# Appendix: External Threats, Capacity, and Repression

## Contents

# A Threat Measurement Model

This section provides a technical description for our Bayesian measurement model of external threat, developed from Quinn's (2004) approach.

We begin with the assumption that observed indicators of threat are proxies for the latent level of threat. Following Quinn's notation, we let $j = 1, ..., J$ input variables (i.e. $j_1$ = rivalry, $j_2$ = territorial dispute, etc.) and $i = 1, ..., N$ represent country-year observations. $N \times J$ equals the matrix **X**, where $X^*$ is the latent variable of interest, threat.

The input variables can be continuous or ordinal. If ordinal, the variable has $C_j > 1$ categories. The matrix $X$ is assumed to be a byproduct of the latent $X^*$ and a set of cutpoints, $\gamma$.

$$x_{ij} = \begin{cases} x^*_{ij} & \text{if j is continuous.} \\ c & \text{if } x^*_{ij} \in [\gamma_{j(c-1)}, \gamma_{jc}] \text{ and j is ordinal.} \end{cases} \tag{1}$$

We assume that $\gamma_{j0} \equiv -\infty$, $\gamma_{j1} \equiv 0$, and $\gamma_{jC_j} \equiv \infty$ for all $j$. The remaining cutpoints are estimated.

The patterns between the observed indicators in **X** are modeled using a factor analytic model for the latent $X^*$:

$$x^*_i = \Lambda\phi_i + \varepsilon_i \tag{2}$$

where $x^*_i$ is a $J$ vector of latent responses mapped to observation $i$, $\Lambda$ is a $J \times K$ matrix of factor loadings, $\phi_i$ is a $K$ vector of factor score corresponding to $i$, and $\varepsilon_i$ is the $J$ vector error.

Assuming that $X^*$ are the latent data, we derive the posterior distributions from the following equation:

$$
\begin{aligned}
p(X^*, \gamma, \Lambda, \Phi, \Psi | X) &\propto p(X|X^*, \gamma) p(X^*|\Lambda, \Phi, \Psi) p(\gamma) p(\Lambda) p(\Phi) p(\Psi) \\
&\propto \left\{ \prod_{i=1}^{N} \prod_{j=1}^{J} \{ I(x_{ij} = x^*_{ij}) I(X_j \text{ continuous}) \right. \\
&+ \sum_{c=1}^{C_j} I(x_{ij} = c) I[(x^*_{ij} \in (\gamma_{j(c-1)}, \gamma_{jc})] I(X_j \text{ ordinal}) \\
&\times p_{\mathcal{N}}(x^*_i | \Lambda \Phi_i, \Psi) p(\Lambda) p(\Phi) p(\Psi),
\end{aligned} \tag{3}
$$

where $I(a)$ is the indicator function, equal to one is a is true, else zero; $p_{\mathcal{N}}(z|\mu, \Sigma)$ is a multivariate normal density with mean of $\mu$ and variance-covariance matrix $\Sigma$ analyzed at $z$; $p(\Lambda), p(\Phi)$, and $p(\Psi)$ are prior densities for $\Lambda$, $\Phi$, and $\Psi$.

Estimates for the parameters are modeled using Markov chain Monte Carlo (MCMC) simulations, using the *MCMCpack* library in R (version 4.0.1). The algorithm within this program samples from the full conditional distributions of $X^*$, $\Lambda$, $\Phi$, and $\Psi$ and uses a Metropolis-Hastings step to sample $\gamma$.

# B Summary Statistics

Table B.1: Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| External Threat | -0.044 | 0.864 | -1.805 | 1.77 | 5287 |
| Fariss et al (2020) Repression | -0.213 | 1.461 | -4.614 | 3.46 | 5997 |
| Fariss (2014) Repression | -0.233 | 1.321 | -4.201 | 3.112 | 5339 |
| PTS Repression | 2.553 | 1.154 | 1 | 5 | 6197 |
| State Killing Estimate | 170.867 | 9901.603 | 0 | 683998 | 4774 |
| Capacity (V-Dem) | 0.59 | 1.055 | -2.869 | 2.838 | 4096 |
| Democracy | 0.4 | 0.245 | 0.015 | 0.913 | 5346 |
| log of Population | 15.162 | 2.266 | 8.941 | 21.058 | 6642 |
| log of GDP per cap | 7.942 | 1.291 | 5.102 | 12.186 | 5455 |
| Ongoing Civil War | 0.128 | 0.335 | 0 | 1 | 7414 |

