Online appendix for "NGO Repression as a Predictor of Worsening Human Rights Abuses"

Contents

Modeling approach

We use Stan (Stan Development Team, 2021) through R (R Core Team, 2021) and **brms** (Bürkner, 2017) to estimate our models. We generate 4 MCMC chains for each model with 2,000 iterations in each chain, 1,000 of which are used for warmup. All chains converge; we assess convergence with visual inspection.

To check for robustness, we also ran models using both country and regional random effects, but doing so made no noticeable difference in the results—for the sake of computational efficiency, we thus do not include regional effects.

Complete results from all the models, along with posterior predictive checks, goodness-of-fit measures, and prediction diagnostics are all available at a companion statistical analysis notebook at https://doi.org/10.17605/OSF.IO/MTR6X. Our general modeling approach can be summarized as follows:

PTS models

Equation

$$
\begin{aligned}
& \textbf{Likelihood for ordinal outcome} \\
& \text{Political Terror Scores (PTS)} \\
y_{i,t+1} &\sim \text{Categorical}(p_{i,t+1}) \\
\\
& \textbf{Parameters} \\
\text{logit}(p_i) &= \alpha_{j[i]} - \phi_{k,t+1} \\
\phi_{k,t+1} &= \beta_1 \text{PTS}_{i,t} + \beta_2 \text{PTS}_{i,t-1} + \\
& \quad \beta_3 \text{Outcome}_{i,t} + \beta_4 \text{Polyarchy}_{i,t} + \\
& \quad \beta_5 \log(\text{GDP per capita}) + \\
& \quad \beta_6 \text{Trade as \% of GDP}_{i,t} + \\
& \quad \beta_7 \text{Armed conflict}_{i,t} \\
\\
\alpha_j &\sim \mathcal{N}(\mu_{\alpha_j}, \sigma_{\alpha_j}), \text{ for country } j \text{ in } 1..J \qquad \text{[country-specific intercepts]} \\
\\
& \textbf{Priors} \\
\mu_{\alpha_j} &\sim \mathcal{N}(0, 3) \qquad \text{[country-specific intercepts]} \\
\beta_{1-7} &\sim \mathcal{N}(0, 3) \qquad \text{[population effects]} \\
\sigma_{\alpha_j} &\sim \text{Cauchy}(0, 1) \qquad \text{[sd for population \& country]}
\end{aligned}
$$

R code

The actual R code for this model is included in the replication code at https://doi.org/10.17605/OSF.IO/MTR6X. This is a simplified representation of the **brms** (Bürkner, 2017) model code.

```
# Ordinal logistic regression for political terror
# (replace `cs_repression` with different measures of de jure and
# de facto civil society repression: barriers_total, advocacy, entry,
# funding, and v2csreprss)
brm(
  bf(PTS_lead1 ~ cs_repression + cs_repression_lag1 +
       PTS + v2x_polyarchy + gdpcap_log +
       un_trade_pct_gdp + armed_conflict + (1 | gwcode)),
  family = cumulative(),
  prior = c(set_prior("normal(0, 3)", class = "Intercept"),
            set_prior("normal(0, 3)", class = "b"),
            set_prior("cauchy(0, 1)", class = "sd")),
  ...
)
```

Latent human rights models

Equation

$$
\begin{aligned}
& \textbf{Likelihood for continuous outcome} \\
& \text{Latent human rights (LHR) values} \\
y_{i,t+1} &\sim \mathcal{N}(y^*_{i,t+1}, \sigma_i) \\
\\
& \textbf{Parameters} \\
y^*_{i,t+1} &= \alpha_{j[i]} + \beta_1 \text{LHR}_{i,t} + \beta_2 \text{LHR}_{i,t-1} \\
& \quad \beta_3 \text{Outcome}_{i,t} + \beta_4 \text{Polyarchy}_{i,t} + \\
& \quad \beta_5 \log(\text{GDP per capita}) + \\
& \quad \beta_6 \text{Trade as \% of GDP}_{i,t} + \\
& \quad \beta_7 \text{Armed conflict}_{i,t} \\
\\
\alpha_j &\sim \mathcal{N}(\mu_{\alpha_j}, \sigma_{\alpha_j}), \text{ for country } j \text{ in } 1..J \qquad \text{[country-specific intercepts]} \\
\\
& \textbf{Priors} \\
\mu_{\alpha_j} &\sim \mathcal{N}(0, 10) \qquad \text{[country-specific intercepts]} \\
\beta_{1-7} &\sim \mathcal{N}(0, 3) \qquad \text{[population effects]} \\
\sigma_i, \sigma_{\alpha_j} &\sim \text{Cauchy}(0, 1) \qquad \text{[sd for population \& country]}
\end{aligned}
$$

