Supplemental Appendix for

The Diversity of Repression: Measuring State Repressive Repertoires with Events Data[1]

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Contents

0.1 Overview

In this supplementary material, we first provide an in-depth discussion of our ICEWS event data (Boschee et al., 2015) formatting decisions, alongside a summary table of the frequencies and proportions of the ICEWS repression categories that were used to create our primary entropy measure. We then present and discuss a series of country-year statistical models of repression entropy, as referenced in our main paper. We next provide a series of plots that directly compare our entropy measure of state repression against a Herfindahl index of state repression. We then reproduce our main paper's Figure 2 whilst employing a variety of Goldstein-scale event data measures, as opposed to our raw count of ICEWS events. This is followed by a series of additional country-specific time series plots, which compare our entropy measure to the alternate human rights measures discussed in the main paper.

0.2 ICEWS Event Data Information

This section provides further detail on our chosen ICEWS actor, and repression event category, aggregation decisions. We first provide additional information on our ICEWS source and target actor choices. We then outline our ICEWS repression event category choices in further detail. Finally, we present a table containing the frequencies and proportions of our aggregated ICEWS events by repression event category.

Turning first to the source and target actors we retained in our ICEWS event sample, and given our interest in repertoires of domestic repression, we first retained only those ICEWS events from 1996-2016 involving source and target actors assigned to the same country. We next retain only those events whose source sector designations include actors coded as "Military," "Government," "Police," or the nation-state itself.[2] We subset all remaining events to include only events that target civilian actors tagged as "General Population," "Civilian," "Social," "Protestors," "Mobs," "Popular Opposition," "Media," "NGOs," and "Business." These steps ensure that our sample of events encompasses domestic interactions involving government initiators and domestic (non-rebel and non-state) targets. We next discuss how we subset these events to only include repression actions.

ICEWS' event action types are recorded under the CAMEO action typology (Schrodt, Gerner and Yilmaz, 2009). This typology categorizes all events into one of 20 "two-digit" action categories, which range from primarily cooperative events (e.g., "03: Express Intent to Cooperate") to primarily conflictive events (e.g., "18: Assault"). Three-digit and four-digit sub-categories are nested within these "two-digit" action categories (e.g., "1831: Carry out suicide bombing"), and are used when sufficiently detailed information is available within a given news story for this level of action coding. Contemporary event data analyses typically divide, and then sum, all resultant CAMEO events into a set of four "quad-count" categories,[3] or a set of five "pentaclass" categories[4] (D'Orazio, Yonamine and Schrodt, 2011; Schrodt, 2011; Schrodt and Yonamine, 2013; Bagozzi, 2015; Chiba and Gleditsch, 2017).

For our analysis of repression repertoires, we accordingly chose to subset our retained events to encompass only those event actions contained within the "material conflict" pentaclass categorywhile also omitting CAMEO category 14 events (i.e., protest events). The latter action category is primarily related to citizen strikes and boycotts that target the government and thus theoretically irrelevant, leading to its exclusion. Our repression data thus include CAMEO categories 15 and 17-20, and all associated subcategories. We then applied 'one-a-day' filtering (Schrodt and Van Brackle, 2013; Beieler et al., 2016)[5] to minimize duplicate records of the same event in our machine coded event data, before summing all remaining events to the country-year-(three-digit)-action category level for the years 1996-2016. We also reanalyze all data without using one-a-day filtering approach for robustness.

[2] I.e., regarding the latter designation, we follow past research (D'Orazio, Yonamine and Schrodt, 2011; Bagozzi, 2015) to treat actions simply coded as arising from the "nation-state" as government directed.

[3] I.e., verbal conflict (CAMEO categories 09-13 and 16, and all subcategories), verbal cooperation (CAMEO categories 01-05 and all subcategories), material conflict (CAMEO categories 14-15 and 17-20, and all subcategories) and material cooperation (CAMEO categories 06, 07, and 08, and all subcategories).

[4] I.e., the four "quad-count" categories defined above, after splitting off all events arising from the two-digit CAMEO categories (and associated subcategories) 01-02 into a fifth, "comments" count measure.

[5] In our case, we only retain one event per given day, for each unique source-target-country-action combination, where action corresponds to the event's CAMEO two-to-four-digit code.

Together, these steps generated country-year repression event counts for every country of the world (aside from the US) during the years 1996-2016, disaggregated according to 30 three-digit CAMEO categories. We report the frequency of identified events within each three-digit CAMEO category, and the proportion of all events that fall within each retained three-digit CAMEO category in Table A.I. As this Table illustrates, we have a degree of coverage within all 30 three-digit repression event categories considered. However, a majority of all events fall within category 173 ("Arrest, detain, or charge with legal action") and category 190 ("Use conventional military force"), which represent 59% of the total sample and 16% of the total sample, respectively. We also evaluate the robustness of our findings to the exclusion of the most common category (173).

Table A.I: Sample frequencies and proportions of retained ICEWS repression categories, 1996-2016.

Code	CAMEO Event Type	Frequency	Proportion
15	EXHIBIT FORCE POSTURE		
150	Demonstrate military or police power, not specified below	21	0
151	Increase police alert status	49	0
152	Increase military alert status	31	0
153	Mobilize or increase police power	109	0
154	Mobilize or increase armed forces	97	0
17	COERCE		
170	Coerce, not specified below	6,405	0.017
171	Seize or damage property	7,842	0.021
172	Impose administrative sanctions	9,287	0.025
173	Arrest, detain, or charge with legal action	219,888	0.587
174	Expel or deport individuals	9,184	0.025
175	Use tactics of violent repression	18,319	0.049
18	ASSAULT		
180	Use unconventional violence, not specified below	2,124	0.006
181	Abduct, hijack, or take hostage	3,940	0.011
182	Physically assault	13,008	0.035
183	Conduct suicide, car, or other non-military bombing	119	0
184	Use as human shield	74	0
185	Attempt to assassinate	24	0
186	Assassinate	442	0.001
19	FIGHT		
190	Use conventional military force, not specified below	59,539	0.159
191	Impose blockade, restrict movement	324	0.001
192	Occupy territory	554	0.001
193	Fight with small arms and light weapons	20,706	0.055
194	Fight with artillery and tanks	579	0.002
195	Employ aerial weapons	957	0.003
196	Violate ceasefire	17	0
20	USE UNCONVENTIONAL MASS VIOLENCE		
200	Use unconventional mass violence, not specified below	0	0
201	Engage in mass expulsion	25	0
202	Engage in mass killings	497	0.001
203	Engage in ethnic cleansing	6	0
204	Use weapons of mass destruction	67	0

0.3 Modeling Repertoires of Repression

Our main paper demonstrated results that suggest that repression entropy has declined over time. To offer possible explanations for this trend, this section of our appendix models the diversity of state repertoires of repression as an outcome variable in a regression context. We employ a relatively straightforward time-series cross-section model using a set of standard independent variables most common to past studies of repression and human rights. Our primary goal is to evaluate the extent to which the factors most commonly used to explain the level of repression also apply in explaining the diversity of state repertoires of repression; and whether these factors might account for the overall global shifts over time. In particular, we are interested in testing the effects on diversity arising from increasing threats (civil war and protest) and from domestic and international institutionalization (democracy and human rights treaties).

