Supporting Information For

Conflict Prevention in Isolated World Ship Societies

Contents

Data and Variables

To determine the impact of the various potential causes discussed above on internal conflict in different types of societies, the analyses reported below rely on a large number of variables used in previous studies of political violence. The unit of analysis is the country-year, i.e., a given country as observed in a given year during the years 1961–2011, the period for which information on all indicators was available, although some dependent variables were only available for shorter periods. Geographically, the resulting dataset includes information on all variables for all countries worldwide. Summary statistics for all variables are reported in Tab. A1, and for the high population density sample in Tab. A2.

Dependent Variables

Above, four distinct categories of political violence were discussed and the most important causes of each were identified. The first violence type analyzed here is nonviolent civil disobedience. Data for coding this indicator, *nonviolent civil disobedience*$_t$, were obtained from the

Nonviolent and Violent Campaigns and Outcomes (NAVCO) V 2.0 Data Project [1]. This dataset includes information on both primarily violent and primarily nonviolent campaigns occurring at the annual country level. This variable is coded as one for any country-year that experienced a civil disobedience campaign and zero otherwise. It is available for the years 1961–2006.

Data for the second indicator, $\textit{coups d'état}_t$, were obtained from the Global Instances of Coups from 1950–Present dataset Powell and Thyne [2]. The compilers of this dataset define a coup d'état as an "overt attempts by the military or other elites within the state apparatus to unseat the sitting head of state using unconstitutional means" [2], even if no casualties were reported. This indicator is coded as one for any country-year that experienced at least one coup d'état attempt – even if it were unsuccessful – and zero otherwise. It is available for the years 1961–2011.

Information on the third dependent variable, $\textit{mass killing}_t$, was obtained from the "Assessing Risks of State-Sponsored Mass Killing" report [3] for the Political Instability Task Force (PITF). The authors define "mass killing" as a campaign that involves at least 1,000 civilian – i.e., noncombatant – casualties, with the last recorded year is defined as the first in a sequence of three during which the number of deaths fell below 100 for three years. This indicator is coded as one for any country-year that experienced at least one mass killing campaign and zero otherwise. It is available for the years 1961–2008.

Data to code the final dependent variable, $\textit{civil war}_t$, were obtained from the UCDP/PRIO Armed Conflict Dataset V 17.1 [4, 5]. Unlike other datasets, which frequently rely on a threshold of 1,000 or more combatant casualties to define a war, the compilers of the UCDP/PRIO Armed Conflict Dataset rely on a lower threshold of 25 or more combatant casualties per year to identify armed conflict. Considering that the relative size of a world ship, even according to the highest estimates, will be around 250,000 people [6], a threshold of 25 combatant deaths is more relevant in this particular context compared with higher thresholds. Accordingly, this indicator is coded as one for any country-year that experienced at least one civil war with 25 or more combatant casualties and zero otherwise. It is available for the years 1961–2011.

Explanatory Variables

The first set of explanations emphasizes the role of ongoing violence in generating conflict. Including such factors in the models is important given that violence frequently breeds more violence. Mass killing and coups d'état, for instance, frequently occur during an ongoing civil war [7]. Accordingly, a proxy indicator measuring the existence of an ongoing civil conflict was included in the model. This indicator – $civil\ war_t$ – is coded as an armed conflict involving at least 25 combatant casualties and obtained from the UCDP/PRIO Armed Conflict Dataset [4, 5]. A second indicator accounting for the effect of ongoing violence on conflict is the one year lag of the dependent variable of interest, DV_{t-1}, which measures whether the dependent variable of interest had a value of one (i.e., occurred) or not in a given country the previous year.

The second set of explanations relates to particular socioeconomic and political conditions that make a country more likely to experience conflict. The first indicator in this category measures a country's annual level of political openness and is used to account for the argument that autocratic and quasi-democratic regimes are more prone to conflict. This indicator, $Polity2_t$, was obtained from the Polity IV dataset coded by Marshall et al. [8]. The second indicator in this category is a measure of population in a given country during a given year, $population_t$. This indicator accounts for the possibility that violence is more likely to arise and be recorded in more populated countries and was obtained from the Expanded Trade and GDP dataset [9]. Finally, research frequently associates gross domestic product (GDP) per capita – as a proxy and state capacity and development – with civil war [10]. Therefore, the indicator $GDP\ pc_t$, a measure of GDP per capita in a given country during a given year was additionally included in the models [9].

