A Bayesian Analysis of the Perception of Transgender Acceptance in the U.S. Military

BIOSTAT 234: Final Data Analysis Project

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Introduction.

LGBT service members face disparate health and social outcomes as compared to their heterosexual and/or cisgender colleagues. In research funded by the U.S. Department of Defense, Dr. Ian Holloway (Luskin School of Public Affairs, UCLA), et al. seek to determine the degree to which LGBT service members are accepted and integrated into the military and what key factors facilitate and impede their acceptance and integration. In particular, the ban on openly-serving transgender service members, lifted in June 2016 only to be reinstated during the Trump administration, is one of many massive structural challenges faced by transgender individuals serving in the U.S. military beyond baseline stigma and interpersonal discrimination. These and similar obstacles warrant the exploring of how well military personnel perceive the acceptance of transgender service members. In other words, we would like to understand what predictors are associated with a decrease in the perceived acceptance of transgender people in the U.S. military so as to enhance unit cohesion and improve integration.

Study design and data description.

Sampling of all active duty participants was performed using respondent driven sampling (RDS), a type of chain-referral sampling first developed for HIV prevention and surveillance with hard to reach populations. It relies on the assumption that hidden populations are better equipped to access peers and employs a dual-incentive where participants receive a primary incentive for their own participation and secondary incentives for recruiting others. A handful of initial participants from the first phase of the study called "seeds" were purposefully selected from each major sub-population of interest, and 55 social network clusters were formed, one of which is the set of clusters of size 1. We assert that grouping these individuals as one large cluster is valid because they are all singletons and should have some similar social characteristics. These 55 clusters are the random effects in this analysis.

The continuous response, perceived acceptance, has a mean and SD of 47.8 $\pm$ 31.9 on a 0-100 scale (Table 1); on average, a service member thinks that transgender people in the military are accepted about 48% of the time, which is considerably less than all of the average perceived acceptance scores of other minority groups in the survey (data not shown). The 541 survey respondents are majority male (59.5%) and majority white (57.9%); yet, 10.7% are transgender and 39.9% are of a sexual minority (Table 1). Most respondents are in the Army (41.2%) or Air Force (33.6%), about a third are officers (33.8%), 64% have someone they consider a military mentor, and approximately seven in ten support transgender service members serving openly. Average age at time of survey was 28, average length of military service was 6.2 (median 4), and about five in eight respondents have a college degree (61.9%). Missingness is present in some covariates and will be handled with multiple imputation (see below).

None of the transgender service members in the dataset were asked if they support transgender individuals serving openly, so gender and responses to that specific question have perfect multicollinearity among the trans men and trans women. The density of the response in Figure 1 shows negligible change when the transgender individuals are removed from the dataset. After consideration, all transgender service members remain in the dataset, but all of their responses to the support question were changed from missing to affirmative, making the logical assumption that they all would agree that they support their own freedom to serve openly. This removed the collinearity between the gender and support variables, and analysis could continue with all predictors.

Prior and model specification.

The density of the continuous response, acceptance, is trimodal (Figure 1); thus, the variable is split into ordinal groups, with categories [0, 30] assigned the label "poorly accepted" (n=207), (30, 70] assigned "sometimes accepted" (n=172), and (70, 100] assigned "well-accepted" (n=162). The response categories have a natural order, so an ordinal logistic regression is appropriate to fit. The proportional odds assumption was tested by likelihood ratio tests and does hold for this data. Thus, the following model is proposed:

$$
\begin{aligned}
log(\frac{P(Y \leq j)}{P(Y > j)}) &= \alpha - (\gamma + X^T\beta) + \epsilon \quad \text{where} \\
j &= \begin{cases} 0 & \text{(poorly accepted)} \\ 1 & \text{(sometimes accepted)} \\ 2 & \text{(well-accepted)} \end{cases} \\
\alpha &= [\alpha_1 \quad ... \quad \alpha_{55}] \quad \text{(random effects)}, \\
\gamma &= [\gamma_1 \quad \gamma_2] \quad \text{(intercepts)}, \\
\beta^T &= [\beta_{gender} \quad ... \quad \beta_{support.trans}] \quad \text{(fixed effects)}
\end{aligned}
$$

All interaction terms added to the model, such as gender × sexual orientation, gender × officer, and sexual orientation $\times$ support were not significant at $\alpha = 0.05$, so they were removed from all models.

