Eliciting Truthful Answers to Sensitive Survey Questions: New Statistical Methods for List and Endorsement Experiments

Kosuke Imai

Princeton University

July 5, 2010

Project Reference

- Imai, Kosuke. "Statistical Inference for the Item Count Technique."
- Bullock, Will, Kosuke Imai, and Jacob Shapiro. "Measuring Political Support and Issue Ownership Using Endorsement Experiments, with Application to Militant Groups in Pakistan."
- Available at http://imai.princeton.edu/projects/sensitive.html

Motivation

- Survey is used widely in social and medical sciences
- Validity of survey depends on the accuracy of self-reports
- Sensitive questions $\Longrightarrow$ social desirability, privacy concerns
  e.g., racial prejudice, drug use, sexual behavior
- Lies and nonresponses

- How can we elicit truthful answers to sensitive questions?
- Survey methodology: protect privacy through indirect questioning
- Statistical methods: efficiently recover underlying responses

Survey Techniques for Sensitive Questions

- Randomized Response Technique (Warner, 1965)
- Most commonly used
- Use randomization to protect privacy
- Difficulties: logistics, lack of understanding among respondents

- Item Count Technique (Miller, 1984)
- Also known as list experiment and unmatched count technique
- Use aggregation to protect privacy
- Develop new estimators to enable multivariate regression analysis
- Application: racial prejudice in the US

- Endorsement Experiments
- Use randomized endorsements to measure support levels
- Develop a measurement model based on item response theory
- Application: Pakistanis' support for Islamic militant groups

Item Count Technique: Example

- The 1991 National Race and Politics Survey
- Randomize the sample into the treatment and control groups
- The script for the control group

```
Now I'm going to read you three things that sometimes
make people angry or upset. After I read all three,
just tell me HOW MANY of them upset you. (I don't
want to know which ones, just how many.)
(1) the federal government increasing the tax on
gasoline;
(2) professional athletes getting million-dollar-plus
salaries;
(3) large corporations polluting the environment.
```


Item Count Technique: Example

- The 1991 National Race and Politics Survey
- Randomize the sample into the treatment and control groups
- The script for the treatment group

```
Now I'm going to read you four things that sometimes
make people angry or upset. After I read all four,
just tell me HOW MANY of them upset you. (I don't
want to know which ones, just how many.)
(1) the federal government increasing the tax on
gasoline;
(2) professional athletes getting million-dollar-plus
salaries;
(3) large corporations polluting the environment;
(4) a black family moving next door to you.
```

Design Considerations and Standard Analysis

- Privacy is protected unless respondents' truthful answers are yes for all sensitive and non-sensitive items (leads to underestimation)
- A larger number of non-sensitive items results in a higher variance
- Less efficient than direct questioning
- Negative correlation across non-sensitive items is desirable

- Standard difference-in-means estimator:

$$\hat{\tau} \;=\; \textit{treatment group mean} - \textit{control group mean}$$

- Unbiased for the population proportion
- Stratification is possible on discrete covariates but requires a large sample size and is not desirable for continuous covariates
- No existing method allows for multivariate regression analysis

Two-Step Nonlinear Least Squares (NLS) Estimator

- Generalize the difference-in-means estimator to a multivariate regression estimator

- The Model:
$$Y_i \;=\; f(X_i, \gamma) + T_i g(X_i, \delta) + \epsilon_i$$
  - Y_i: response variable
  - T_i: treatment variable
  - X_i: covariates
  - $f(x, \gamma)$: model for non-sensitive items, e.g., $J \times \text{logit}^{-1}(x^\top \gamma)$
  - $g(x, \gamma)$: model for sensitive item, e.g., $\text{logit}^{-1}(x^\top \delta)$

- Two-step estimation procedure:
  1. Fit the model to the control group via NLS and obtain $\hat{\gamma}$
  2. Fit the model to the treatment group via NLS after subtracting $f(X_i, \hat{\gamma})$ from Y_i and obtain $\hat{\delta}$
- Standard errors via the method of moments
- When no covariate, it reduces to the difference-in-means estimator

Extracting More Information from the Data

- Define a "type" of each respondent by $(Y_i(0), Z_{i,J+1})$
  - $Y_i(0)$: total number of yes for non-sensitive items $\{0, 1, \ldots, J\}$
  - $Z_{i,J+1}$: truthful answer to the sensitive item $\{0, 1\}$
- A total of $(2 \times J)$ types
- Example: two non-sensitive items ($J = 2$)

