihood of contributing to **nonresponse bias**, used to target sample members for interventions

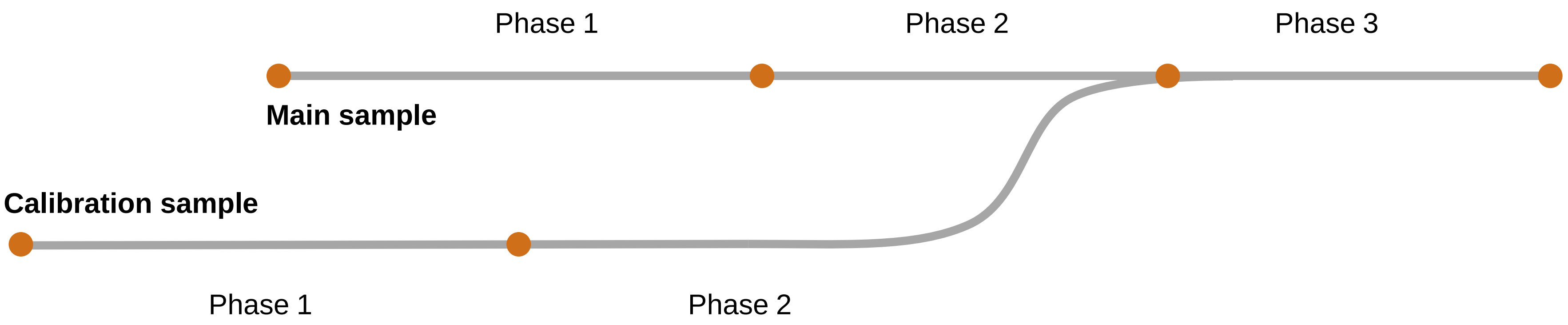
Case study background

Calibration subsample

- Fielded **8 weeks** in advance of the main sample to **experimentally test** the effectiveness of planned interventions in phase 1 and phase 2
- Subsample of about 15 percent of total sample, n = 3,300
- Interventions applied over **3 phases** of interest

Phases

- **Phase 1:** baseline incentive (monetary)
- **Phase 2:** Incentive *boosts* (monetary)
- **Phase 3:** Field interviewing (CAPI), abbreviated interview; calibration and main sample aligned



Case study background

Subgroups

- Stratified based on **previous-round experience** with cohort
- Differentiated so that customized interventions could be developed (informed by prior rounds), and applied to subgroups independently

Second follow-up subgroups

Subgroup A
High school late / alternative / noncompleters

Had not completed HS; were still enrolled in HS; received alt. credential; completed HS late; had dropout with unknown HS completion status

Subgroup B
Ultra-cooperative respondents

HS completers that participated in base year, first follow-up, and 2013 Update without incentive offer

Subgroup C
All other cases

Early / on-time regular diploma completers (not subgroup B) and cases with unknown HS completion status (not subgroup A)

Case study background

Modeling

Response propensity model

Estimates unit-level response probability

- **Covariates:** Model covariates combine paradata (prior-round paradata and demographics) and key variables of interest found to maximize prior-round response prediction
- **Dependent variable:** 2013 Update response (immediately prior round)
- **Estimation:** Once, prior to data collection start

Application

Used in phase 3 (field interviewing) to exclude pursuit of low response propensity cases

Bias likelihood model

Identifies nonrespondents in the most underrepresented groups

- **Covariates:** Chosen such that differences should proxy nonresponse bias; *excludes paradata*
- **Dependent variable:** Current-round response
- **Estimation:** Re-estimated throughout data collection, before intervention deployment

Application

Used in phase 2 (boosts) and phase 3 (field interviewing) to target cases for incentive increases and field interviewing

Case study background

Calibration-informed adaptive components

Incentives selected

- Best-performing incentives (baseline and boosts) were offered to main sample cases

Redefined subgroup B

- To conserve project resources, the subgroup B (ultra-cooperative) set definition **was expanded** for the **main study** only
- Expanded definition sought to identify **relatively homogeneous** group of highly cooperative sample members within subgroup C (all other cases), one key attribute was **response propensity > 0.90**
- Portion (19 percent) of subgroup C was reallocated to subgroup B, based on new definition
- Redefining subgroup categorization could have impact on use of calibration sample outcomes to estimate behavior of main sample

Simulation

Simulation background

Goals

- Formally incorporate **prior knowledge** derived from sample into models to **estimate important survey design parameters**
  - **Sample member response propensities**
  - **Contact propensities**
  - Participation costs
  - Contact costs
- **Update knowledge** as data collection progresses
- Goals are naturally well-suited to Bayesian framework
- Exploratory case study using HSLS:09 data

Models
In this exploratory analysis we focus only on the **response propensity** and **contact models**