This is novel research; questions like this have never been posed to a sample with these characteristics before. Thus, three sets of proper weakly informative priors proposed by Gelman, et al. (2008) will be applied to the parameters in a sensitivity analysis to test the robustness of posterior estimates as the tail thickness of the prior densities vary. The priors are:

$$
\begin{aligned}
\beta_i &\sim D(0, 2.5^2) \quad \forall i \\
\gamma_j &\sim D(0, 10^2) \quad j = 1, 2 \\
\alpha_k &\sim N(0, 10^2) \quad k = 1, ..., 55 \\
\sigma &\sim \text{Half-t}(0, 10^2, df = 3),
\end{aligned}
$$

where D is either (1) Gaussian, (2) t-distributed with 7 degrees of freedom, or (3) Cauchy.

Gelman notes that the t family is chosen because such flat-tailed distributions allow for robust inference and provide weakly informative prior information that constrains coefficients to a reasonable range (effect sizes are unlikely to be larger than 5 on the log scale). The Cauchy distribution is the most conservative of the three, allowing for an occasional larger coefficient, whereas the t_7 model is chosen because of its similarity to the likelihood of a logistic regression with only a constant term. The prior for σ is chosen as half t-distributed with a large scale parameter because it is weakly informative, with a peak at 0 and a gentle slope, as opposed to the gamma which typically provides little density near zero. It is worth mentioning that Gelman recommends that all binary variables be centered and scaled such that they are mean 0, and that all continuous variables are centered and scaled such that they are mean 0, scale 0.5. The scaling of the continuous variables render the coefficients rather uninterpretable so for clarity age and length of service were left uncentered and unscaled.

64 subjects have missing data in one or more columns, likely missing at random. Multiple imputation, used with the R package `mice` was performed; missing values are imputed 10 times leading to 10 fully imputed datasets. The models were then fitted to each of those datasets separately and results are pooled across the 10 for each model. The Bayesian analysis was performed in R with the package `brms` that uses the probabilistic programming language Stan. All models were run with 10 imputed datasets with 5 chains of 5000 iterations each. 1000 iterations were removed from each chain for burn-in, and the thinning parameter was set to 10 for the t-distributed models and 2 for the Gaussian model. 100000 and 20000 total iterations for each parameter were saved for the normal and t-distributed models, respectively. All ACFs and trace plots behaved well, indicating good convergence and good mixing (results not shown).

Results and discussion.

All three models perform essentially identically. Since Gelman's priors prevent large log odds and there were no extreme log odds parameters, the likelihoods were substantially more dominant than the priors, and estimates are shown to be highly robust to changes in tail thickness of the prior distributions (Table 2).

Gender identity and sexual orientation are significant predictors of perceived transgender acceptance. For female service members, the odds of perceiving transgender service members as at least one level more accepted is 0.48 (95% CI: 0.31-0.75) as compared to male service members (Table 2). Similarly, the odds of transgender men perceiving trans service members as more accepted is 0.35 (95% CI: 0.15-0.80) when compared to cisgender men; however, unexpectedly, transgender women have essentially no difference in odds compared to cisgender men (Figure 2a). The odds of homosexual service members perceiving trans service members as more accepted is 0.28 (95% CI: 0.17-0.47), and the odds of bisexuals perceiving trans service members as more accepted is 0.5 (95% CI: 0.23-1.06) as compared to heterosexual service members (Figure 2b). Military branch and race are both insignificant predictors, although Black service members have 0.67 (95% CI: 0.37-1.19) the odds of perceiving trans service members as more accepted as opposed to Whites, which is suggestive (Figures 2c, 2d).