Y_i	Treatment group	Control group
3	(2,1)	
2	(1,1) (2,0)	(2,1) (2,0)
1	(0,1) (1,0)	(1,1) (1,0)
0	(0,0)	(0,1) (0,0)

- *Joint distribution* is identified

Extracting More Information from the Data

- Define a "type" of each respondent by $(Y_i(0), Z_{i,J+1})$
  - $Y_i(0)$: total number of yes for non-sensitive items $\{0, 1, \ldots, J\}$
  - $Z_{i,J+1}$: truthful answer to the sensitive item $\{0, 1\}$
- A total of $(2 \times J)$ types
- Example: two non-sensitive items ($J = 2$)

Y_i	Treatment group	Control group
3	(2,1)	
2	(1,1) (2,0)	(2,1) (2,0)
1	~~(0,1)~~ ~~(1,0)~~	(1,1) ~~(1,0)~~
0	~~(0,0)~~	~~(0,1)~~ ~~(0,0)~~

- *Joint distribution* is identified:

$$\Pr(\text{type} = (y, 1)) \quad = \quad \Pr(Y_i \leq y \mid T_i = 0) - \Pr(Y_i \leq y \mid T_i = 1)$$

Extracting More Information from the Data

- Define a "type" of each respondent by $(Y_i(0), Z_{i,J+1})$
  - $Y_i(0)$: total number of yes for non-sensitive items $\{0, 1, \ldots, J\}$
  - $Z_{i,J+1}$: truthful answer to the sensitive item $\{0, 1\}$
- A total of $(2 \times J)$ types
- Example: two non-sensitive items ($J = 2$)

Y_i	Treatment group	Control group
3	(2,1)	
2	(1,1) (2,0)	(2,1) (2,0)
1	~~(0,1)~~ (1,0)	(1,1) (1,0)
0	~~(0,0)~~	~~(0,1)~~ ~~(0,0)~~

- *Joint distribution* is identified:

$$\Pr(\text{type} = (y, 1)) = \Pr(Y_i \le y \mid T_i = 0) - \Pr(Y_i \le y \mid T_i = 1)$$

$$\Pr(\text{type} = (y, 0)) = \Pr(Y_i \le y \mid T_i = 1) - \Pr(Y_i < y \mid T_i = 0)$$

The Likelihood Function

- $g(x, \delta)$: model for sensitive item, e.g., logistic regression
- $h_z(y; x, \psi_z) = \Pr(Y_i(0) = y \mid X_i = x, Z_{i,J+1} = z)$: model for non-sensitive item given the response to sensitive item, e.g., binomial or beta-binomial regression
- The likelihood function:

$$\prod_{i \in \mathcal{J}(1,0)} (1 - g(X_i, \delta)) h_0(0; X_i, \psi_0) \prod_{i \in \mathcal{J}(1,J+1)} g(X_i, \delta) h_1(J; X_i, \psi_1)$$
$$\times \prod_{y=1}^{J} \prod_{i \in \mathcal{J}(1,y)} \{g(X_i, \delta) h_1(y-1; X_i, \psi_1) + (1 - g(X_i, \delta)) h_0(y; X_i, \psi_0)\}$$
$$\times \prod_{y=0}^{J} \prod_{i \in \mathcal{J}(0,y)} \{g(X_i, \delta) h_1(y; X_i, \psi_1) + (1 - g(X_i, \delta)) h_0(y; X_i, \psi_0)\}$$

where $\mathcal{J}(t, y)$ represents a set of respondents with $(T_i, Y_i) = (t, y)$

- It would be a nightmare to maximize this!

Missing Data Framework and the EM Algorithm

- Consider $Z_{i,J+1}$ as missing data
- For some respondents, $Z_{i,J+1}$ is observed
- The complete-data likelihood has a much simpler form:

$$\prod_{i=1}^{N} \left\{ g(X_i, \delta) h_1(Y_i - 1; X_i, \psi_1)^{T_i} h_1(Y_i; X_i, \psi_1)^{1-T_i} \right\}^{Z_{i,J+1}}$$
$$\times \quad \{(1 - g(X_i, \delta)) h_0(Y_i; X_i, \psi_0)\}^{1-Z_{i,J+1}}$$

- The EM algorithm: only separate optimization of $g(x, \delta)$ and $h_z(y; x, \psi_z)$ is required
  - weighted logistic regression
  - weighted binomial regression
- Both can be implemented in standard statistical software