Simulation background

BADEN Gibbs sampler

Approach

- Leveraged Gibbs sampler and approach developed by Schouten et al. (2017) to estimate survey design parameters
- Gibbs sampler allows for estimation of joint posterior distributions of interest that cannot be expressed in closed form

- Generate **simulation** data set using
  - Known distribution of auxiliary variables (of interest)
  - Auxiliary variables were kept simple: only **sex** (Female, Male) and **subgroup** (A, B, C)
  - Aggregated sample paradata through phases (e.g., probability of contact, probability of participation)
- **Elicit priors** (informed and uninformed)
- Construct generalized linear models to estimate design parameters of interest
  - Response propensity (probit)
  - Contact propensity (probit)
- **Estimate posterior** regression parameters using Gibbs sampler

Simulation background

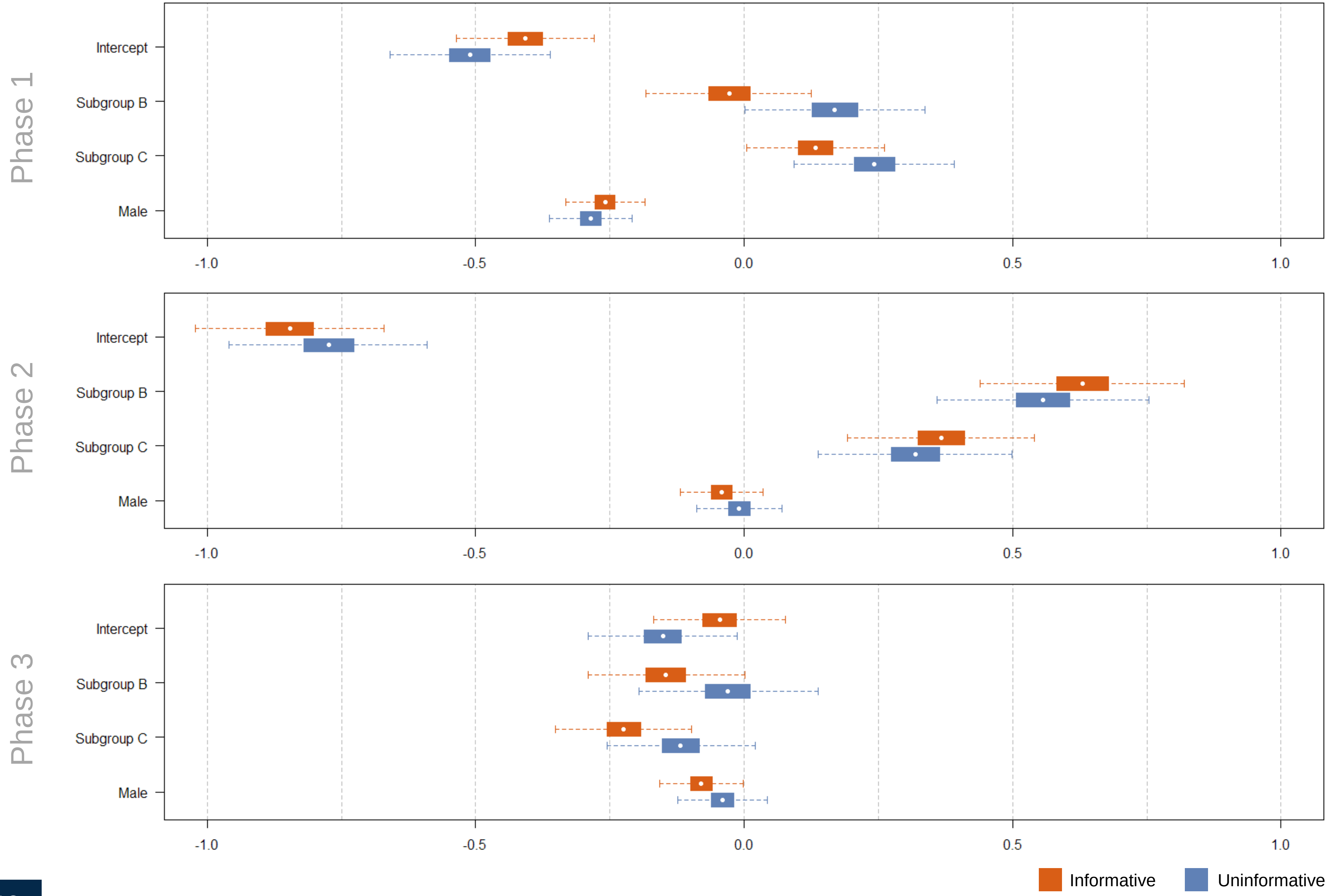
BADEN Gibbs sampler

Priors

Prior distribution for the regression parameters is multivariate normal

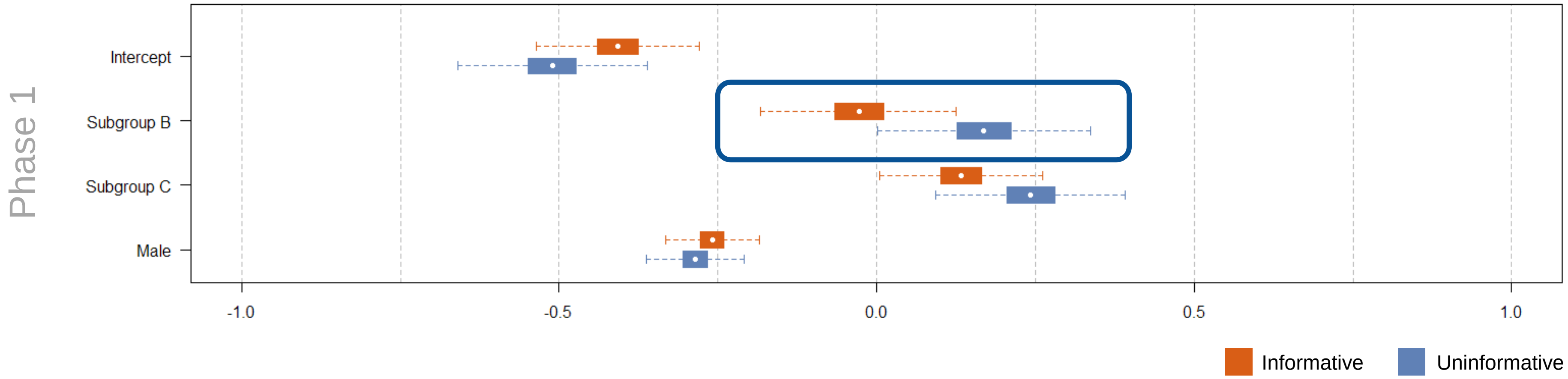
- **Informative prior:** elicited from calibration sample data
- **Uninformative prior:** equivalent variance for all covariates; priors express lack of knowledge at the start of data collection