We thus include independent variables measuring protest, civil war, democracy (the Polity2 measure), a count of human rights treaty (and optional protocol) ratifications, logged GDP per capita, and logged population. To ensure that the results are not being simply driven by variation in the volume of events observed, we also control for the logged total number of (ICEWS) repression events for each country-year. To ensure full temporal coverage, our protest variable is drawn from ICEWS events data as well, isolating the count of material-conflict events directed at the government by non-state actors (excluding armed groups) and creating a dichotomous variable for the top quartile of values. We dichotomize this protest measure to minimize its otherwise high correlation with our logged total repression events control. In some models, we also include a lagged dependent variable, a time trend, and year, region, or country fixed effects. In several models, we likewise control for existing measures of the level of repression, to isolate the "off-diagonal" variation in entropy, alternately using Human Rights Scores (Fariss, 2014), the Political Terror Scale (Wood and Gibney, 2010), the Cingranelli-Richards measure of physical integrity rights (Cingranelli and Richards, 1999), and a measure of physical integrity rights from the more recent Varieties of Democracy project (Coppedge et al., 2020).[6]

As the entropy measure may be unreliable for country-years with small numbers of observed events, and cannot be computed at all with no events, we limit the sample to only observations with ten or more observed state repressive events. We also vary this choice in robustness checks and find very similar results. Table A.II presents our primary results across a series of different modeling choices. For comparison, we also present results for standard intensity-level measures as outcome variables (Table A.IV), using either the logged count of repression events, a (reversed) Goldstein (1992) scale of repression event intensity, or four existing standards measures of the level of repression (in some cases reversed such that higher values reflect higher levels of repression). To ensure comparability, we still limit the sample in each of the models in Table A.IV to only observations with ten or more observed state repressive events.

Do similar factors explain the level of repression and the diversity of state repertoires of repression? While

[6]Following Fariss (2018*a*), we use the indicators on political killings and torture as indicative of physical integrity rights.

one could imagine different explanations for each outcome, we in fact find that they are highly similar. The results in Table A.II confirm that many well-supported explanations for the level of repression also explain the diversity of repression, even when also controlling for existing measures of the level of repression. Positive and significant coefficients for protest and civil war demonstrate that higher levels of threat and dissent are associated with states employing broader repertoires of repression. Negative and significant coefficients for democracy extend the "domestic democratic peace" (Davenport, 2007) finding to also demonstrate that democracies employ narrower repertoires of repression. Negative and—in most models—significant coefficients for human rights treaties suggest that states committed to more international human rights institutions tend to employ narrower repertoires of repression as well, complementing recent work on treaties and the level of repression (Hill Jr, 2010; Fariss, 2018*b*). Lastly, economic development is also significantly associated with narrower repertoires of repression. This latter finding complements earlier work by Davenport (1995), who similarly finds that economic development is associated with lower overall levels of state repression.

Our finding of statistically significant effects for protests, civil war, democracy, human rights treaties, and economic development, even after controlling for existing measures of state repression, suggests that our repression entropy measure captures distinct features of the process by which states select repertoires of repressive tactics. The narrowing effects of domestic and international institutions suggest that the constraining and monitoring roles of these institutions and of domestic and international audiences serve to render certain repressive tactics less acceptable and thus remove them from state repertoires. This strongly follows the arguments made by Ron (1997; 2003) in the cases of Israel and Serbia. The narrowing effect of economic development also suggests that increasing state capacity serves to remove certain tactics from state repertoires, possibly consistent with a principal-agent approach (Mitchell, 1991) that sees particularly egregious abuses as often committed by unconstrained state agents acting beyond their mandate. Our results thus suggest that twin processes of institutionalization—at international and domestic levels—account for the overall decline in the diversity of state repertoires of repression.

In Table A.III, we show results for several alternate measures of entropy or of the diversity of repression repertoires. First, we skip the step of one-a-day filtering of events to remove potential duplicates. Results remain highly similar. Second, we aggregate the categories of repressive tactics from 30 three-digit CAMEO codes to only five two-digit CAMEO codes, thus coarse-graining the measure of entropy. The results are mostly similar, although the coefficient for democracy flips in sign and is no longer statistically significant.

Third, we omit the most frequent three-digit category of repression events, "Arrest, detain, or charge with legal action" or Code 173, from both the numerator and denominator in calculating entropy. Although the results are mostly consistent, the coefficient for civil war becomes negative and significant, rather than positive. This suggests that while governments facing civil conflict shift to employ more diverse repertoires of repression overall, their non-imprisonment tactics actually become more concentrated. In evaluating the entropy measure in relation to the large proportion of repression events comprising this one category, the consistency of information-theoretic entropy under coarse graining is highly useful. This feature of the measure means that the overall entropy can be understood as an average of entropy omitting Code 173 (weighted by the share of Code 173 as a proportion of all events), and the entropy between Code 173 and all other categories combined together. Fourth, we thus model the simple share of each country-year's events comprising Code 173, "Arrest, detain, or charge with legal action." Here, higher values suggest a less diverse repertoire (focused more fully on imprisonments alone), while lower values suggest a more diverse repertoire (more tactics being employed alongside imprisonments), with coefficients thus being reversed in direction. Indeed, the results remain largely similar to the models of overall repression entropy.

Fifth, we employ a different approach to measuring the diversity of repression tactics, using an inverse Herfindahl index. Again, the direction of this measure is reversed, such that higher values of the Herfindahl index reflect more concentrated repertoires, and lower values more diversity. The findings remain highly similar to the models of entropy, suggesting that the choice of diversity measure does not disproportionately drive the results. Nonetheless, the statistical properties mentioned in the main text lead us to prefer the entropy measure over a Herfindahl index.

Sixth, we also measure entropy with a Miller-Maddow (MM) correction for counts with large numbers of zeroes (Miller, 1995). The MM measure correlates with the original one at 0.996, and the results barely change. Lastly, Table A.V varies the threshold of observed events for inclusion of observations in the sample, using observations with at least 1, 5, or twenty events, rather than the standard of ten used in the other models. The results remain highly similar.

Finally, we also consider another alternate measure of repression entropy using only events from publications that were included since ICEWS' inception (i.e., since 1995). This retains ICEWS events that were coded from only 39 publications, rather than the 270 included in the full sample. Notably, ICEWS' original set of publications leans more towards global newswires and media outlets, whereas the later additions tend more towards local and regional publications. By only including events that were coded from a consistent set of news sources throughout our entire 1995-2016 period of analysis, we seek to investigate concerns that our results might be biased by over-time changes in the reporting of more subtle forms of repression as more local media enter the events sample. However, the results of this model are largely similar to the main results.