Support of trans service members serving openly is another strong predictor of perceived acceptance, and officer status and length of service are both suggestive. For officers, the odds of perceiving trans people as more accepted is 0.59 (95% CI: 0.34-1.04) compared to those who are not officers (Table 2; Figure 3a). For every additional year of service, the odds of perceiving trans service members as more accepted is 0.93 (95% CI: 0.87-1.00) (Figure 3f). Most critically, those who support trans service members serving openly are 4.67 (95% CI: 2.91-7.56) times more likely to perceive trans service members as more accepted (Figure 3d). Although statistically insignificant, the odds of perceiving trans service members as more accepted for those with a college degree is 1.40 (95% CI: 0.83-2.36) compared to those without, an unanticipated direction of association considering college-educated people are typically more informed about challenges in the transgender community (Figure 3b).

Limitations and next steps.

The study design, even though adjusted, is not ideal; a stratified or cluster random sampling scheme is preferred. Additionally, results may have more precision if the response was kept continuous and a mixture of 3 normal or t models for the three groupings were used instead. Finally, as per the underlying research objectives, integrating in a measure of unit cohesion as a predictor would be helpful for satisfying all aims of the project.

Conclusion.

Gender identity, sexual orientation, and support of open service were strongly associated with the perceived acceptance of transgender service members, while officer status and length of service were suggestive. By improving acceptance and integration of LGBT service members into military units, unit cohesion and readiness will be significantly improved and will lead to improved military performance, enhanced psychosocial well-being, and reduced attrition from service.

Appendix.

Table 1. Characteristics of sample.

Variable	Level	Mean(SD)/Freq(%)
Perceived acceptance [0-100]		47.8 (31.9)
Perceived acceptance (ordinal)	Poorly accepted	207 (38.3)
	Sometimes accepted	172 (31.8)
	Well-accepted	162 (29.9)
Gender	Male	322 (59.5)
	Female	161 (29.8)
	Trans male	32 (5.9)
	Trans female	26 (4.8)
Sexual orientation	Heterosexual	314 (58.0)
	Homosexual	173 (32.0)
	Bisexual	43 (7.9)
	Missing	11 (2.0)
Race	White	313 (57.9)
	Black	91 (16.8)
	Hispanic	73 (13.5)
	Other	61 (11.3)
	Missing	3 (0.6)
Military Branch	Army	223 (41.2)
	Air Force	182 (33.6)
	Marines	52 (9.6)
	Navy	84 (15.5)
Officer	Yes	183 (33.8)
	No	358 (66.2)
College degree	Yes	335 (61.9)
	No	171 (31.6)
	Missing	35 (6.5)
Age		27.7 (6.1)
Length of service		6.2 (5.4)
	Missing	35 (6.5)
Have military mentor?	Yes	346 (64.0)
	No	191 (35.3)
	Missing	4 (0.7)
Support trans in the military?	Yes	379 (70.1)
	No	144 (26.6)
	Missing	18 (3.3)

Table 2. Posterior odds ratio estimates from proportional odds models.