Empirical Application: Racial Prejudice in the US

- Kukulinski *et al*. (1997) analyzes the 1991 National Race and Politics survey with the standard difference-in-means estimator
- Finding: Southern whites are more prejudiced against blacks than non-southern whites – no evidence for the “New South”
- The limitation of the original analysis:
  So far our discussion has implicitly assumed that the higher level of prejudice among white southerners results from something uniquely “southern,” what many would call southern culture. This assumption could be wrong. If white southerners were older, less educated, and the like – characteristics normally associated with greater prejudice – then demographics would explain the regional difference in racial attitudes, leaving culture as little more than a small and relatively insignificant residual.
- Need for a multivariate analysis

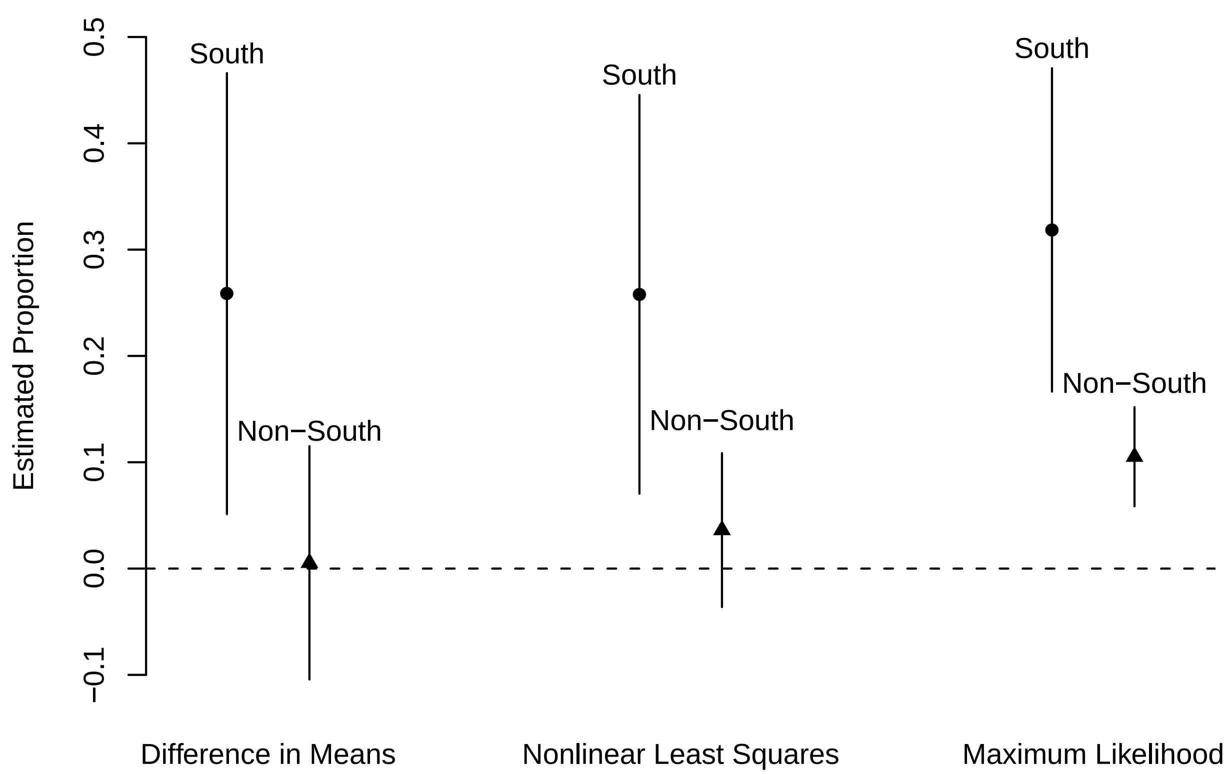
Results of the Multivariate Analysis

- Logistic regression model for sensitive item
- Binomial regression model for non-sensitive item (not shown)
- Likelihood ratio test supports the constrained model

	Nonlinear Least Squares		**Maximum Likelihood**			
			Constrained		Unconstrained	
Variables	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	−7.084	3.669	−5.508	1.021	−6.226	1.045
South	2.490	1.268	1.675	0.559	1.379	0.820
Age	0.026	0.031	0.064	0.016	0.065	0.021
Male	3.096	2.828	0.846	0.494	1.366	0.612
College	0.612	1.029	−0.315	0.474	−0.182	0.569

- The original conclusion is supported
- Standard errors are much smaller for ML estimator