Table A.II: Main results. Linear models of repression entropy with standard errors clustered by country. Sample restricted to observations with ten or more events observed.

	Dependent variable:									
	Repression Entropy									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Protest	0.455**	0.393**	0.386**	0.386**	0.382**	0.269**	0.363**	0.377**	0.381**	0.380**
	(0.041)	(0.032)	(0.032)	(0.032)	(0.031)	(0.035)	(0.033)	(0.031)	(0.035)	(0.031)
Civil War	0.142**	0.107**	0.107**	0.105**	0.105**	0.064*	0.079**	0.074**	0.101**	0.092**
	(0.037)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.030)	(0.028)	(0.032)	(0.028)
Democracy (Polity2)	−0.011**	−0.008**	−0.010**	−0.010**	−0.011**	−0.007	−0.006*	−0.006*	−0.006*	−0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
HR Treaties	−0.020**	−0.017**	−0.009	−0.009	−0.002	0.002	−0.011*	−0.015**	−0.018**	−0.015**
	(0.007)	(0.005)	(0.007)	(0.007)	(0.006)	(0.011)	(0.005)	(0.005)	(0.006)	(0.005)
Log GDP/capita	−0.086**	−0.064**	−0.065**	−0.065**	−0.050**	−0.171†	−0.037*	−0.035**	−0.054**	−0.037**
	(0.016)	(0.012)	(0.012)	(0.012)	(0.019)	(0.100)	(0.015)	(0.013)	(0.015)	(0.013)
Log Population	0.022	0.003	−0.002	−0.003	0.001	−0.118	−0.012	−0.008	−0.008	0.002
	(0.020)	(0.015)	(0.015)	(0.016)	(0.016)	(0.176)	(0.015)	(0.014)	(0.015)	(0.015)
Log Repression Event Count	0.003	−0.012	−0.002	−0.001	0.005	0.075**	−0.017	−0.018	−0.019	−0.021
	(0.025)	(0.019)	(0.019)	(0.020)	(0.020)	(0.027)	(0.020)	(0.019)	(0.021)	(0.020)
Lag Entropy		0.283**	0.281**	0.284**	0.263**	0.088**	0.230**	0.263**	0.247**	0.267**
		(0.029)	(0.029)	(0.029)	(0.026)	(0.025)	(0.029)	(0.028)	(0.030)	(0.028)
Time			−0.007**							
			(0.003)							
HR Scores (reversed)							0.086**			
							(0.020)			
Political Terror Scale								0.084**		
								(0.017)		
CIRI Phys. Int. (reversed)									0.025**	
									(0.010)	
V-Dem Phys. Int. (reversed)										0.034**
										(0.009)
Constant	1.937**	1.689**	1.754**	1.791**	1.478**	4.182	1.804**	1.438**	1.783**	1.570**
	(0.306)	(0.230)	(0.229)	(0.247)	(0.279)	(3.207)	(0.241)	(0.237)	(0.250)	(0.234)
Year FE				X	X	X				
Region FE					X					
Country FE						X				
Observations	2,303	2,302	2,302	2,302	2,302	2,302	1,936	2,300	1,682	2,302
Adjusted R^2	0.347	0.414	0.417	0.416	0.430	0.518	0.405	0.425	0.392	0.422

Note: $\dagger p < 0.1; *p < 0.05; **p < 0.01$

Table A.III: Robustness checks using alternative measures of entropy or other repertoire-based measures as outcome variable. Linear models with standard errors clustered by country. Note that for both Code 173 share of events, and for Herfindahl index, higher values reflect less diverse repertoires – the reverse of the other measures. Sample restricted to observations with ten or more events observed.

	Dependent variable:						
	Entropy (No Filtering)	Entropy (Two-Digit)	Entropy (Omit Code 173)	Code 173 Share of Events	Herfindahl Index	Entropy (MM Correction)	Entropy (1995 Publications)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Protest	0.421**	0.201**	0.125**	−0.137**	−0.131**	0.396**	0.401**
	(0.032)	(0.020)	(0.033)	(0.012)	(0.011)	(0.034)	(0.041)
Civil War	0.099**	0.084**	−0.057†	−0.049**	−0.035**	0.113**	0.079**
	(0.027)	(0.021)	(0.031)	(0.010)	(0.009)	(0.029)	(0.030)
Democracy (Polity2)	−0.010**	0.003	−0.006*	0.002*	0.003**	−0.008**	−0.007*
	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
HR Treaties	−0.015**	−0.009**	−0.014**	0.004**	0.004*	−0.018**	−0.010
	(0.005)	(0.003)	(0.004)	(0.002)	(0.002)	(0.005)	(0.006)
Log GDP/capita	−0.065**	−0.067**	−0.018	0.021**	0.020**	−0.067**	−0.101**
	(0.011)	(0.008)	(0.012)	(0.004)	(0.004)	(0.012)	(0.013)
Log Population	−0.004	−0.003	0.018	0.007	−0.0004	0.007	−0.025
	(0.015)	(0.010)	(0.015)	(0.005)	(0.005)	(0.016)	(0.017)
Log Repression Event Count	−0.051**	−0.017	0.263**	0.033**	0.025**	−0.043*	0.035†
	(0.019)	(0.012)	(0.025)	(0.006)	(0.006)	(0.020)	(0.020)
Lag Entropy (No Filter)	0.298**						
	(0.028)						
Lag Entropy (Two-Digit)		0.313**					
		(0.030)					
Lag Entropy (Omit Code 173)			0.158**				
			(0.025)				
Lag Code 173 Share of Events				0.380**			
				(0.032)			
Lag Herfindahl Index					0.321**		
					(0.028)		
Lag Entropy (MM Correction)						0.276**	
						(0.029)	
Lag Entropy (1995 Publications)							0.182**
							(0.027)
Constant	1.874**	1.191**	0.554*	−0.020	0.084	1.851**	2.374**
	(0.223)	(0.176)	(0.254)	(0.080)	(0.076)	(0.245)	(0.260)
Observations	2,302	2,302	2,302	2,294	2,302	2,302	1,592
Adjusted R^2	0.395	0.376	0.479	0.417	0.381	0.367	0.360
Note:							$\dagger p < 0.1; *p < 0.05; **p < 0.01$

Table A.IV: Alternate models using non-repertoire measures as outcome variable. Linear models with standard errors clustered by country. Sample restricted to observations with ten or more events observed.