The third set of explanations emphasizes the ability of military organizations to support their troops. These explanations associate violence with weaker military capacity. The first proxy in this category, *country area*, accounts for a given country's geographic area, under the assumption that logistic support will be harder to achieve in larger countries. Because this variable is constant, i.e., does not vary over time, the notation t was suppressed. The second indicator, $\textit{military exp.}_t$, denotes the amount (in thousand U.S. Dollars) a given state spent on its military forces during a given year and was obtained from the National Material Capabilities (v5.0) dataset coded by the Correlates of War project [11].

A fourth set of explanations argues that profitable natural resources such as oil or diamonds are strong drivers of violent conflict. The first two proxies in this category, $\textit{oil prices}_t$ and $\textit{gas prices}_t$, are two indicators measuring annual oil and gas prices per barrel (in USD) in a given country, respectively, obtained from the Oil and Gas Data, 1932-2014 dataset [12]. A third indicator, $\textit{iron/steel}_t$, measures the annual levels of given country's total iron and steel production (in thousands of tons). Like $\textit{military exp.}_t$, data on this variable were obtained from the National Material Capabilities (v5.0) dataset.

Another argument that has gained support in recent years associates climatic variability and natural disasters with political violence [13]. Although earthly disasters will be unlikely on a world ship, in the models these variables substitute for the types of disasters that a world ship could experience – crop failures, mechanical failures, collisions with space objects, etc. To measure the exogenous effect of the unforeseeable disasters that might occur in outer space, an indicator denoting the total number of natural disasters in a given country during a given year, $\textit{natural disasters}_t$, was coded. This indicator, which covers all natural disasters – including all biological (e.g., locust), climatological (e.g., droughts), geological (e.g., earthquakes), hydrological (e.g., tsunamis) and meteorological (e.g., heat waves) events – occurring annually within each country, was obtained from EM-Dat International Disaster Database coded by the Centre for Research on the Epidemiology of Disasters – CRED [14].

A sixth set of conflict predictors relates to social and political cleavages. To account for the potential effect of such cleavages, two indicators, *eth. fractionalization* and *rel. fractionalization*, are used to account for the impact of ethnic and religious fractionalization, respectively. The first index measures the number of individuals in a country that hail from different ethno-linguistic groups, combined with the share of the population that are from the largest ethnic group and the number of distinct languages spoken by groups Fearon and Laitin [10]. The second index measures the number of individual in a country that come from different religious groups Fearon and Laitin [10]. Both are constant for the period of analysis, although variations in the composition of cleavages within countries – if occurred – are likely to be relatively small.

Finally, recent research identified strong linkages between food production and food prices on the one hand and social conflict on the other [15, 16]. Two indicators were coded to account for how variations in domestic agricultural output from one year to the next affect the propensity of violent and nonviolent conflict within a given society. These indicators, *maize (kg pc)*$_t$ and *wheat (kg pc)*$_t$, code the annual availability – in kilogram per capita – of maize and wheat, respectively, within a given country. Data for coding both indicators were obtained from the Food and Agricultural Organization of the United Nations [17].

In addition to these explanatory indicators, the predictive models reported below also account for temporal dependencies and potential time-related endogeneities unaccounted for by the DV_{t-1} measure. To do so, the linear time trend, which was given a value of one for the first year in the data (1961) with one being added to each consecutive year (e.g., a value of two for 1962, three for 1963 and so forth), is included in each model alongside its quadratic and cubic time polynomials to account for time trends in binary data [18].

Methodology

Statistical inference is a useful tool for gauging associations between different factors that are unlikely to be random. However, the focus on statistically significant relationships alone strongly limits – and in fact may actually hinder – the predictive model's ability to generalize to out-of-sample situations, such as the future incidence of political violence [19]. Therefore,