R code

The actual R code for this model is included in the replication code at https://doi.org/10.17605/OSF.IO/MTR6X. This is a simplified representation of the **brms** (Bürkner, 2017) model code.

```
# Gaussian regression for latent human rights
# (replace `cs_repression` with different measures of de jure and
# de facto civil society repression: barriers_total, advocacy, entry,
# funding, and v2csreprss)
brm(
  bf(latent_hr_mean_lead1 ~ cs_repression + cs_repression_lag1 +
       latent_hr_mean + v2x_polyarchy + gdpcap_log +
       un_trade_pct_gdp + armed_conflict + (1 | gwcode)),
  family = gaussian(),
  prior = c(set_prior("normal(0, 10)", class = "Intercept"),
            set_prior("normal(0, 3)", class = "b"),
            set_prior("cauchy(0, 1)", class = "sd")),
  ...
)
```

Improved cases

Table 1: Country-year cases where including civil society restrictions improved PTS predictions

Country	Year	Actual	Baseline prediction	Total NGO barriers included	Civil society repression included
Guatemala	2013	Level 3	Level 2	Level 3	Level 3
Kosovo	2012	Level 1	Level 2	Level 1	Level 1
Sierra Leone	2011	Level 3	Level 2	Level 3	—
Congo - Brazzaville	2011	Level 3	Level 2	Level 3	Level 3
Somalia	2013	Level 5	Level 4	Level 5	—
Bahrain	2011	Level 3	Level 2	Level 3	Level 3
Bahrain	2013	Level 3	Level 2	Level 3	Level 3
Libya	2011	Level 4	Level 5	—	Level 4

Complete model results

Table 2: Full results from ordered logistic regression models predicting political terror

	Outcome in t + 1				
	Total barriers	Barriers to advocacy	Barriers to entry	Barriers to funding	Civil society repression
Total legal barriers	0.157				
	[-0.019, 0.308]				
Total legal barriers (t - 1)	0.021				
	[-0.144, 0.186]				
Barriers to advocacy		0.457			
		[-0.160, 1.100]			
Barriers to advocacy (t - 1)		-0.092			
		[-0.730, 0.596]			
Barriers to entry			0.270		
			[-0.068, 0.580]		
Barriers to entry (t - 1)			0.056		
			[-0.256, 0.404]		
Barriers to funding				0.273	
				[-0.070, 0.616]	
Barriers to funding (t - 1)				0.066	
				[-0.284, 0.418]	
Civil society repression					-0.382
					[-0.666, -0.122]
Civil society repression (t - 1)					0.081
					[-0.189, 0.346]
PTS = 2	2.250	2.288	2.259	2.257	2.265
	[1.948, 2.542]	[1.990, 2.583]	[1.981, 2.572]	[1.973, 2.580]	[1.969, 2.571]
PTS = 3	4.221	4.305	4.242	4.236	4.297
	[3.857, 4.609]	[3.926, 4.685]	[3.867, 4.630]	[3.868, 4.625]	[3.921, 4.690]
PTS = 4	6.227	6.344	6.255	6.215	6.340
	[5.720, 6.696]	[5.887, 6.878]	[5.776, 6.733]	[5.727, 6.692]	[5.864, 6.826]
PTS = 5	8.566	8.628	8.588	8.535	8.619
	[7.924, 9.193]	[8.012, 9.278]	[7.977, 9.223]	[7.906, 9.135]	[7.998, 9.240]
Polyarchy index	-2.215	-2.302	-2.369	-2.239	-1.273