	Dependent variable:					
	Log Repression Event Count	HR Scores (reversed)	Political Terror Scale	CIRI Physical Integrity (reversed)	Goldstein Repression Scale (reversed)	V-Dem Physical Integrity (reversed)
	(1)	(2)	(3)	(4)	(5)	(6)
Protest	0.623**	0.036**	0.150**	0.376**	0.512**	0.087**
	(0.043)	(0.009)	(0.030)	(0.069)	(0.056)	(0.031)
Civil War	0.120**	0.034**	0.164**	0.434**	0.230**	0.049†
	(0.035)	(0.011)	(0.033)	(0.082)	(0.051)	(0.028)
Democracy (Polity2)	−0.003	−0.003**	−0.009**	−0.041**	−0.003	−0.017**
	(0.003)	(0.001)	(0.002)	(0.005)	(0.005)	(0.004)
HR Treaties	−0.015**	−0.001	−0.008*	−0.002	−0.023*	0.003
	(0.005)	(0.002)	(0.004)	(0.009)	(0.009)	(0.003)
Log GDP/capita	0.037**	−0.011**	−0.110**	−0.196**	−0.153**	−0.040**
	(0.012)	(0.004)	(0.014)	(0.028)	(0.022)	(0.010)
Log Population	0.097**	0.001	0.035**	0.123**	−0.101**	0.003
	(0.016)	(0.004)	(0.013)	(0.030)	(0.022)	(0.010)
Lag Log Repression Event Count	0.570**					
	(0.023)					
Lag HR Scores (reversed)		0.969**				
		(0.006)				
Lag Political Terror Scale			0.696**			
			(0.025)			
Lag CIRI Phys. Int. (reversed)				0.656**		
				(0.029)		
Lag Goldstein Repression (reversed)					0.317**	
					(0.045)	
Lag V-Dem Phys. Int. (reversed)						0.933**
						(0.012)
Constant	−0.234	0.041	1.135**	0.753†	7.264**	0.109
	(0.246)	(0.071)	(0.210)	(0.448)	(0.625)	(0.190)
Observations	2,302	1,936	2,298	1,678	2,302	2,302
Adjusted R^2	0.834	0.988	0.789	0.796	0.385	0.968

Note: $\dagger p < 0.1; *p < 0.05; **p < 0.01$

Table A.V: Alternate models varying sample restrictions. First model restricted to observations with one or more events observed. Second model restricted to observations with five or more events observed. Third model restricted to observations with twenty or more events observed. Linear models of repression entropy with standard errors clustered by country.

	Dependent variable:		
	Repression Entropy		
	(1)	(2)	(3)
Protest	0.206**	0.381**	0.394**
	(0.038)	(0.032)	(0.033)
Civil War	0.068*	0.094**	0.121**
	(0.029)	(0.026)	(0.026)
Democracy (Polity2)	−0.006*	−0.009**	−0.007**
	(0.003)	(0.003)	(0.003)
HR Treaties	−0.012*	−0.016**	−0.017**
	(0.005)	(0.005)	(0.006)
Log GDP/capita	−0.065**	−0.062**	−0.059**
	(0.011)	(0.011)	(0.012)
Log Population	−0.021	−0.003	0.004
	(0.015)	(0.014)	(0.015)
Log Repression Event Count	0.166**	0.020	−0.032
	(0.023)	(0.019)	(0.020)
Lag Entropy	0.283**	0.264**	0.315**
	(0.024)	(0.025)	(0.034)
Constant	1.361**	1.653**	1.658**
	(0.228)	(0.218)	(0.232)
Observations	3,012	2,600	1,842
Adjusted R^2	0.477	0.397	0.453
Note:			$\dagger p < 0.1; *p < 0.05; **p < 0.01$

0.4 Comparisons of Entropy to Inverse Herfindahl Index

In this section, we compare our primary (Shannon's H) entropy measure of state repression to an inverse Herfindahl index of state repression. Note that we use an inverse Herfindahl index here, as opposed to a standard Herfindahl index, because the latter (standard index) directly measures "concentration" as opposed to "diversity."

To implement these comparisons, we begin by revisiting our main paper's Figure 2, which compared our primary entropy measure to the (reverse ordered) latent human rights scores developed by Fariss (2014). Figure 2 illustrated that our entropy measure exhibited a notably stronger association with Fariss' standards-based measure of repression than did a simple count of ICEWS' repressive events. For comparison, the left subfigure in Figure A.1 again compares our entropy measure to Fariss' human rights scores,[7] whereas the right subfigure in Figure A.1 now instead plots our inverse Herfindahl index of repression against Fariss' human rights scores.

First and foremost, we observe in Figure A.1 that both measures of repressive repertories exhibit similar levels of overall association with Fariss' human rights scores. For the purposes of measuring global repression via political event data, this finding suggests that information entropy and the inverse Herfindahl index are comparable. This reinforces the robustness analyses discussed above, which illustrated that our core model-based findings were robust to the choice of an entropy-based measure of repression versus a Herfindahl-based measure of repression when modeling country-year determinants of repressive repertoires.

That being said, we also find in Figure A.1 that our entropy-based measure exhibits a clearer association with Fariss' human rights scores than does the inverse Herfindahl-based measure. This can be evidenced by (1) the slightly steeper slope in the entropy bivariate regression line on the left-hand side of A.1,[8] (2) the tendency for the Herfindahl-based measure to overstate high diversity in country-level repressive repertoires,[9] and (3) the higher R-squared value for the underlying bivariate regression that was used to create this plotted line of best fit (of 0.52) in relation to that obtained from the inverse Herfindahl index's corresponding line of best fit (R-squared = 0.44).

[7]This subfigure appeared in the right panel of our original Figure 2.

[8]To this end, we can further note that the (country-level) pairwise correlation between our entropy measure and Fariss' measure is 0.72, whereas the pairwise correlation between Fariss' measure and our inverse Herfindahl index is 0.66.

[9]Note, especially, the higher inverse Herfindahl scores for countries such as Slovenia, Botswana, Mongolia, Guinea, Bahrain, and Djibuti within the center and upper-right areas of the right-hand plot in Figure A.1—relative to either Fariss' human rights scores or our entropy-based measure. These country outliers suggest a degree of compression in the Herfindahl index's "moderately high" and "high diversity" repression range (and thus country cases).