Table A1: Summary Statistics of All Variables – Full Sample

	Minimum	Median	Mean	Max	SD
Dependent variables					
Nonviolent civil disobedience$_t$	0	0	0.011	1	0.103
Coups d'état$_t$	0	0	0.042	1	0.201
Mass killing$_t$	0	0	0.012	1	0.109
Civil war$_t$	0	0	0.017	1	0.130
Explanatory variables					
Polity2$_t$	-10	0	0.506	10	7.472
Population$_t$[1]	4.701	8.932	8.883	14.096	1.670
GDP pc$_t$[1]	4.897	8.258	8.327	13.357	1.238
Country area[1]	5.707	12.335	12.056	16.707	2.040
Military exp.$_t$[1]	0	19.249	18.991	27.265	3.740
Oil prices$_t$	7.879	24.955	32.659	85.171	21.015
Gas prices$_t$	2.087	3.151	3.810	9.009	1.563
Iron/steel$_t$[1]	0	0	6.759	20.343	7.169
Natural disasters$_t$	0	1	1.490	38	3.031
Eth. fractionalization	0.001	0.373	0.406	0.925	0.284
Rel. fractionalization	0	0.375	0.379	0.783	0.218
Maize (kg pc)$_t$[1]	0	2.000	1.989	5.184	1.515
Wheat (kg pc)$_t$[1]	0	3.816	3.354	5.467	1.550

[1] natural log

Table A2: Summary Statistics of All Variables – High Population Density Sample

	Minimum	Median	Mean	Max	SD
Dependent variables					
Nonviolent civil disobedience$_t$	0	0	0.016	1	0.124
Coups d'état$_t$	0	0	0.024	1	0.151
Mass killing$_t$	0	0	0.012	1	0.110
Civil war$_t$	0	0	0.016	1	0.124
Explanatory variables					
Polity2$_t$	-10	77	3.285	10	7.400
Population$_t$[1]	4.701	9.157	9.181	14.096	2.048
GDP pc$_t$[1]	5.100	8.713	8.631	11.405	1.292
Country area[1]	5.707	10.656	10.614	14.957	2.349
Military exp.$_t$[1]	0	20.227	19.801	27.265	3.522
Oil prices$_t$	7.879	24.955	32.375	85.171	20.952
Gas prices$_t$	2.087	3.125	3.796	9.009	1.555
Iron/steel$_t$[1]	0	12.612	9.021	20.343	7.396
Natural disasters$_t$	0	1	2.368	38	4.888
Eth. fractionalization	0.001	0.166	0.271	0.887	0.261
Rel. fractionalization	0.039	0.476	0.410	0.773	0.205
Maize (kg pc)$_t$[1]	0	1.687	1.679	4.739	1.260
Wheat (kg pc)$_t$[1]	0	4.195	3.591	5.375	1.504

[1] natural log

the analyses reported below rely on receiver-operator characteristic (ROC) curves, a method designed to compare the *predictive* power of different models rather than evaluate the statistical significance of particular variables. Originally created to help training radio operators during the Second World War, ROC curves measure the ratio of true positives – i.e., events the model correctly predicts – to false negatives – or events the model fails to predict [20]. A model whose area under the ROC curve (AUC) is equal to one perfectly predicts every event. A model with an AUC of zero failed to successfully predict any of the events in the data. A completely random (i.e., "coin flip") model has an AUC of 0.5.

The advantage of the predictive approach is in leveraging a combined statistical-computational framework to overcome the limitations inherent to each method. As a result, the reliance on a combination of statistical analysis to create explanatory models of violence and then machine learning algorithms to predict future conflicts has been use by both government agencies and private organizations [21, 22]. Moreover, as used here, this combined methodology allows each model to identify the *substantive impact* of each variable within the context of the entire model and not just as a simple "all-else-equal" scenario where the model's dimensionality is reduced to one.

This analysis is done in several stages. First, for each dependent variable a set of logistic regression (i.e., logit) models designed to handle binary dependent variables is first estimated. The first model in each conflict type analysis includes all the indicators discussed above, while in each successive regression a different predictor is removed. The predicted probability of a non-zero event (e.g., whether civil war is likely to occur or not) is then calculated on out-of-sample data using a process called k-fold cross-validation, where k=100. In this process, the country-year data are randomly divided into k=100 segments. 99 of these segments are combined to create a "training set" used to (i) reestimate the model and (ii) generate a set of predicted probabilities of events. The 100th segment, or "test set," is then utilized to assess the ratio of true-to-false positives predicted by the model estimated on said training set. This process is repeated 100 times (once for each data segment) and the resulting estimates are combined to calculate the size ROC curve for the model, i.e., its *predictive power*.