# C Alternative Measures for Capacity

The main analysis in the manuscript focuses on fiscal capacity, as measured by V-Dem. We assume that a state's ability to extract fiscal resources will correspond with other elements of capacity, including bureaucratic quality. To ensure that our measurement choice does not drive our results, we examine an alternative capacity measure from O'Reilly and Murphy (2022). The authors created a capacity index using not only V-Dem information on fiscal capacity, but also on the rule of law, control over territory, the rigorousness and impartiality of public administration, provision of public goods, and education. This provides a broader conceptualization and measurement of capacity. Table C.2 shows that using this alternative variable does not change our main inferences.

Table C.2: Alternative Capacity Measure Analysis

| | Government Repression (1) | State Capacity (2) | Government Repression (3) |
|---|---|---|---|
| External Threat | 0.267* | 0.110* | 0.298* |
| | (0.030) | (0.024) | (0.031) |
| Capacity (O&M) | | | -0.229* |
| | | | (0.023) |
| Democracy | -1.733* | 1.988* | -1.280* |
| | (0.078) | (0.072) | (0.092) |
| log of Population | 0.584* | 0.083 | 0.583* |
| | (0.060) | (0.047) | (0.060) |
| log of GDP per cap | -0.139* | 0.241* | -0.082* |
| | (0.031) | (0.027) | (0.030) |
| Ongoing Civil War | 0.319* | -0.092* | 0.288* |
| | (0.020) | (0.019) | (0.021) |
| Constant | 0.112 | 0.026 | 0.137* |
| | (0.069) | (0.053) | (0.069) |
| R-Sq | 0.32 | 0.34 | 0.34 |
| N | 5366 | 5101 | 5088 |
| Indirect Effect | | | -0.021* |
| of Threat | | | (0.005) |

Robust standard errors in parentheses. Year fixed effects included but not reported.
Estimates represent within-unit fixed-effects. * p<0.05.

# D Alternative Threat Measures

This section examines how the threat component variables directly and indirectly affect repression. Replicating Model 3 from the main analysis in Table D.3, we find that each proxy directly affects repression in the expected direction except total borders. Rivalries, territorial disputes, buffer status, and time since targeted are statically different than zero. The components all show the expected direction for indirect effects, but are not statistically significant. Again, these measures are only imperfect measures of threat. In addition, most of these variables do not vary substantially within countries. As a result, a within-estimator model would make it difficult to connect the components to outcomes of interest. Capturing more of the within-country variance of external threat was our main motivation for creating a latent measure of threat.

Table D.3: Alternative Threat Measure Analysis

| | (1) | (2) | (3) | | | |
|---|---|---|---|---|---|---|
| Rivalry | 0.115* | | | | | |
| | (0.038) | | | | | |
| Territorial Dispute | | 0.139* | | | | |
| | | (0.049) | | | | |
| Buffer State | | | 0.153* | | | |
| | | | (0.077) | | | |
| Total Borders | | | | -0.269* | | |
| | | | | (0.088) | | |
| Neighbors' Military Spending | | | | | 0.036 | |
| | | | | | (0.019) | |
| Years since Targeted | | | | | | -0.092* |
| | | | | | | (0.013) |
| Capacity | -0.033 | -0.078* | -0.067* | -0.057 | -0.026 | -0.061* |
| | (0.030) | (0.035) | (0.032) | (0.032) | (0.034) | (0.030) |
| Democracy | -1.781* | -1.881* | -1.859* | -1.824* | -1.547* | -1.843* |
| | (0.084) | (0.098) | (0.085) | (0.085) | (0.107) | (0.081) |
| log of Population | 0.571* | 0.444* | 0.421* | 0.413* | 0.445* | 0.485* |
| | (0.068) | (0.098) | (0.069) | (0.069) | (0.073) | (0.062) |
| log of GDP per cap | -0.247* | -0.094* | -0.103* | -0.103* | -0.070 | -0.108* |
| | (0.042) | (0.041) | (0.036) | (0.036) | (0.037) | (0.034) |
| Ongoing Civil War | 0.277* | 0.274* | 0.248* | 0.249* | 0.222* | 0.245* |
| | (0.025) | (0.030) | (0.026) | (0.026) | (0.028) | (0.025) |
| Constant | 0.091 | 0.075 | 0.072 | 0.075 | 0.060 | 0.096 |
| | (0.081) | (0.085) | (0.079) | (0.079) | (0.083) | (0.078) |
| R-Sq | 0.32 | 0.28 | 0.30 | 0.30 | 0.24 | 0.31 |
| N | 3349 | 2271 | 3252 | 3252 | 2393 | 3572 |
| Indirect Effect | -0.002 | -0.001 | -0.003 | -0.014 | -0.001 | -0.001 |
| of threat proxy | (0.002) | (0.002) | (0.006) | (0.008) | (0.002) | (0.001) |