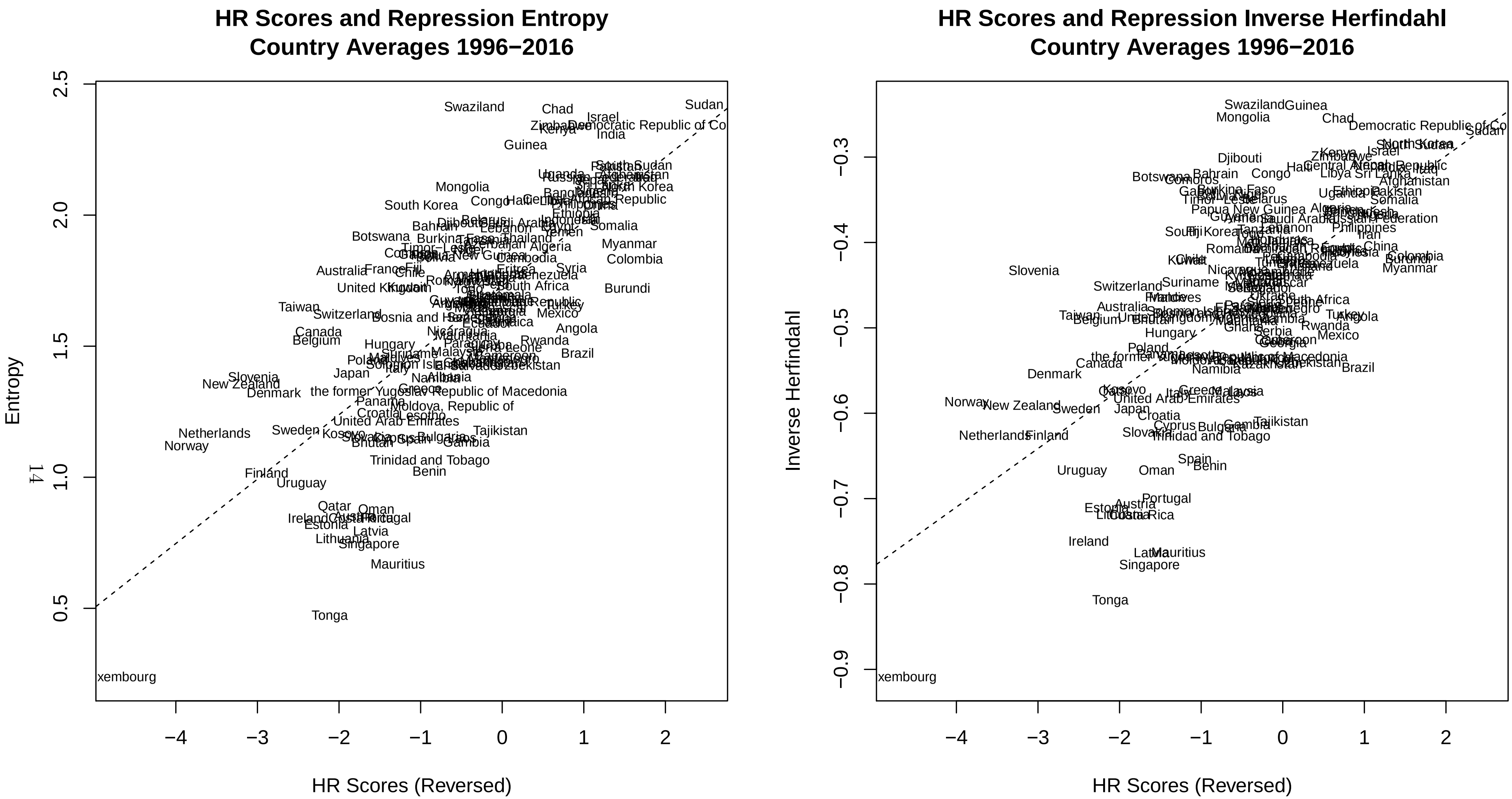

Figure A.1: Comparison between existing repression measure, inverse herfindahl index of state repressive events, and entropy of state repressive events. Each point represents the averages for each country across all observed years.

To compare our country-averaged measures of repressive repertoires more directly, we next plot a comparison of (i) our country-averaged repression entropy measure and (ii) our country-averaged (inverse) Herfindahl repression measure in Figure A.2. The overriding pattern in this Figure is consistent with the core observation discussed above: by-and-large, our entropy- and Herfindahl-based measures of state repressive repertoires are very comparable. Nevertheless, one can again observe a degree of compression and thresholding in our moderate-to-high repression diversity cases for the Herfindahl index, as evidenced by the relatively higher (inverse) Herfindahl scores assigned countries such as Qatar, Bhutan, Slovenia, Jamaica, and Mongolia.[10] These conclusions are supported by a more direct comparison of the distributions of our *country-year* entropy- and Herfindahl-based measures of repressive repertories, wherein we find slightly higher (i.e., more positive) kurtosis in the case of our entropy measure, and a smoother distribution of overall cases across the recovered range of diversity in state repression (see Figure A.3).

[10]Note that several of these country cases where also identified as instances of compression in the inverse Herfindahl-subfigure to Figure A.1 above.

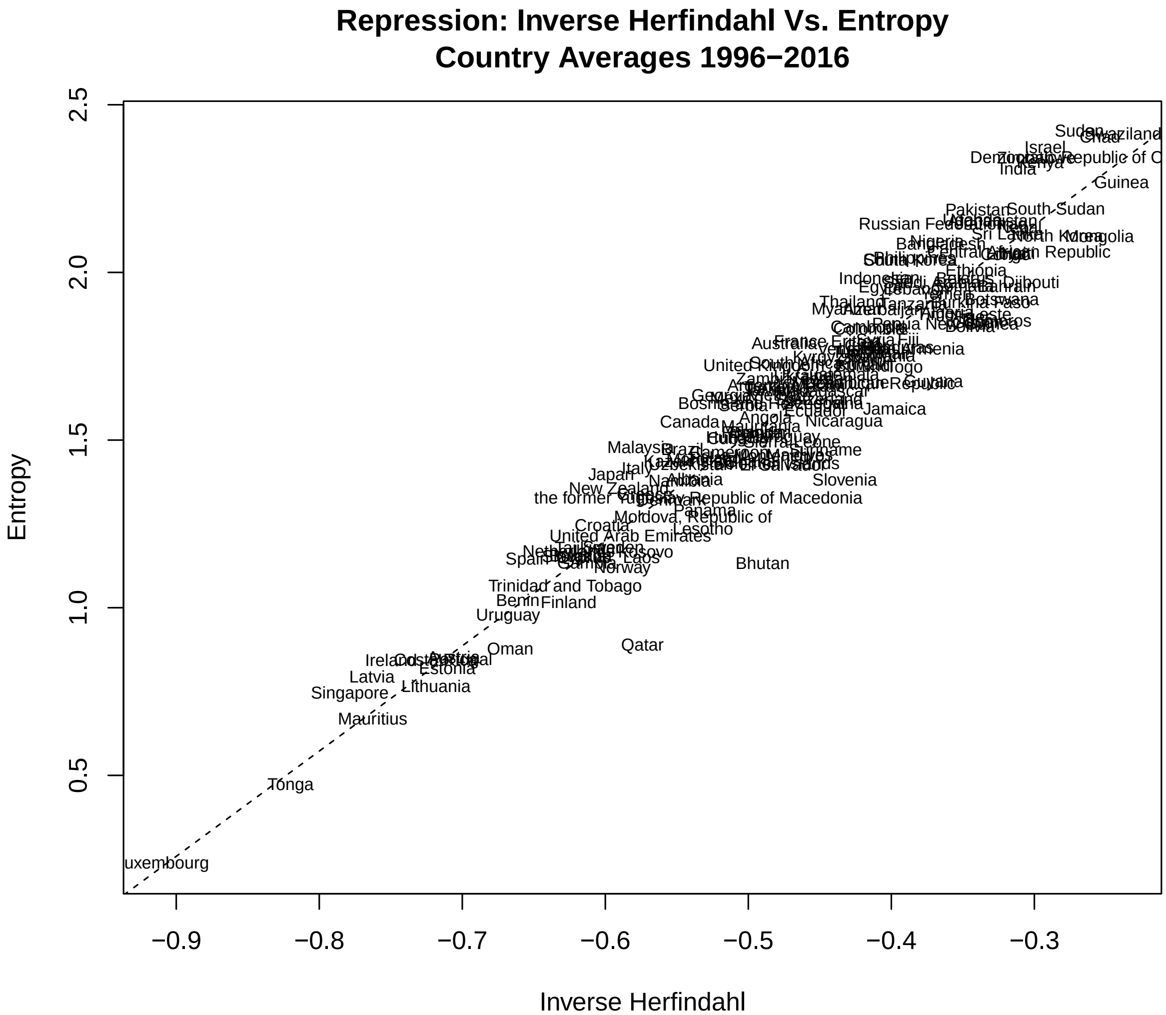

Figure A.2: Direct comparison of inverse herfindahl index of state repressive events and entropy of state repressive events. Each point represents the averages for each country across all observed years.