Estimated Proportion of Prejudiced Whites



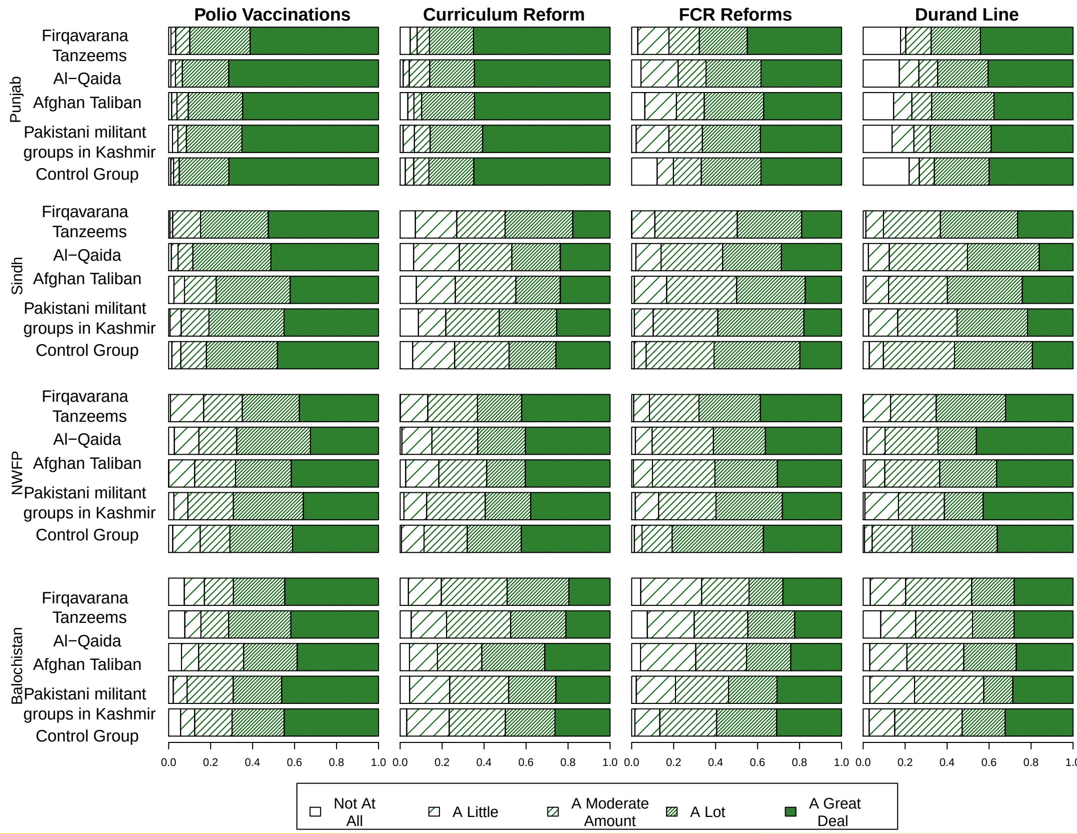
Endorsement Experiments

- Measuring support for political actors (e.g., candidates, parties) when studying sensitive questions
- Ask respondents to rate their support for a set of policies endorsed by randomly assigned political actors
- Experimental design:
  1. Select policy questions
  2. Randomly divide sample into control and treatment groups
  3. Across respondents and questions, randomly assign political actors for endorsement (no endorsement for the control group)
  4. Compare support level for each policy endorsed by different actors

The Pakistani Survey Experiment

- 6,000 person urban-rural sample
- Four very different groups:
  - Pakistani militants fighting in Kashmir (a.k.a. Kashmiri tanzeem)
  - Militants fighting in Afghanistan (a.k.a. Afghan Taliban)
  - Al-Qa'ida
  - Firqavarana Tanzeems (a.k.a. sectarian militias)
- Four policies:
  - WHO plan to provide universal polio vaccination across Pakistan
  - Curriculum reform for religious schools
  - Reform of FCR to make Tribal areas equal to rest of the country
  - Peace jirgas to resolve disputes over Afghan border (Durand Line)
- Response rate; over 90%

Distribution of Responses



Endorsement Experiments Framework

- Data from an endorsement experiment:
  - N respondents
  - J policy questions
  - K political actors
  - $Y_{ij} \in \{0, 1\}$: response of respondent i to policy question j
  - $T_{ij} \in \{0, 1, \ldots, K\}$: political actor randomly assigned to endorse policy j for respondent i
  - $Y_{ij}(t)$: potential response given the endorsement by actor t
  - Covariates measured prior to the treatment