	Gaussian			t, df=7			Cauchy		
	Est.	2.5%	97.5%	Est.	2.5%	97.5%	Est.	2.5%	97.5%
Intercept 1	0.31	0.06	1.70	0.31	0.06	1.74	0.31	0.06	1.73
Intercept 2	2.42	0.44	13.59	2.44	0.45	13.71	2.45	0.44	13.75
Gender (F)	0.48	0.31	0.75	0.48	0.31	0.76	0.49	0.31	0.77
Gender (TM)	0.35	0.15	0.80	0.35	0.15	0.81	0.36	0.15	0.82
Gender (TF)	0.98	0.36	2.74	0.98	0.35	2.72	0.99	0.36	2.67
Sex Ortn (Gay)	0.28	0.17	0.47	0.28	0.17	0.47	0.28	0.17	0.47
Sex Ortn (Bi)	0.50	0.23	1.06	0.50	0.24	1.06	0.51	0.24	1.08
Race (Black)	0.67	0.37	1.19	0.67	0.38	1.17	0.67	0.38	1.18
Race (Hisp)	1.16	0.63	2.10	1.16	0.63	2.09	1.16	0.64	2.12
Race (Other)	0.94	0.51	1.72	0.94	0.51	1.71	0.95	0.52	1.72
Branch (AirF)	1.04	0.60	1.82	1.04	0.60	1.81	1.04	0.60	1.81
Branch (Mar)	0.91	0.42	1.97	0.91	0.42	1.96	0.91	0.42	1.96
Branch (Navy)	1.11	0.57	2.16	1.12	0.58	2.16	1.11	0.57	2.15
Officer	0.59	0.34	1.04	0.59	0.34	1.03	0.59	0.34	1.05
Education	1.40	0.83	2.36	1.40	0.83	2.33	1.39	0.84	2.35
Age	1.03	0.96	1.10	1.03	0.96	1.10	1.03	0.96	1.10
Length Serv	0.93	0.87	1.00	0.93	0.87	1.00	0.93	0.87	1.00
Mentor	1.12	0.75	1.67	1.12	0.74	1.69	1.12	0.75	1.68
Support T	4.67	2.91	7.56	4.65	2.93	7.41	4.59	2.86	7.39

Figure 1. Density of perceived acceptance of transgender service members.