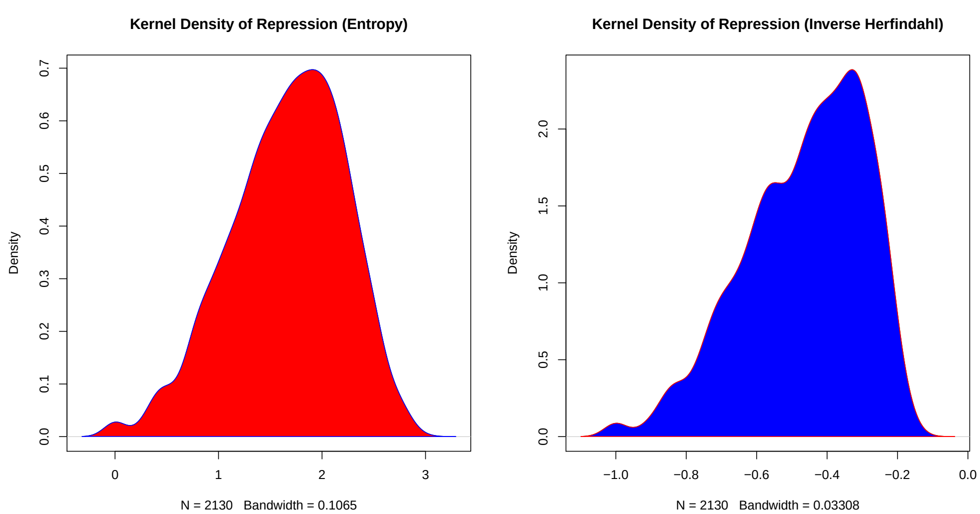

Figure A.3: Densities of entropy of state repressive events and herfindahl index of state repressive events.

0.5 Comparisons of Entropy to Goldstein Scales

In this section, we present an alternate set of comparison plots to those included in Figure 2 of the main paper. Recall that Figure 2 in the main paper presented two sub-plots. Both sub-plots included Fariss' (2014) human rights scores on the horizontal axis (but reversed such that higher values reflect more repression), which was intended to capture existing standards-based measures of the level of repression. The first sub-plot then plotted the logged count of repressive events on the vertical axis, while the second showed our new entropy measure on the vertical axis. In both panels, the placement of each country reflected averaged values over the entire observed period since 1996. We found in the main paper's discussion of Figure 2 that there was a moderate positive relationship between the level of repression and the count of repressive events, but also a great deal of unrelated variation. By contrast, we then noted in Figure 2 that the correspondence between our entropy measure of repressive events was far higher, albeit with some remaining variation.

We recreate these comparison plots here when using a Goldstein repression scale (Goldstein, 1992) in place of our raw count of repressive events. Given that Goldstein scales are commonly used to aggregate and analyze political event data, such a scale provides an alternate point of reference when comparing the relative strengths of our entropy measure vis-à-vis Fairiss' human rights scores. We construct our repression-specific Goldstein scale by calculating each country-year Goldstein value according to an averaging of all repressive events' standard Goldstein weights.[11] Hence, unlike a standard Goldstein scale covering a single cooperative-to-conflictive continuum, our Goldstein scale instead reflects a single continuum of state repression intensity, and is accordingly most comparable to our original count of repressive events.

We plot this Goldstein measure against Fariss' human rights scores in the left-hand panel of Figure A.4. Note that before doing so, we calculate a country average Goldstein repression scale for each country across all years considered, and reverse code this average Goldstein value so that higher values correspond to more intense repression. The left panel of Figure A.4 illustrates that there is a clear positive association between our Goldstein scale and Fariss' human rights scores. This association also appears to be moderately stronger than was the case for our raw count of repressive events in Figure 2 of the main paper. That being said, the positive association between Fariss' human rights scores and our entropy measure within the right panel of A.4 appears stronger still—and exhibits less unrelated variation—than the association between our Goldstein repression scale and that of Fariss' human rights scores. This again suggests that repression entropy provides a closer correspondence to extant human rights metrics than do extant means of aggregating event data on state repression.

[11] The Goldstein weights associated with our CAMEO repressive event categories are based upon a standard generalization of the WEIS Goldstein weights to CAMEO Goldstein weights (Schrodt, 2007).