To identify specific predictors that are likely to impact world-ship-like environments, specially, rather than pinpoint important determinants of conflict more broadly, each analysis is repeated twice. In the first stage the sample analyzed includes *all countries* – large and small, more or less densely populated – over the 1961–2011 period. In the second stage the same models and approach are used, only this time the sample analyzed is limited to *high population density countries*, i.e., countries that were above the 75th percentile in terms of their average population densities for the 1961–2011 period. To estimate population density, a country's average population over the 1961–2011 period is divided by that country's area. A list of the states in the high density sample are reported in Table A3, and the results of these two stages are reported below. After reporting the results from each analysis stage separately, results from the first two stages are compared to identify factors that gain predictive strength as one moves from the full to the high-population-density sample.

The underlying assumption is that predictors whose substantive predictive impact increases in the high population density sample will become increasingly more important (linearly) as population density goes up, with world ships being an extreme case of a high population density society.

Table A3: Countries in the High Population Density Sample

United States	Haiti	Dominican Republic	Jamaica
Trinidad and Tobago	Barbados	El Salvador	United Kingdom
Netherlands	Belgium	Luxembourg	Switzerland
Portugal	Poland	Hungary	Czech Republic
Slovakia	Italy	Malta	Yugoslavia
Moldova	Armenia	Denmark	Burundi
Rwanda	Comoros	Mauritius	Lebanon
Israel	Bahrain	China	North Korea
South Korea	Japan	India	Pakistan
Bangladesh	Sri Lanka	Maldives	Nepal
Viet Nam	Singapore	Philippines	

The Effect of Predictive indicators

Full sample

Table A4 reports the results of a series of k-fold cross-validations estimated on the entire sample for the 1961–2011 period. Each of the four columns corresponds to one of the four dependent variables discussed above – *nonviolent civil disobedience*$_t$, *coups d'état*$_t$, *mass killing*$_t$ and *civil war*$_t$. Each row reports the difference (in percent) in the AUC of each ROC curve when the particular indicator in question is removed from the model. Additionally, the Z values of each variable in the fully specific model – i.e., a model that includes all explanatory variables – are reported in parentheses (in absolute value) to illustrate each indicator's level of statistical significance.

The first column in Table A4 shows the effect of the different predictors on the probability of nonviolent civil disobedience cases. The strongest indicator in terms of predictive strength is political openness or lack thereof (captured by the ordinal *Polity2*$_t$ variable). This variables improves the fully-specified model's predictive strength by $\sim$3.11%, followed by *population*$_t$, with a predictive improvement of $\sim$2.7%, and *wheat (kg pc)*$_t$, with a predictive improvement of $\sim$1.5%. Note that the $|Z|$ score of *wheat (kg pc)*$_t$ is lower than that of *country area* despite the fact that the former provides a noticeably better predictive improvement. The strongest predictors of *coups d'état*$_t$ are its one-year lag ($\sim$2.5%), *civil war*$_t$ (1.7%) and *GDP pc*$_t$ ($\sim$0.8%).

For *coups d'état*$_t$, the strongest predictor is the occurrence of a coup the previous year ($\sim$2.5%), followed by an ongoing civil war ($\sim$1.7%.) and *GDP pc*$_t$ ($\sim$1%). For *mass killing*$_t$, the strongest predictive indicator is *civil war*$_t$ ($\sim$8%), which follows theoretical expectations. Interestingly, the variables *military exp.*$_t$, *iron/steel*$_t$, *maize (kg pc)*$_t$ and the lag of the dependent variable all *reduce* the mass killing model's predictive strength. Finally, it appears the none of the indicators is a particularly strong predictor of *civil war*$_t$ in the full sample excluding perhaps ethnic fractionalization, which improves the model's predictive fit by $\sim$1.4%. For illustration purposes, each indicator's improvement in the fully specified model's predictive strength (in percents) across the four dependent variables is plotted against their statistical standard difference from the mean (i.e., their Z score, reported in absolute values) in Fig. A1.