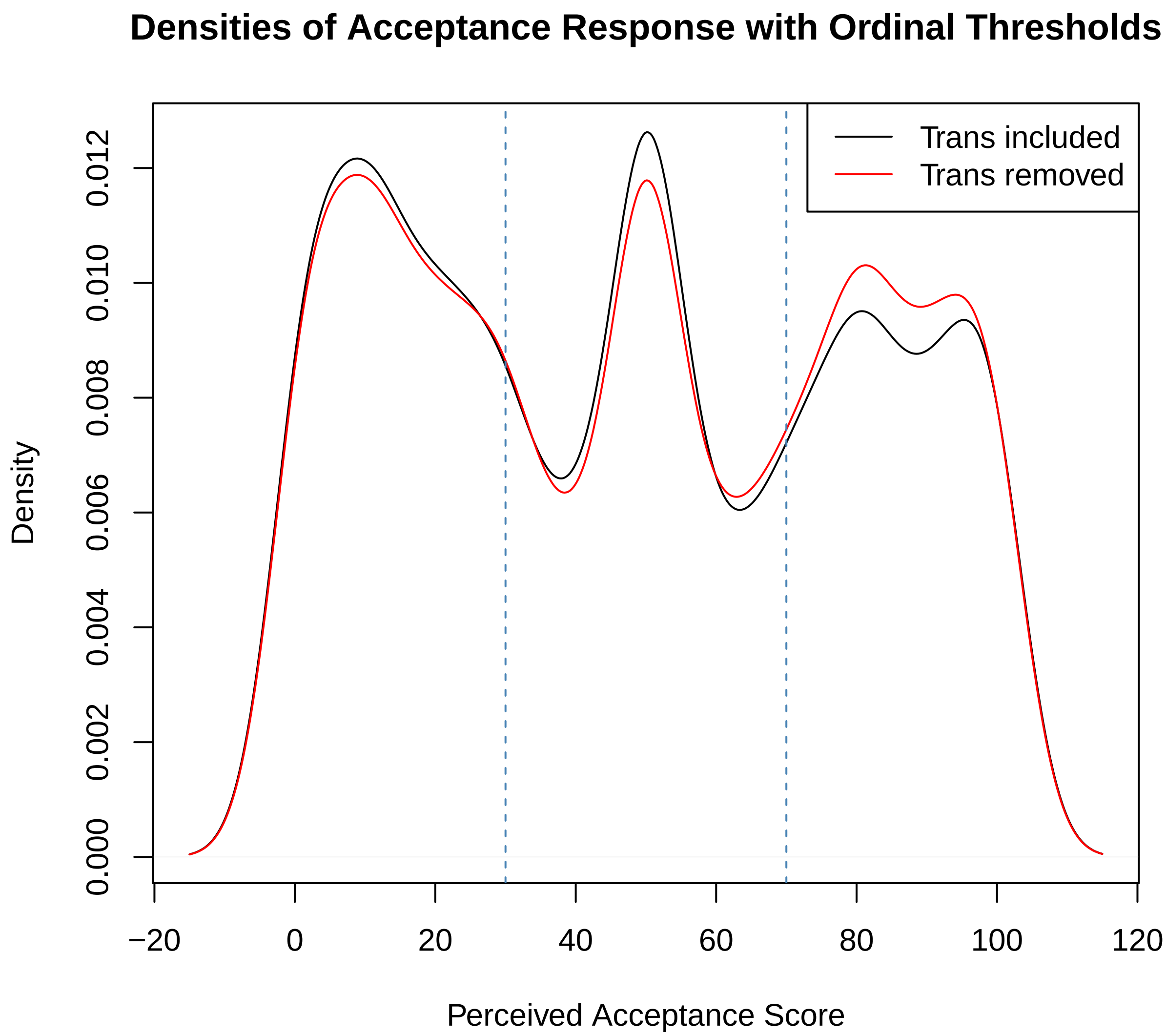


Figure 2. Posterior distributions of log-odds for multinomial fixed effects.