Estimates represent within-unit fixed-effects. Year fixed effects included but not reported. * p<0.05.

# E Nordhaus, Oneal, Russett's Threat Measure

This section shows the results of the validation analysis in Table 2 in the manuscript using Nordhaus, Oneal and Russett's (2012) threat measure. Table E.4 shows the results. Model 1 demonstrates that this alternative measure does predict being targeted, but Model 2 shows that the between variance (differences between states) matters more than the within variance (changes within a state). The results for military spending (Models 3 and 4) are consistent with our latent measure of threat. Using Nordhaus, Oneal and Russett's (2012) measure of threat, we also find no relationship between threat and capacity or threat and repression (results in replication materials).

Table E.4: Validation Comparison to Nordhaus, Oneal, and Russett's (NOR) Threat Measure

| Dependent Variable: | Targeted in MID | | Military Spending | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Threat (NOR) | 3.827* | | 0.108* | |
| | (0.928) | | (0.048) | |
| (Within) Threat (NOR) | | -0.200 | | 0.235* |
| | | (3.788) | | (0.096) |
| (Between) Threat (NOR) | | 4.229* | | 0.094* |
| | | (1.129) | | (0.047) |
| L.log Military Spending | | | 0.932* | 0.932* |
| | | | (0.018) | (0.018) |
| Constant | -4.374* | -4.473* | 0.052* | 0.054* |
| | (0.340) | (0.374) | (0.017) | (0.018) |
| R2 | | | 0.89 | 0.89 |
| Log-Like | -420 | -419 | | |
| N | 3160 | 3160 | 2435 | 2435 |

$*p < 0.05$; Standard errors cluster on countries reported in parentheses.

# F Extended Latent Measure, 1919-2016

The main analysis in the manuscript uses our new latent measure of external threat that covers the years 1960-2016. We restricted the sample to these years because of the availability of the component variables, specifically SIPRI's data on military spending. Before 1960 the SIPRI data source is sparse for many developing countries. While the measurement model can utilize missing data to inform the latent outcome, we did not want to rely on missingness for an extended portion of the measure.

We did take an alternative approach to extend the data back to 1919. Instead of using SIPRI's military spending data, we use military expenditure data from the National Material Capabilities (NMC) dataset (Singer et al., 1972, v6). These data provide better temporal coverage and allow us to consider the percentage change in military expenditures in non-allied neighbors. With this alternative component, we re-analyze the measurement model and produce a latent measure of external threat that extends from 1919 to 2016. We analyze the extended measure's validity much in the same way we examined the original measure in the manuscript. The extended version performs well. To begin, Table F.5 reports the posterior distribution statistics for the extended latent measure. These are comparable to the original version.

Table F.5: Posterior Density Summary of Measurement Model for External Threat, 1919-2016

| | Interstate Rivalry | Territorial Dispute | Buffer State | Total Borders | Military Expenditure in Neighbor (NMC) | Years since Targeted |
|---|---|---|---|---|---|---|
| $\lambda_1$ | 0.971 | 1.365 | 0.767 | 0.465 | 0.520 | -0.480 |
| | (0.032) | (0.059) | (0.045) | (0.012) | (0.011) | (0.011) |
| $\lambda_0$ | -0.708 | -0.533 | -2.055 | | | |
| | (0.019) | (0.025) | (0.045) | | | |
| $\psi$ | | | | 0.783 | 0.729 | 0.767 |
| | | | | (0.013) | (0.012) | (0.011) |

Means are reported without parentheses; standard deviations are reported with parentheses.