Posterior response model coefficients



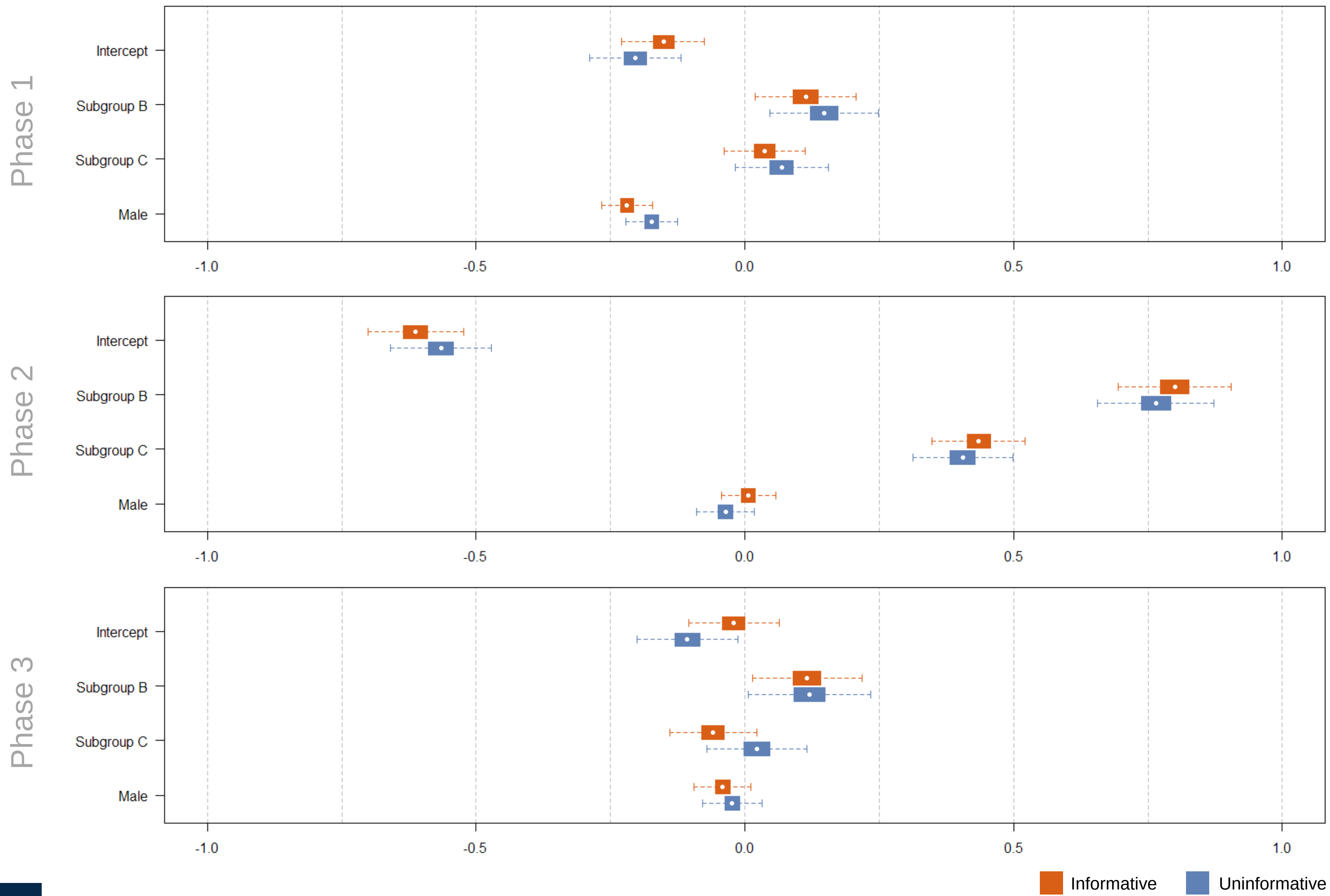
Posterior response model coefficients

Impact of redefining subgroup B



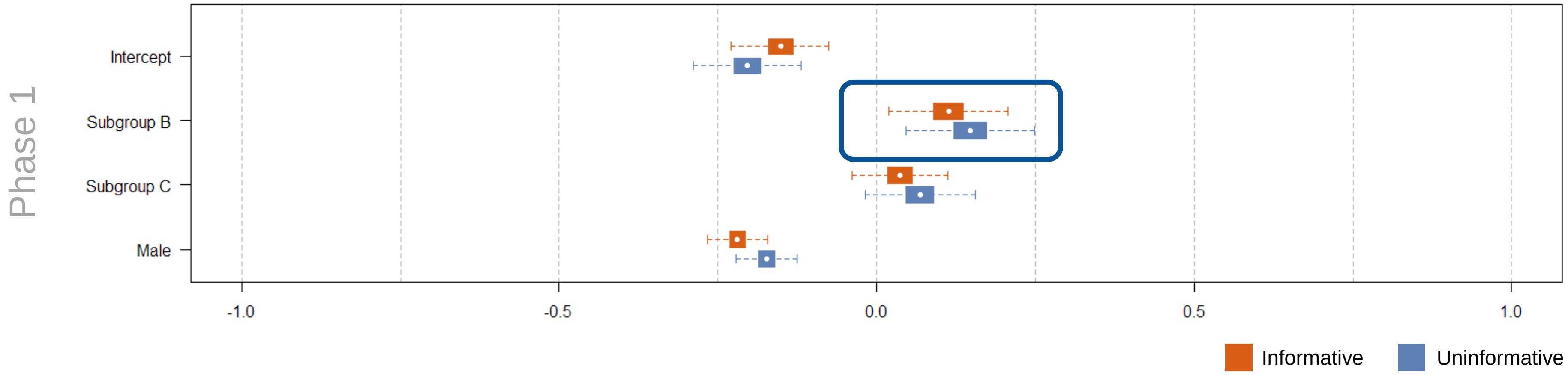
- **Very large differences** on posterior distribution of regression coefficients associated with subgroup (particularly subgroup B), depending on usage of **informative or uninformative priors**
- Suggests calibration-informed prior is misspecified
- Especially marked effect during phase 1, before incentive boosts deployed in phase 2
- Despite efforts to redefine subgroup B with similarly cooperative respondents, changes to prior mid-data collection can have substantive impacts on posterior distributions
- Testing interventions with calibration sample may have caused further misspecification

Posterior contact model coefficients



Posterior contact model coefficients

Impact of redefining subgroup B



- Similar impact for contact parameters not observed
- Subgroup B and subgroup C do not appear to differ in their parameters for contact, but their behavior for response does seem to significantly differ under the calibration study (i.e., informed priors)

Discussion

Calibration-informed priors

- While being responsive to client and resource constrains, adaptations mid-collection can reduce utility of prior with cascading effect on posterior
- Prior and observed data should share the same underlying probability mechanism in order to provide added value
- Making decisions based on the calibration sample with misspecified prior may lead to different actions being applied during the main sample; takes time for effect of prior to be reduced
- Use of calibration study as prior (with goal of experimentally testing incentives, definitions, etc.) vs. use of field test (closer to a survey "dry run") as prior

Next steps

- Testing various calibration sample sizes with various main sample sizes
- Considering methods to formally attach less weight to prior that we know differs. Any utility?
- Using estimates from phase one as priors for phase two, etc. Given phase differences, does this make sense?

Thank you

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