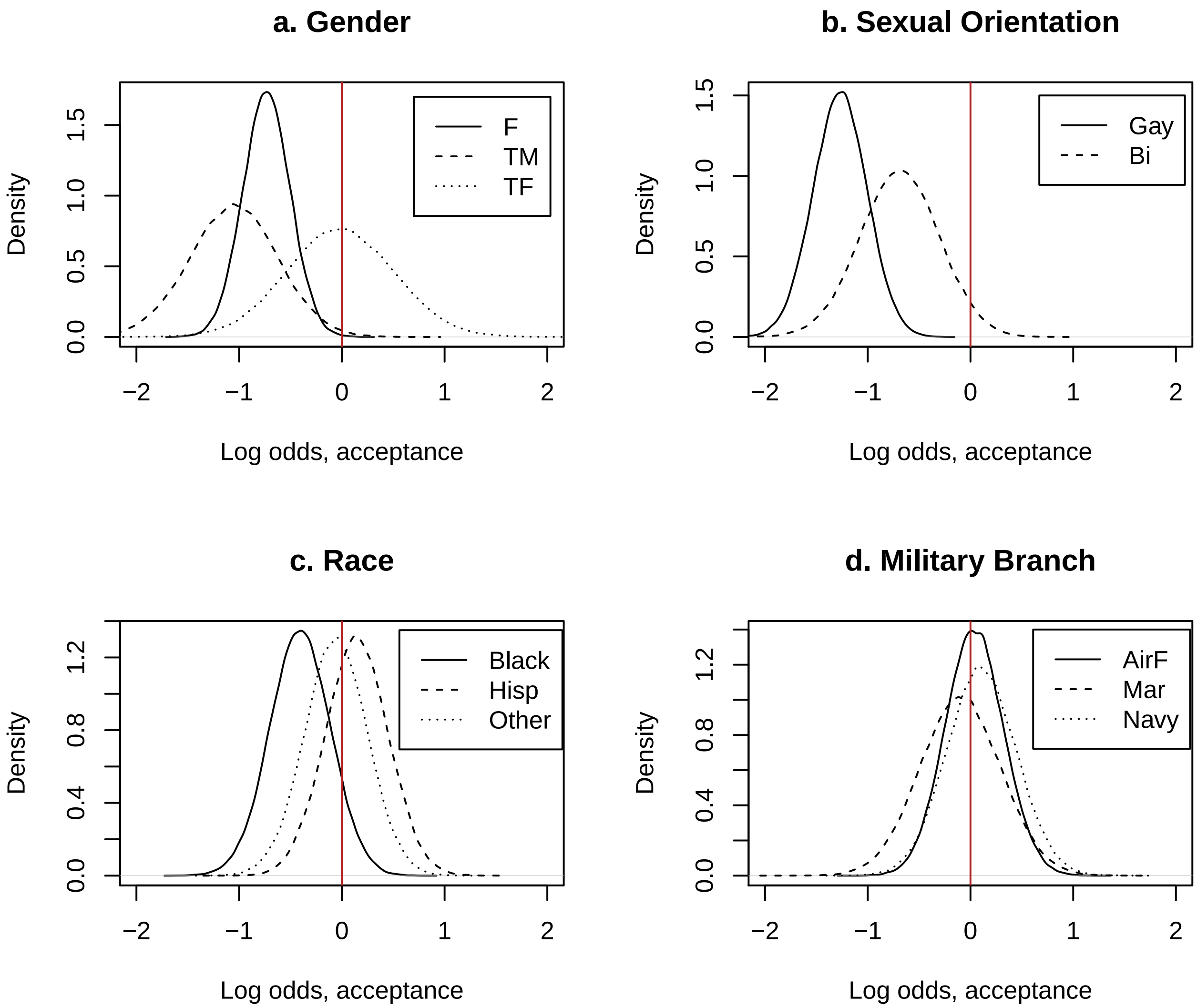
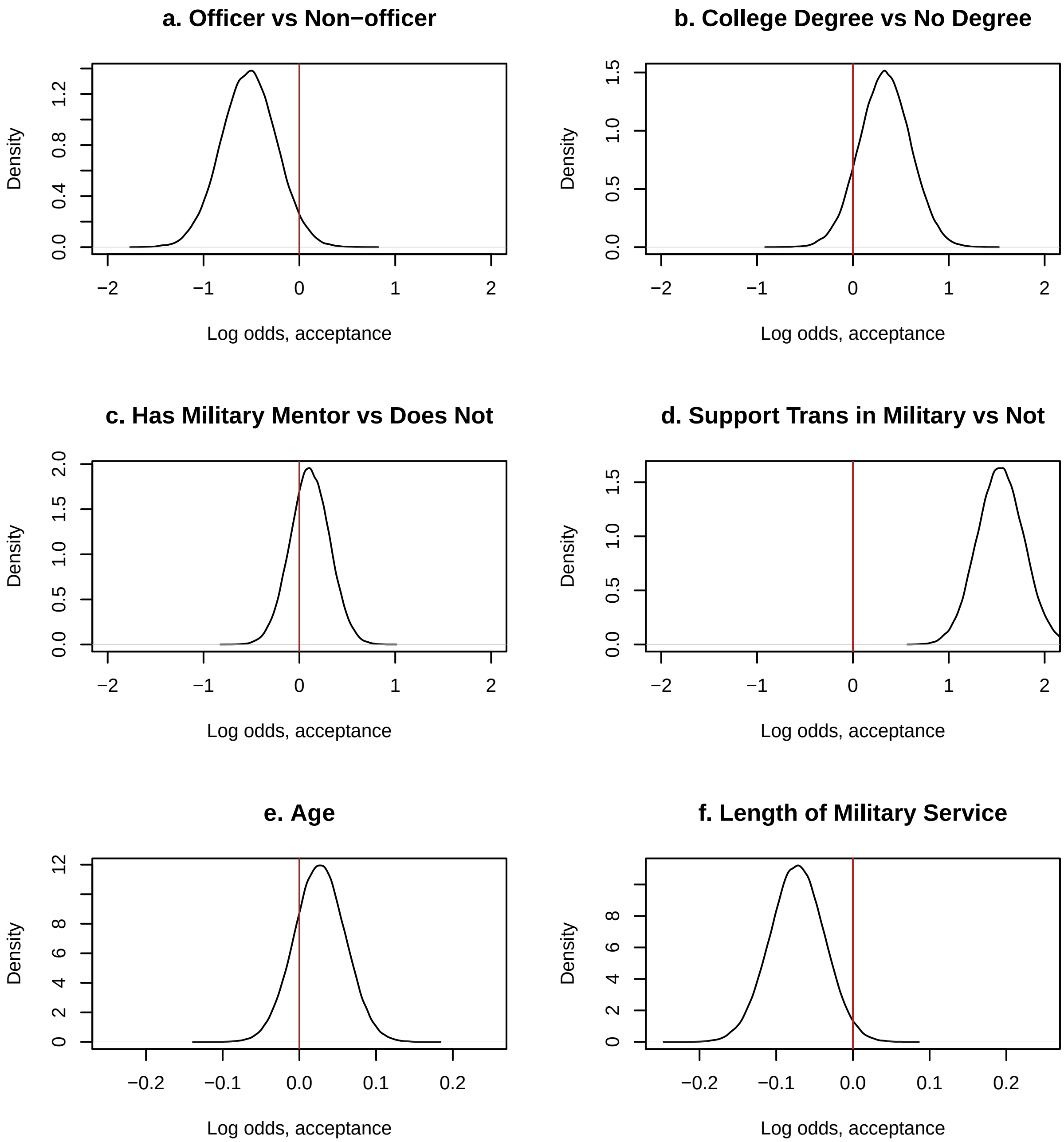