Next, we examine how well the extended measure helps explain targeting and military spending. Table F.6 again shows results similar to the validation models in the manuscript.

Table F.6: Validation of Latent External Threat Measure, 1919-2016

| Dependent Variable: | Targeted in MID | | Military Spending | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Threat | 2.113* | | 0.011* | |
| | (0.439) | | (0.004) | |
| (Within) Threat | | 2.390* | | 0.010* |
| | | (0.567) | | (0.004) |
| (Between) Threat | | 2.048* | | 0.013* |
| | | (0.459) | | (0.006) |
| L.log Military Spending | | | 0.947* | 0.947* |
| | | | (0.012) | (0.012) |
| Constant | -5.018* | -5.052* | 0.051* | 0.051* |
| | (0.484) | (0.501) | (0.014) | (0.014) |
| R2 | | | 0.92 | 0.92 |
| Log-Like | -458 | -457 | 2442 | 2442 |
| N | 5884 | 5884 | 4980 | 4980 |

$*p < 0.05$; Standard errors cluster on countries reported in parentheses.

Finally, we replicate the main analysis on repression and substitute the extended external threat measure. The analysis here is still restricted to 1980 because of data availability on the dependent variable. The alternative latent measure produces results similar to the original measure in Table F.7.[1]

We provide this extended version of external threat to scholars interested in the effects of external threats pre-1960.[2] We also provide the code for the measurement model in the replication files if scholars want to amend our model or extend it even further back with alternative data sources.

[1]The original measure and the extended measure are correlated at 0.92.

[2] We thank an anonymous reviewer for this suggestion.

Table F.7: External Threats, Capacity, and State-Killings, 1980 - 2016

| | Government Repression (1) | State Capacity (2) | Government Repression (3) |
|---|---|---|---|
| External Threat (1919) | 0.160* | 0.046* | 0.165* |
| | (0.027) | (0.012) | (0.027) |
| Capacity | | | -0.099* |
| | | | (0.033) |
| Democracy | -1.841* | 0.155* | -1.822* |
| | (0.095) | (0.068) | (0.094) |
| log of Population | 0.455* | -0.181* | 0.438* |
| | (0.072) | (0.046) | (0.073) |
| log of GDP per cap | -0.128* | 0.217* | -0.104* |
| | (0.035) | (0.023) | (0.036) |
| Ongoing Civil War | 0.283* | -0.039* | 0.278* |
| | (0.028) | (0.013) | (0.028) |
| Constant | -0.004 | -0.215* | -0.021 |
| | (0.104) | (0.069) | (0.103) |
| R-Sq | 0.29 | 0.16 | 0.29 |
| N | 3179 | 3373 | 3179 |
| Indirect Effect of Threat | | | -.005 |
| | | | (0.002) |

Robust standard errors in parentheses. Year fixed effects included but not reported.
Estimates represent within-unit fixed effects. * $p < 0.05$.

# G Sample Limitations

In the manuscript, we limit the analysis to non-OECD countries and to the year 1980 and after. This section examines whether are results are sensitive to those design choices.

## G.1 OECD Countries

The main analysis in the manuscript only examines developing (non-OECD) countries for several reasons. First, developing states have yet to complete the consolidation of their state capacity and thus have the ability to improve capacity. If states already have developed advanced capacity, we do not expect external threats to affect capacity as much. In addition, there is a major overlap between developed countries and NATO, which may also mitigate the effects of threats. To test that possibility, we examine the relationship between external threats and capacity in Table G.8. Model 1 shows that external threat has a small and statistically insignificant relationship with capacity, as expected. Model 2 examines repression and finds that external threats increase repression, which is consistent to the relationship in developing countries.

Models 3 and 4 examine the full sample of states (OECD and non-OECD countries) to see if the direct or indirect are smaller compared to the non-OECD sample in the manuscript. We find we that the direct effect is nearly identical in the full sample (0.303) compared to the non-OECD sample (0.311), whereas the indirect effect is roughly halved in size for the full sample. Given that the indirect effects operate through increased capacity, we expected that OECD states' political development would be less sensitive to external threats.