The Proposed Model

- Quadratic random utility model:

$$\begin{aligned} U_i(\zeta_{j1}, k) &= -\|(x_i + s_{ijk}) - \zeta_{j1}\|^2 + \eta_{ij}, \\ U_i(\zeta_{j0}, k) &= -\|(x_i + s_{ijk}) - \zeta_{j0}\|^2 + \nu_{ij}, \end{aligned}$$

  where x_i is the ideal point and s_{ijk} is the support level
- The statistical model (item response theory):

$$\begin{aligned} \Pr(Y_{ij} = 1 \mid T_{ij} = k) &= \Pr(Y_{ij}(k) = 1) = \Pr(U_i(\zeta_{j1}, k) > U_i(\zeta_{j0}, k)) \\ &= \Pr(\alpha_j + \beta_j(x_i + s_{ijk}) > \epsilon_{ij}) \end{aligned}$$

- Hierarchical modeling:

$$\begin{aligned} x_i &\overset{\text{indep.}}{\sim} \mathcal{N}(Z_i^\top \delta,\ \sigma_x^2) \\ s_{ijk} &\overset{\text{indep.}}{\sim} \mathcal{N}(Z_i^\top \lambda_{jk},\ \omega_{jk}^2) \\ \lambda_{jk} &\overset{\text{i.i.d.}}{\sim} \mathcal{N}(\theta_k, \Phi_k) \end{aligned}$$

- "Noninformative" hyper prior on $(\alpha_j, \beta_j, \delta, \theta_k, \omega_{jk}^2, \Phi_k)$

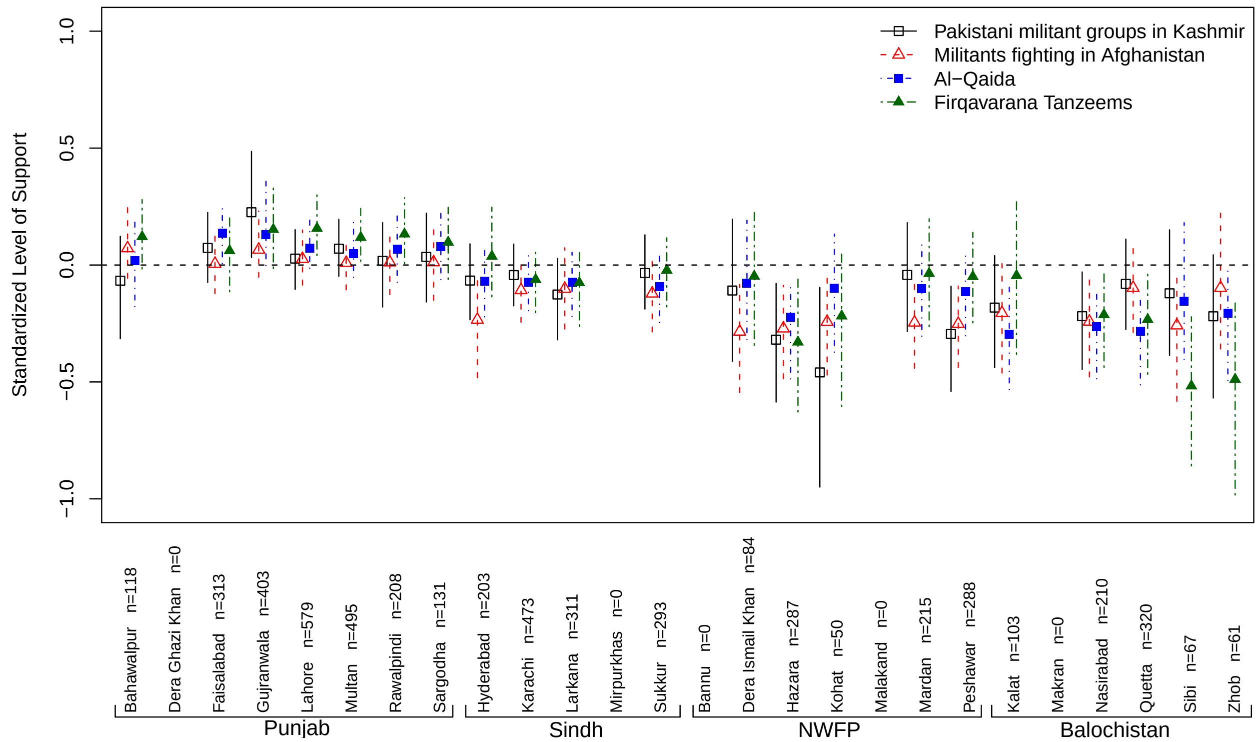
Quantities of Interest and Model Fitting