Figure A1: Correlation Between Each Indicator's Predictive Strength and its $|Z|$ Scores – Full Sample

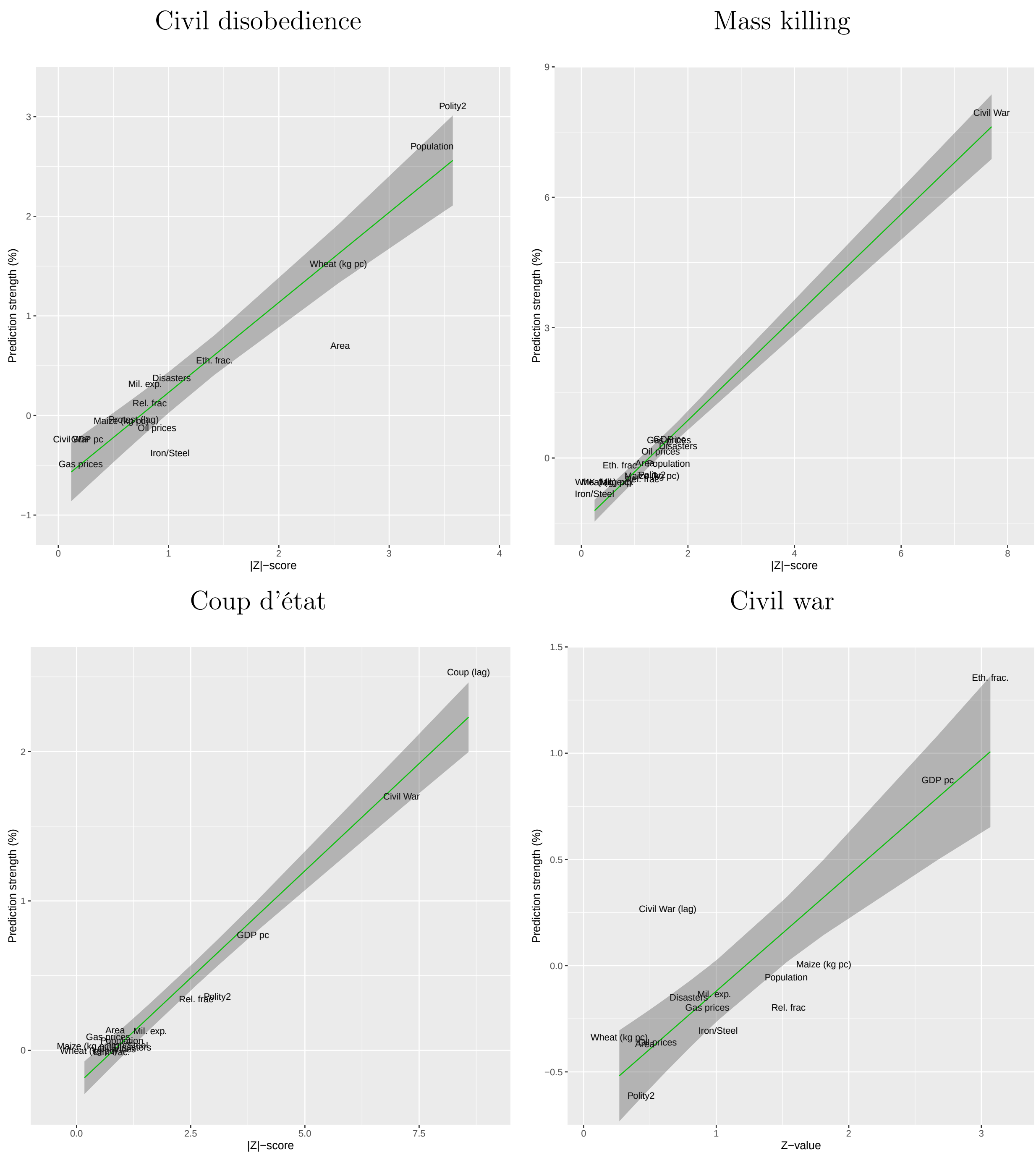

Table A4: Percent Change in Predictor Strength in Models of Social Conflict, 1961–2011 – Entire Sample