## G.2 1960-2016

Two of the dependent variables analyzed in the manuscript (PTS and estimated government killing) have limited or no data available before 1980. Fariss, Kenwick and Reuning (2020) and Fariss's (2014) latent measure of repression ( Human Rights Protection Scores v4.01 and v2.04,

Table G.8: External Threats, Capacity, and Repression, 1980 - 2016

| | OECD Countries | | Full Sample | |
|---|---|---|---|---|
| | State Capacity | Government Repression | State Capacity | Government Repression |
| | (1) | (2) | (3) | (4) |
| External Threat | 0.005 | 0.196* | 0.108* | 0.303* |
| | (0.027) | (0.060) | (0.019) | (0.035) |
| Capacity | | 0.238* | | -0.088* |
| | | (0.098) | | (0.031) |
| Democracy | 1.266* | -1.661* | 0.278* | -1.788* |
| | (0.092) | (0.247) | (0.044) | (0.081) |
| log of Population | -0.172 | 1.555* | -0.085* | 0.583* |
| | (0.102) | (0.227) | (0.034) | (0.063) |
| log of GDP per cap | -0.106 | -0.944* | 0.223* | -0.102* |
| | (0.057) | (0.129) | (0.018) | (0.034) |
| Constant | -0.142* | 0.151 | -0.158* | 0.099 |
| | (0.058) | (0.130) | (0.042) | (0.078) |
| R-Sq | 0.30 | 0.52 | 0.14 | 0.32 |
| N | 585 | 567 | 3654 | 3572 |
| Indirect Effect | | 0.005 | | -0.010* |
| of Threat | | (0.007) | | (0.004) |

respectively) do extend back to 1946, but the several components that underlie the latent measure are missing pre-1980 (i.e. CIRI, ITT, PTS, and others). As a result, the standard deviation of Fariss, Kenwick and Reuning's (2020) measure pre-1980 is 39 percent higher than after 1980. For ensure we are analyzing comparable samples across the different dependent variable models, we restrict the sample to 1980 and after.

To demonstrate that this decision does not affect out main inferences, we replicate the main analysis with Fariss, Kenwick and Reuning (2020) and Fariss's (2014) latent measure of repression and extend the analysis to 1960. Table G.9 reports the results. Consistent with the main analysis, external threats increase repression directly, but indirectly decreases repression through higher state capacity.

Table G.9: External Threats, Capacity, and Repression, 1960 - 2016

| | State Capacity (1) | Repression (HRPSv4) (2) | Repression (HRPSv2) (3) |
|---|---|---|---|
| External Threat | 0.096* | 0.125* | 0.136* |
| | (0.019) | (0.036) | (0.032) |
| Capacity | | -0.091* | -0.072* |
| | | (0.029) | (0.025) |
| Democracy | 0.199* | -1.629* | -1.513* |
| | (0.060) | (0.086) | (0.079) |
| log of Population | -0.111* | 0.359* | 0.286* |
| | (0.031) | (0.053) | (0.056) |
| log of GDP per cap | 0.266* | -0.216* | -0.162* |
| | (0.021) | (0.032) | (0.031) |
| Ongoing Civil War | -0.044* | 0.358* | 0.336* |
| | (0.016) | (0.027) | (0.026) |
| Constant | -0.103 | -0.023 | 0.038 |
| | (0.062) | (0.091) | (0.077) |
| R-Sq | 0.17 | 0.27 | 0.33 |
| N | 3638 | 3571 | 3059 |
| Indirect Effect of Threat | | -0.009* | -0.008* |
| | | (0.003) | (0.003) |

# H Democracy and External Threats

This section examines the possibility that external threats' effects on both repression and capacity vary by regime type. Given previous research, it is plausible that the relationship between threats, capacity, and repression differ in democracies and non-democracies. For example, democracies may form more credible alliances and thus are less affected by threats (Digiuseppe and Poast, 2018; Leeds, Mattes and Vogel, 2009). Alternatively, democracies may enjoy better access to alternative sources of finance, such as sovereign credit, that would allow democracies to address threats without added capacity (Schultz and Weingast, 2003; Shea, 2014). In addition, democratic leaders may be too constrained to use repression even in times of heightened threat (Davenport, 2007). Similarly, autocratic leaders may prefer repression but low capacity allows state agents to avoid fulfilling these demands.