- Average support level for each militant group k

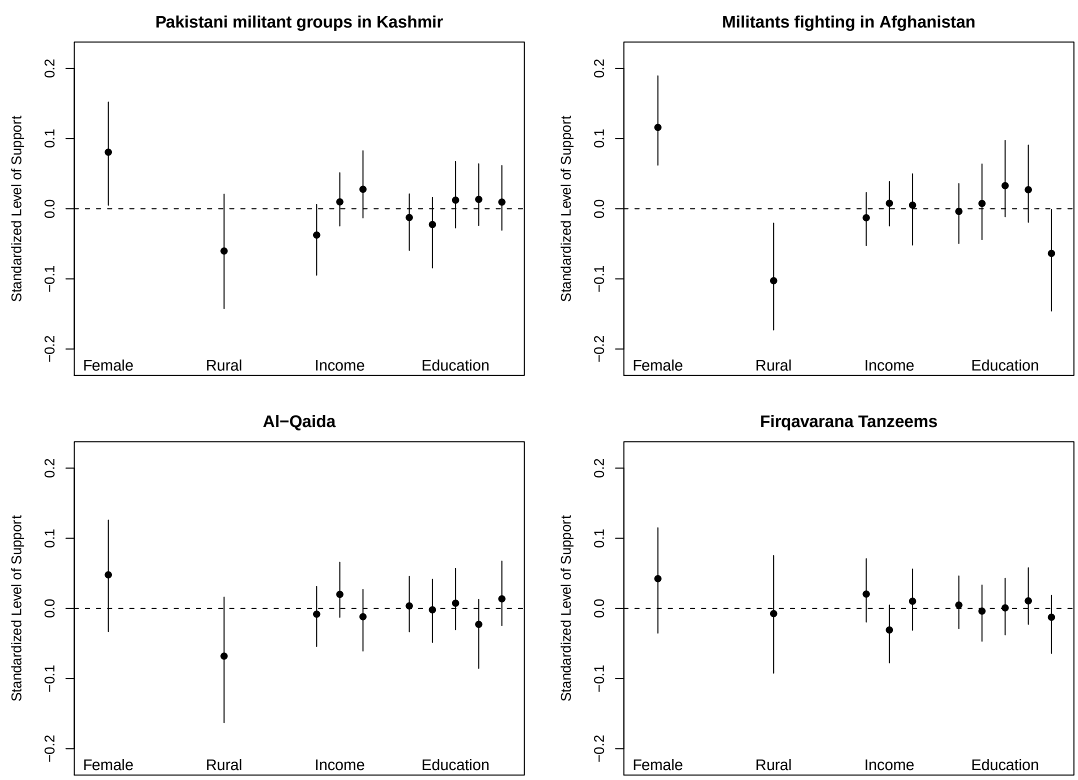
$$\begin{aligned} \tau_{jk}(Z_i) &= Z_i^\top \lambda_{jk} && \text{for each policy } j \\ \kappa_k(Z_i) &= Z_i^\top \theta_k && \text{averaging over all policies} \end{aligned}$$

- Standardize them by dividing the (posterior) standard deviation of ideal points
- Issue ownership: variation of average support for each group across policies
- Bayesian Markov chain Monte Carlo algorithm
- Multiple chains to monitor convergence
- Implementation via `JAGS` (Plummer)