Figure 3. Posterior distributions of log-odds for binary and continuous fixed effects.



Calls to Stan in R.

```
brm_multiple(acceptance_grp ~ . - cluster_id + (1|cluster_id),
                      data = imp_data,
                      family = cumulative("logit"),
                      inits = "0",
                      chains = 5,
                      iter = 5000,
                      warmup = 1000,
                      thin = 2,
                      prior = c(set_prior("normal(0, 10)",
                                          class = "Intercept"),
                                set_prior("normal(0, 2.5)",
                                          class = "b"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd"),
                                set_prior("normal(0, 10)",
                                          class = "sd",
                                          coef = "Intercept",
                                          group = "cluster_id"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd",
                                          group = "cluster_id"))
                      )

brm_multiple(acceptance_grp ~ . - cluster_id + (1|cluster_id),
                      data = imp_data,
                      family = cumulative("logit"),
                      inits = "0",
                      chains = 5,
                      iter = 5000,
                      warmup = 1000,
                      thin = 10,
                      prior = c(set_prior("student_t(7, 0, 10)",
                                          class = "Intercept"),
                                set_prior("student_t(7, 0, 2.5)",
                                          class = "b"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd"),
                                set_prior("normal(0, 10)",
                                          class = "sd",
                                          coef = "Intercept",
                                          group = "cluster_id"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd",
                                          group = "cluster_id"))
                      )

brm_multiple(acceptance_grp ~ . - cluster_id + (1|cluster_id),
                      data = imp_data,
                      family = cumulative("logit"),
                      inits = "0",
                      chains = 5,
                      iter = 5000,
```

```
                      warmup = 1000,
                      thin = 10,
                      prior = c(set_prior("cauchy(0, 10)",
                                          class = "Intercept"),
                                set_prior("cauchy(0, 2.5)",
                                          class = "b"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd"),
                                set_prior("normal(0, 10)",
                                          class = "sd",
                                          coef = "Intercept",
                                          group = "cluster_id"),
                                set_prior("student_t(3, 0, 10)",
                                          class = "sd",
                                          group = "cluster_id"))
                      )
```

References.

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