To examine these possibilities, we first focus on the direct relationship between threats and repression, conditional on regime type. In Model 1 in Table H.10, we interact the external threat measure with V-Dem's polyarchy measure. The interaction term is negative but not significant. This result in itself is not conclusive, as interaction models have strong assumptions of coverage and non-constant effects (Hainmueller, Mummolo and Xu, 2019). To test the robustness of the interaction term, we use Hainmueller, Mummolo and Xu's (2019) 'interflex' approach. The first part of the approach is to bin the moderator into 3 groups and test the effect of threat across all three terciles.[3] The point estimates in Figure H.1a correspond to the low, medium, and high tercile of the data and compare the estimates to the linear prediction from Model 1. A Wald test rejects the null hypothesis that tercile point effects and the linear prediction are the same. The point estimates suggest a non-constant effect of threat across the moderator variable, where the effect is strongest for the smallest and largest values. In other words, it is not that democracies and non-democracies

[3]This process is done automatically using Hainmueller, Mummolo and Xu's (2019) interflex package in Stata or R. The choice of 3 groups is the default option, though arbitrary. We examine other bin numbers and find consistent results.

react differently to threats. Instead, they act similarly, and mixed regimes respond less.

To consider this point further, we continue with Hainmueller, Mummolo and Xu's (2019) 'interflex' approach and use their kernel estimator. This estimator incorporates Blackwell and Olson's (2021) recommendation to model each interaction between the moderator and other covariates in the model. To avoid overfitting, a double-selection approach using lasso estimators selects the most-relevant interactions and omits those with small effects.[4] The resulting graph from this approach is in Figure H.1b. The kernel estimate shows that the effect of external threat is strongest for the most authoritarian countries. As a state's polyarchy value increases the effect of threats diminishes, only to increase again for the highest valued democracies.

To further explore the possibility of a non-constant effect of threat, we consider an alternative, non-continuous, measure of democracy: Boix, Miller and Rosato's (2013) binary measure of democracy. Model 2 examines this interaction, and we find no conditional relationship. Of course, the binary measure would not capture the non-constant effects if the heterogeneous effects are most pronounced in extreme values of democracy and authoritarian regimes. If and why these heterogeneous effects exist, as shown in Figure H.1b, should be explored in future research. For now, we consider whether the indirect effects vary by regime type. To the best of our knowledge, we have not found an empirical approach to address heterogeneity in indirect effects in mediation analysis. So we simply split the sample into democracies and non-democracies (using Boix, Miller and Rosato's (2013) binary measure of democracy) and compare the effects across samples in Model 3 and 4 in Table H.10. We find that external threats still increase repression in democracies (Model 3), but the negative effect of capacity is smaller and statistically insignificant. In non-democracies, external threats also increase repression but more capacity decreases repression. The indirect effects in both samples are negative. However, the indirect effects in democracies are smaller and statistically insignificant. In other words, capacity's dampening effect on repression is more uncertain in democracies, if it exists at all.

[4] Again, this process is automated in the interflex packages.

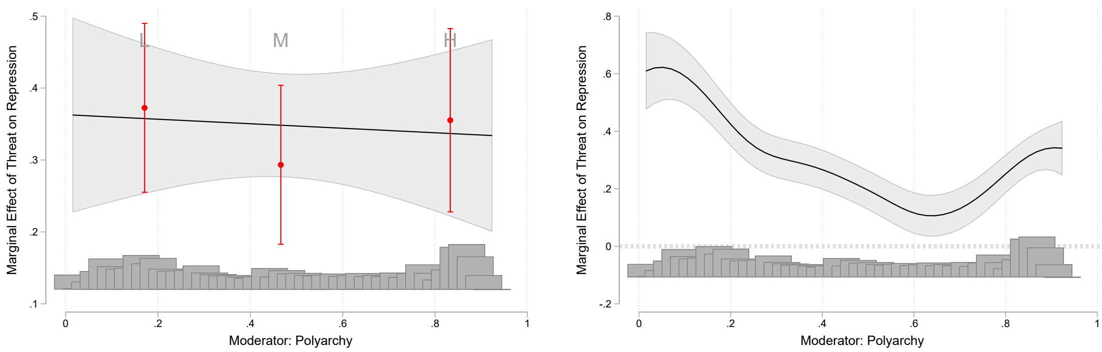
The results here suggest some interesting paths for future research, most notably the non-constant effects. Any explanation we would provide for these here would be ad-hoc, as these non-constant effects are surprising and puzzling. We plan to return to these issues in future research.