Estimated Division Level Support



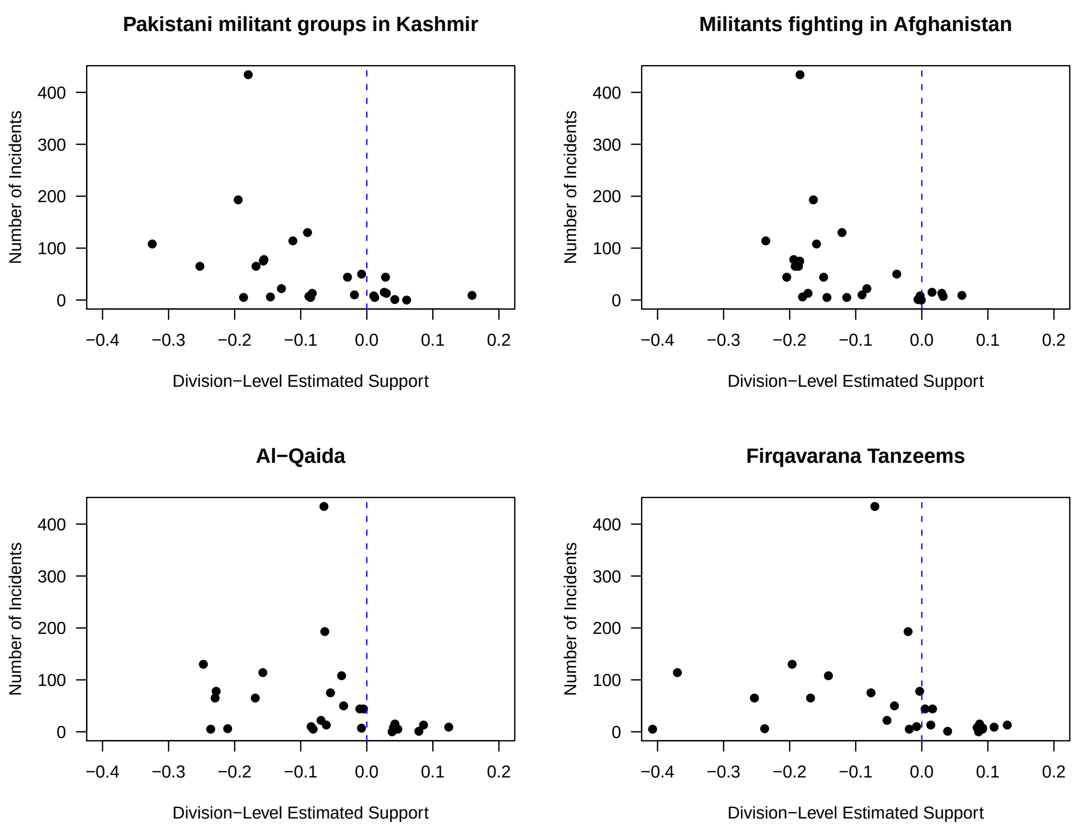
Estimated Effects of Individual Covariates