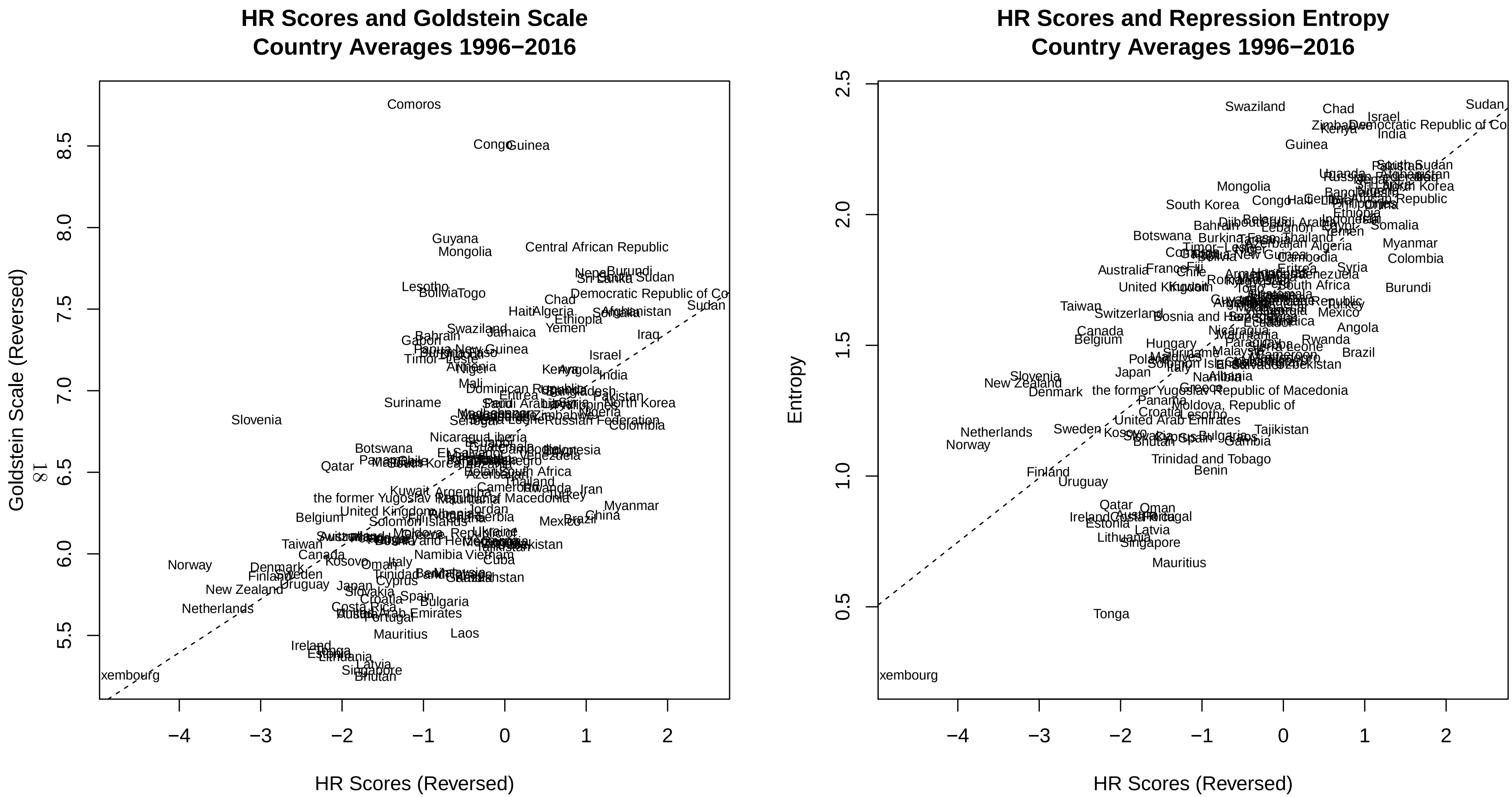

Figure A.4: Comparison between existing repression measure, a goldstein repression scale, and entropy of state repressive events. Each point represents the averages for each country across all observed years.

0.6 Additional Country-Level Plots

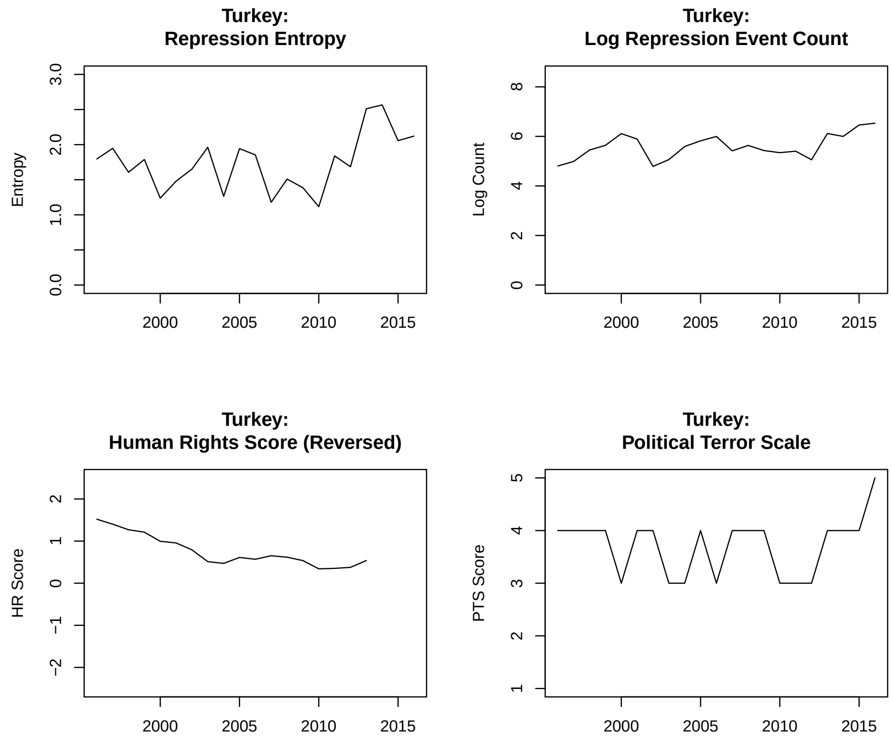

Figure A.5: Comparison of four measures for Turkey, 1996-2016 (only through 2013 for Human Rights Scores).

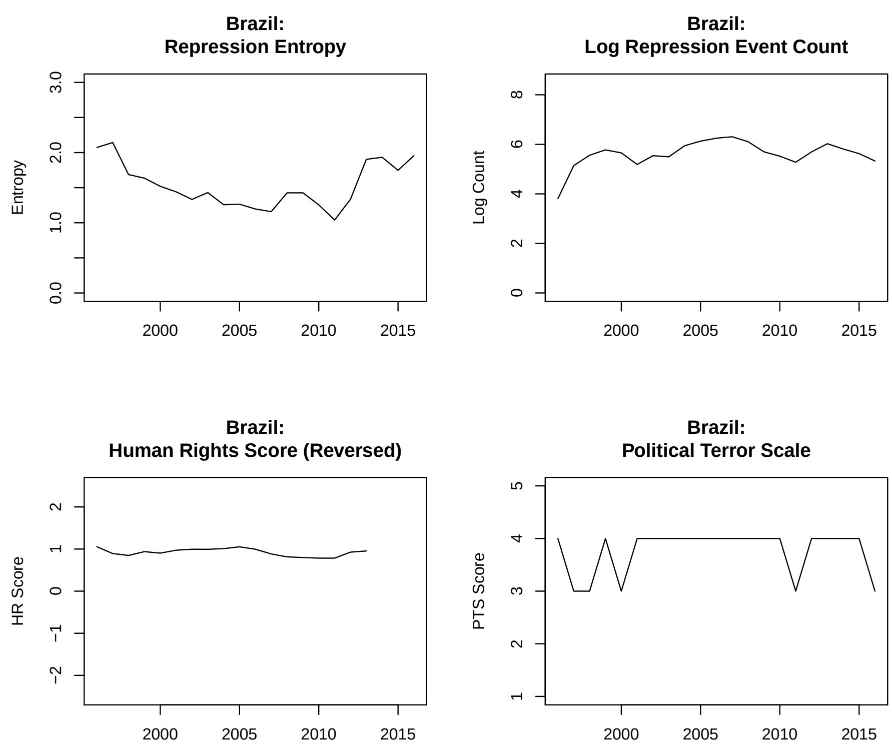

Figure A.6: Comparison of four measures for Brazil, 1996-2016 (only through 2013 for Human Rights Scores).

Figure A.7: Comparison of four measures for Kenya, 1996-2016 (only through 2013 for Human Rights Scores).