Table H.10: External Threats, Democracies, and Repression: Heterogenous Effects

| | | | Democracy | Non-Democracy |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| External Threat | 0.363* | 0.373* | 0.256* | 0.423* |
| | (0.071) | (0.047) | (0.051) | (0.053) |
| Capacity | -0.162* | -0.153* | -0.053 | -0.221* |
| | (0.032) | (0.032) | (0.046) | (0.046) |
| Polyarchy (V-Dem) | -0.145* | | | |
| | (0.035) | | | |
| Democracy (Boix) | | -0.108* | | |
| | | (0.019) | | |
| External Threat × Polyarchy (V-Dem) | -0.031 | | | |
| | (0.128) | | | |
| External Threat × Democracy (Boix) | | -0.023 | | |
| | | (0.067) | | |
| log of Population | 0.484* | 0.414* | 0.071 | 0.505* |
| | (0.069) | (0.068) | (0.112) | (0.099) |
| log of GDP per cap | -0.078* | -0.096* | -0.160* | -0.080 |
| | (0.036) | (0.036) | (0.079) | (0.043) |
| Ongoing Civil War | 0.247* | 0.252* | 0.284* | 0.231* |
| | (0.027) | (0.026) | (0.041) | (0.035) |
| Constant | 0.360* | 0.312* | 0.090 | 0.345* |
| | (0.082) | (0.080) | (0.151) | (0.103) |
| Indirect Effect | | | -0.005* | -0.026* |
| of Threat | | | (0.005) | (0.007) |
| R-Sq | 0.23 | 0.24 | 0.25 | 0.19 |
| N | 3572 | 3507 | 1764 | 1743 |

$*p < 0.05$; Robust standard errors reported in parentheses

Figure H.1: **External Threats, Democracy, and Repression**




(a) Tercile Estimates (b) Kernel Estimates

# References


Blackwell, Matthew and Michael P Olson. 2021. "Reducing model misspecification and bias in the estimation of interactions." *Political Analysis* pp. 1–20.

Boix, Carles, Michael Miller and Sebastian Rosato. 2013. "A complete data set of political regimes, 1800–2007." *Comparative political studies* 46(12):1523–1554.

Davenport, Christian. 2007. "State repression and political order." *Annu. Rev. Polit. Sci.* 10:1–23.

Digiuseppe, Matthew R. and Paul Poast. 2018. "Arms versus Democratic Allies." *British Journal of Political Science* 48(4):981–1003.

Fariss, Christopher J. 2014. "Respect for human rights has improved over time: Modeling the changing standard of accountability." *American Political Science Review* 108(2):297–318.

Fariss, Christopher J, Michael R Kenwick and Kevin Reuning. 2020. "Estimating one-sided-killings from a robust measurement model of human rights." *Journal of peace research* 57(6):801–814.

Hainmueller, Jens, Jonathan Mummolo and Yiqing Xu. 2019. "How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice." *Political Analysis* 27(2):163–192.

Leeds, Brett Ashley, Michaela Mattes and Jeremy S Vogel. 2009. "Interests, institutions, and the reliability of international commitments." *American Journal of Political Science* 53(2):461–476.

Nordhaus, William, John R. Oneal and Bruce Russett. 2012. "The Effects of International Security Environment on National Military Expenditures: A Multi-Country Study."." *International Organization* 66(3).

O'Reilly, Colin and Ryan H Murphy. 2022. "An Index Measuring State Capacity, 1789–2018." *Economica* .

Quinn, Kevin M. 2004. "Bayesian factor analysis for mixed ordinal and continuous responses." *Political Analysis* 12(4):338–353.

Schultz, Kennth A. and Barry Weingast. 2003. "The Democratic Advantage: The Institutional Sources of International Competition." *International Organization* 57(1):3–42.

Shea, Patrick. 2014. "Financing Victory: Credit, Democracy, and War Outcomes." *Journal of Conflict Resolution* 58(5):771–796.

Singer, J David, Stuart Bremer, John Stuckey et al. 1972. "Capability distribution, uncertainty, and major power war, 1820-1965." *Peace, war, and numbers* 19(48):9.