- Demographics play a small role in explaining support for groups

Regional Clustering of the Support for Al-Qaida

Correlation between Support and Violence

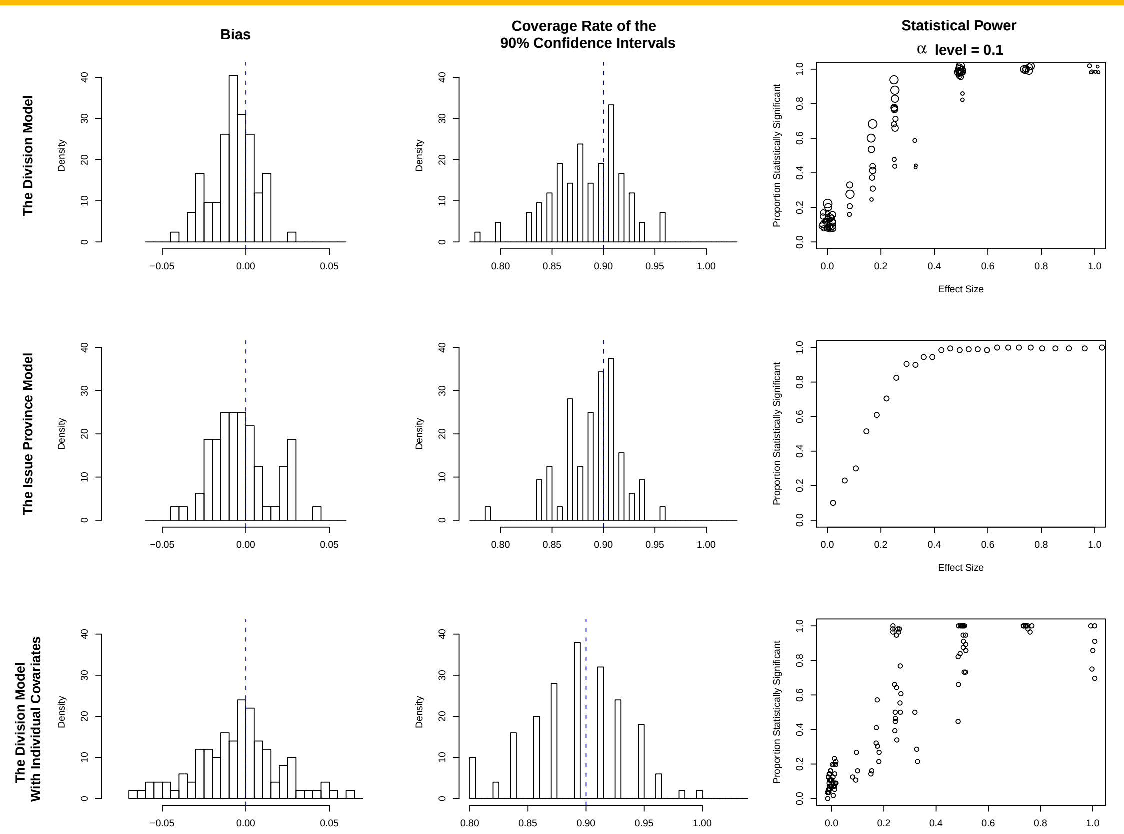


Simulation Studies

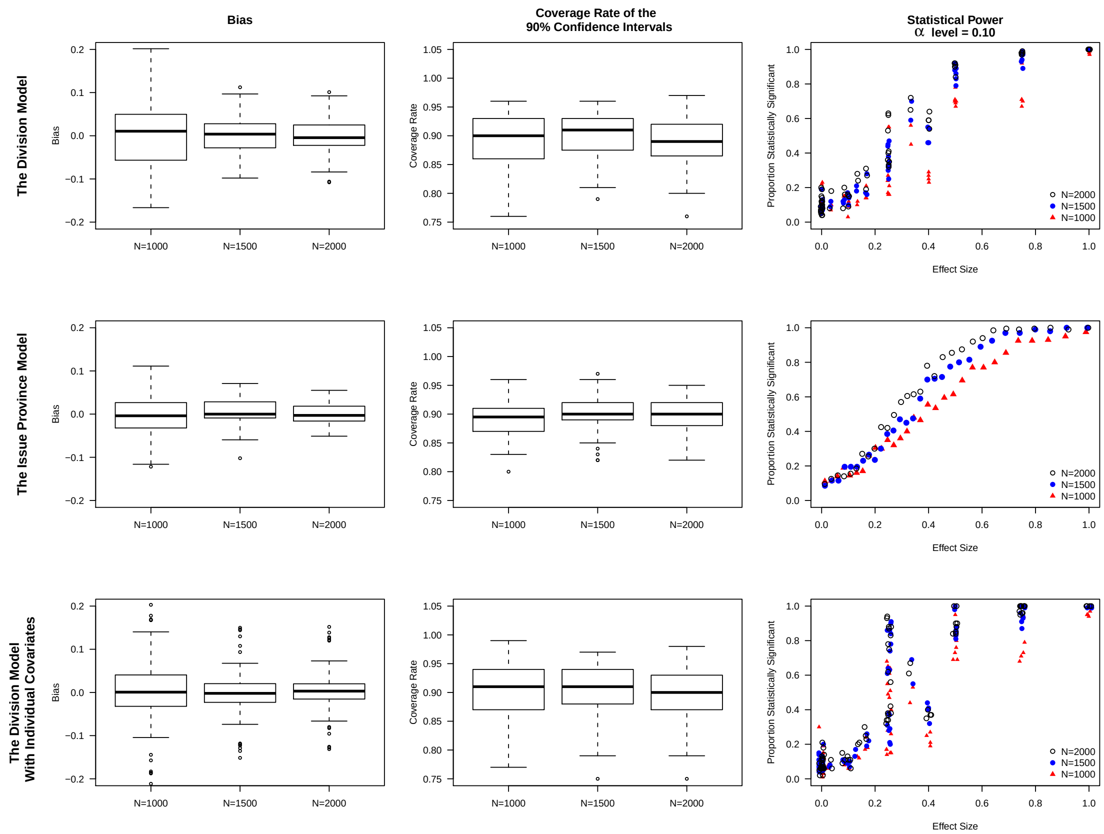
1. Based on the Pakistani Data
   - Same 2 models plus province-level issue ownership model
   - Top-level parameters held constant across simulations
   - Sample sizes and distribution same as before
   - Ideal points, endorsements and responses follow IRT models
2. Varying sample sizes
   - Model for division-level estimates with no covariates
   - Model for province-level estimates with no covariates but support varying across policies
   - $N = 1000, 1500, 2000$
   - Again, top-level parameters held constant across simulations while ideal points, endorsements and responses follow IRT models

- 100 simulations under each scenario (3 chains, 60000 iterations)
- Frequentist evaluation of Bayesian estimators

Monte Carlo Evidence based on the Pakistani Data



Monte Carlo Evidence with Varying Sample Size



Concluding Remarks

- Viable alternatives to the randomized response technique
- Item Count Technique
  - Easy for researchers to implement
  - Easy for respondents to understand
  - Widely applicable
  - Need to carefully choose non-sensitive items
  - Aggregation $\Longrightarrow$ loss of efficiency
- Endorsement Experiments
  - Most indirect questioning
  - Applicability limited to measuring support
  - Need to carefully choose policy questions
  - Many groups $\Longrightarrow$ loss of efficiency
- New statistical methods for efficient inference
- Free easy-to-use software is coming soon