	[-2.957, -1.555]	[-2.959, -1.610]	[-3.095, -1.725]	[-2.962, -1.589]	[-2.287, -0.303]
Log GDP per capita	-0.471	-0.434	-0.443	-0.471	-0.424
	[-0.621, -0.320]	[-0.574, -0.288]	[-0.584, -0.299]	[-0.626, -0.321]	[-0.560, -0.284]
Trade as	[-0.751, -0.118]	[-0.743, -0.096]	[-0.722, -0.097]	[-0.729, -0.096]	[-0.740, -0.101]
Armed conflict	1.083	1.067	1.077	1.089	1.054
	[0.767, 1.411]	[0.737, 1.363]	[0.770, 1.375]	[0.769, 1.392]	[0.758, 1.363]
Num.Obs.	3594	3594	3594	3594	3612
R2	0.807	0.806	0.807	0.807	0.806
R2 Marg.	0.711	0.709	0.710	0.706	0.714
LOOIC	5194.4	5219.3	5199.7	5197.7	5252.0
LOOIC s.e.	97.0	97.2	97.2	97.0	97.3
WAIC	5193.8	5218.6	5199.0	5197.0	5251.4

Posterior means; 95% credible intervals in brackets

Table 3: Full results from Gaussian regression models predicting latent human rights

	Outcome in t + 1				
	Total barriers	Barriers to advocacy	Barriers to entry	Barriers to funding	Civil society repression
Total legal barriers	-0.013				
	[-0.031, 0.005]				
Total legal barriers (t - 1)	0.007				
	[-0.012, 0.025]				
Barriers to advocacy		-0.024			
		[-0.092, 0.049]			
Barriers to advocacy (t - 1)		0.007			
		[-0.064, 0.080]			
Barriers to entry			-0.027		
			[-0.062, 0.008]		
Barriers to entry (t - 1)			0.019		
			[-0.018, 0.053]		
Barriers to funding				-0.016	
				[-0.053, 0.021]	
Barriers to funding (t - 1)				0.006	
				[-0.030, 0.046]	
Civil society repression					0.053
					[0.024, 0.083]
Civil society repression (t - 1)					-0.037
					[-0.067, -0.007]
Latent human rights (t)	0.964	0.964	0.964	0.965	0.963
	[0.951, 0.975]	[0.952, 0.975]	[0.951, 0.976]	[0.952, 0.975]	[0.952, 0.974]
Polyarchy index	0.074	0.080	0.082	0.076	0.017
	[0.032, 0.115]	[0.040, 0.126]	[0.040, 0.126]	[0.032, 0.117]	[-0.053, 0.085]
Log GDP per capita	0.008	0.007	0.007	0.008	0.009
	[-0.001, 0.015]	[0.000, 0.015]	[-0.001, 0.015]	[0.000, 0.016]	[0.002, 0.017]
Trade as	[0.002, 0.044]	[0.004, 0.044]	[0.003, 0.044]	[0.004, 0.043]	[0.002, 0.042]
Armed conflict	-0.004	-0.005	-0.004	-0.005	-0.003
	[-0.029, 0.021]	[-0.032, 0.019]	[-0.030, 0.022]	[-0.030, 0.022]	[-0.027, 0.023]
Intercept	-0.073	-0.075	-0.073	-0.076	-0.074
	[-0.136, -0.010]	[-0.133, -0.011]	[-0.138, -0.010]	[-0.136, -0.014]	[-0.134, -0.012]
Num.Obs.	3609	3609	3609	3609	3629
R2	0.969	0.968	0.969	0.968	0.968

R2 Marg.	0.968	0.968	0.968	0.968	0.968
LOOIC	47.9	49.4	51.5	49.3	61.6
LOOIC s.e.	351.7	351.1	352.4	351.2	350.5
WAIC	46.5	48.4	50.1	48.6	60.3
RMSE	0.79	0.79	0.79	0.79	0.79

Posterior means; 95% credible intervals in brackets

References

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