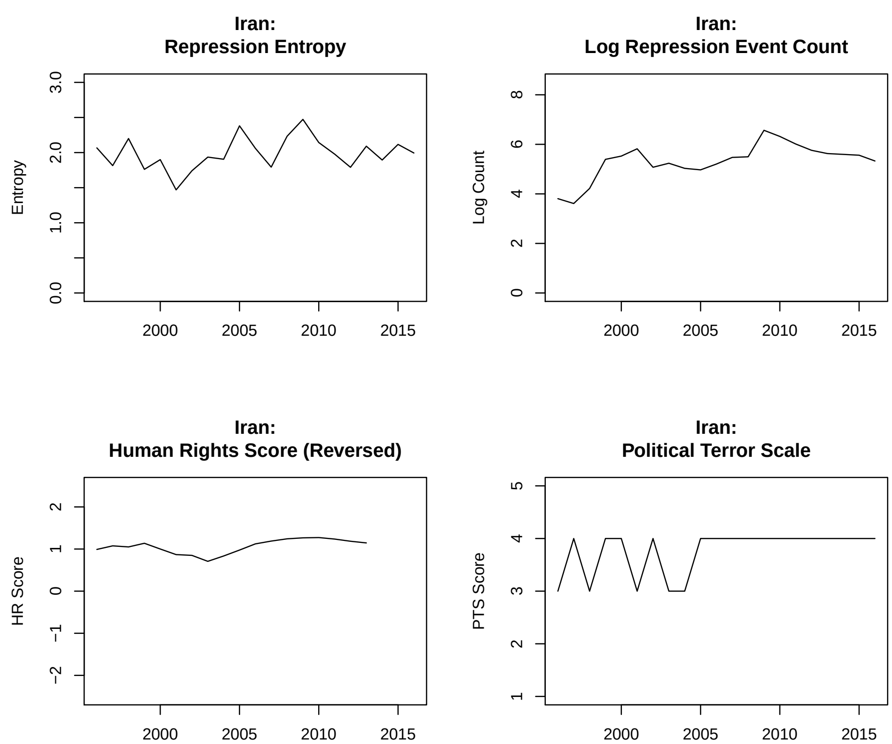

Figure A.8: Comparison of four measures for Iran, 1996-2016 (only through 2013 for Human Rights Scores).

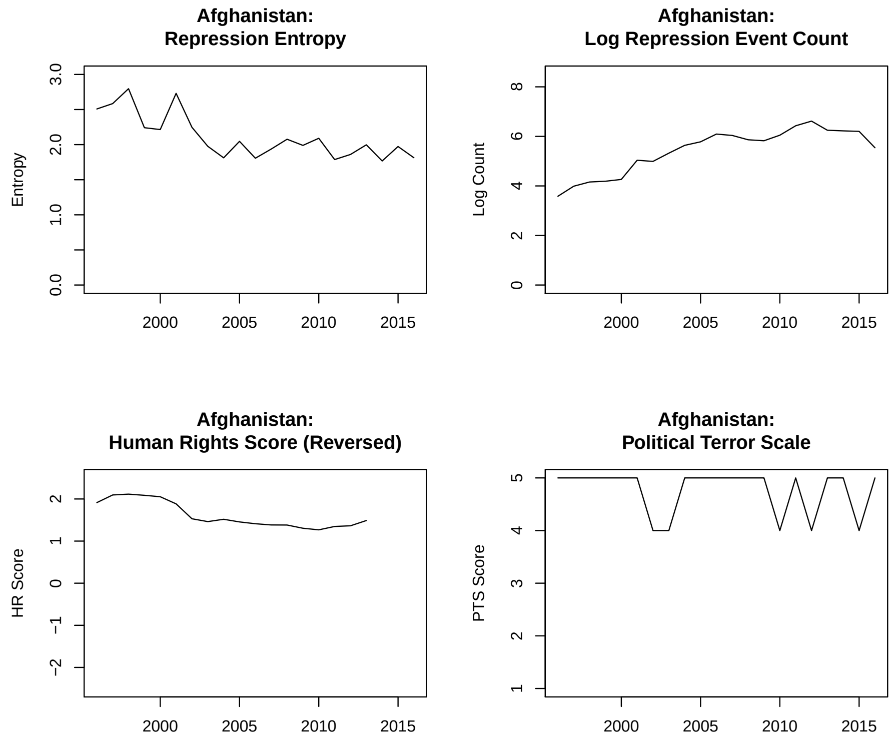

Figure A.9: Comparison of four measures for Afghanistan, 1996-2016 (only through 2013 for Human Rights Scores).

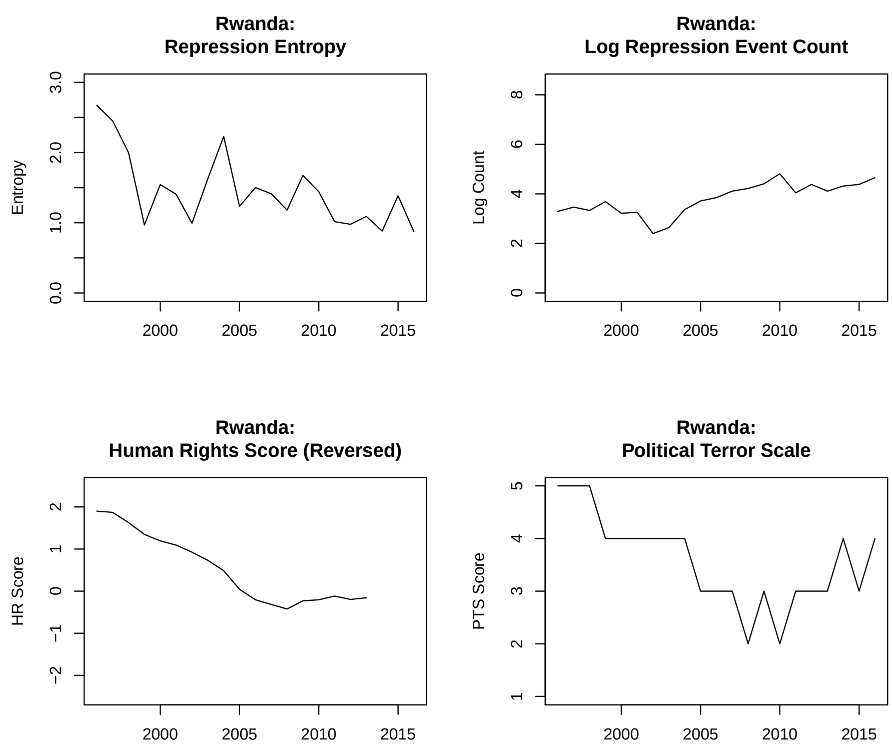

Figure A.10: Comparison of four measures for Rwanda, 1996-2016 (only through 2013 for Human Rights Scores).

Figure A.11: Comparison of four measures for Singapore, 1996-2016 (only through 2013 for Human Rights Scores).

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