	Nonviolent civil disobedience$_t$	***Coups d'état$_t$***	***Mass killing$_t$***	***Civil war$_t$***
DV_{t-1}	-0.040%	2.531%	-0.547%	0.268%
	(0.684)	(8.583)	(0.330)	(0.634)
Civil war$_t$	-0.237%	1.700%	7.953%	–
	(0.118)	(7.117)	(7.699)	
Polity2$_t$	3.111%	0.360%	-0.385%	-0.611%
	(3.577)	(3.084)	(1.329)	(0.434)
Population$_t$[1]	2.705%	0.067%	-0.123%	-0.055%
	(3.390)	(0.992)	(1.636)	(1.528)
GDP pc$_t$[1]	-0.238%	0.773%	0.441%	0.875%
	(0.262)	(3.863)	(1.655)	(2.671)
Country area[1]	0.702%	0.137%	-0.116%	-0.368%
	(2.556)	(0.846)	(1.195)	(0.461)
Military exp.$_t$[1]	0.319%	0.132%	-0.552%	-0.132%
	(0.787)	(1.613)	(0.666)	(0.985)
Iron/steel$_t$[1]	-0.376%	0.034%	-0.814%	-0.305%
	(1.013)	(1.137)	(0.248)	(1.014)
Oil prices$_t$	-0.122%	0.009%	0.160%	-0.360%
	(0.897)	(0.879)	(1.489)	(0.558)
Gas prices$_t$	-0.486%	0.090%	0.413%	-0.197%
	(0.204)	(0.692)	(1.644)	(0.933)
Natural disasters$_t$	0.377%	0.020%	0.280%	-0.150%
	(1.029)	(1.219)	(1.817)	(0.794)
Eth. fractionalization	0.557%	-0.009%	-0.163%	1.357%
	(1.417)	(0.771)	(0.745)	(3.068)
Rel. fractionalization	0.125%	0.344%	-0.483%	-0.196
	(0.829)	(2.619)	(1.139)	(1.546)
Maize (kg pc)$_t$[1]	-0.053%	0.030%	-0.408%	0.007%
	(0.572)	(0.174)	(1.324)	(1.812)
Wheat (kg pc)$_t$[1]	1.523%	-0.002%	-0.549%	-0.337%
	(2.540)	(0.268)	(0.420)	(0.269)

Note: The change in the fully specified model's predictive power when the variable is removed (in percents). Values in parentheses are $|Z|$ scores of each variable in the fully specified model.

[1] In natural log form.

High population density sample

While these results are useful in identifying some salient predictors of conflict, the sample used is overly generalized and – while providing a baseline for comparison – is not necessarily a good measure of how such violence might unfold on interstellar world ships. Thus, to (i) identify predictive indicators that are more valid in the high population density contexts likely to characterize interstellar world ships and (ii) gauge how the impact of each indicator changes as one move from global to high density contexts, Table A5 reports four additional sets of k-fold cross validation-analyses. Each of the columns in Table A5 again corresponds to one of the four types of conflict discussed previously and each model specification is identical to the models from Table A4. However, the sample analyzed in Table A5 consists solely of densely populated countries, i.e., countries that were above the 75th percentile threshold in terms of average population density for the 1961–2011 period (see Tab. A3).

Turning to the first column – $\textit{nonviolent civil disobedience}_t$ – the only indicators that improve the fully specified model's predictive strength are political openness ($\textit{Polity2}_t$) and wheat availability per capita ($\textit{wheat (kg pc)}_t$). For $\textit{coups d'état}_t$, ongoing civil war leads the strongest predictive improvement (∼4%) while $\textit{gas prices}_t$ and $\textit{maize (kg pc)}_t$ yield predictive increases of ∼1% and ∼0.9%, respectively. For $\textit{mass killing}_t$, the variable $\textit{civil war}_t$ provides the greatest predictive improvement (∼3%), followed by $\textit{wheat (kg pc)}_t$ (∼2%), $\textit{maize (kg pc)}_t$ (∼1.5%), $\textit{GDP pc}_t$ (∼1.4%) and $\textit{Polity2}_t$ (∼0.5%). Finally, for $\textit{civil war}_t$, $\textit{GDP pc}_t$ yields the strongest predictive improvement (∼7.3%), followed by the number of natural disasters (∼3.3%), the lag of the dependent variable (∼2.6%), ethnic fractionalization (∼2.5%), gas prices (∼1%) and military expenditure (∼0.6%). Again, for illustration purposes, each indicator' predictive strength is plotted against its statistical standard difference from the mean (i.e., their Z score, reported in absolute values) for each dependent variable in Fig. A2.

Figure A2: Correlation Between Each Indicator's Predictive Strength and its $|Z|$ Scores – High Density Sample

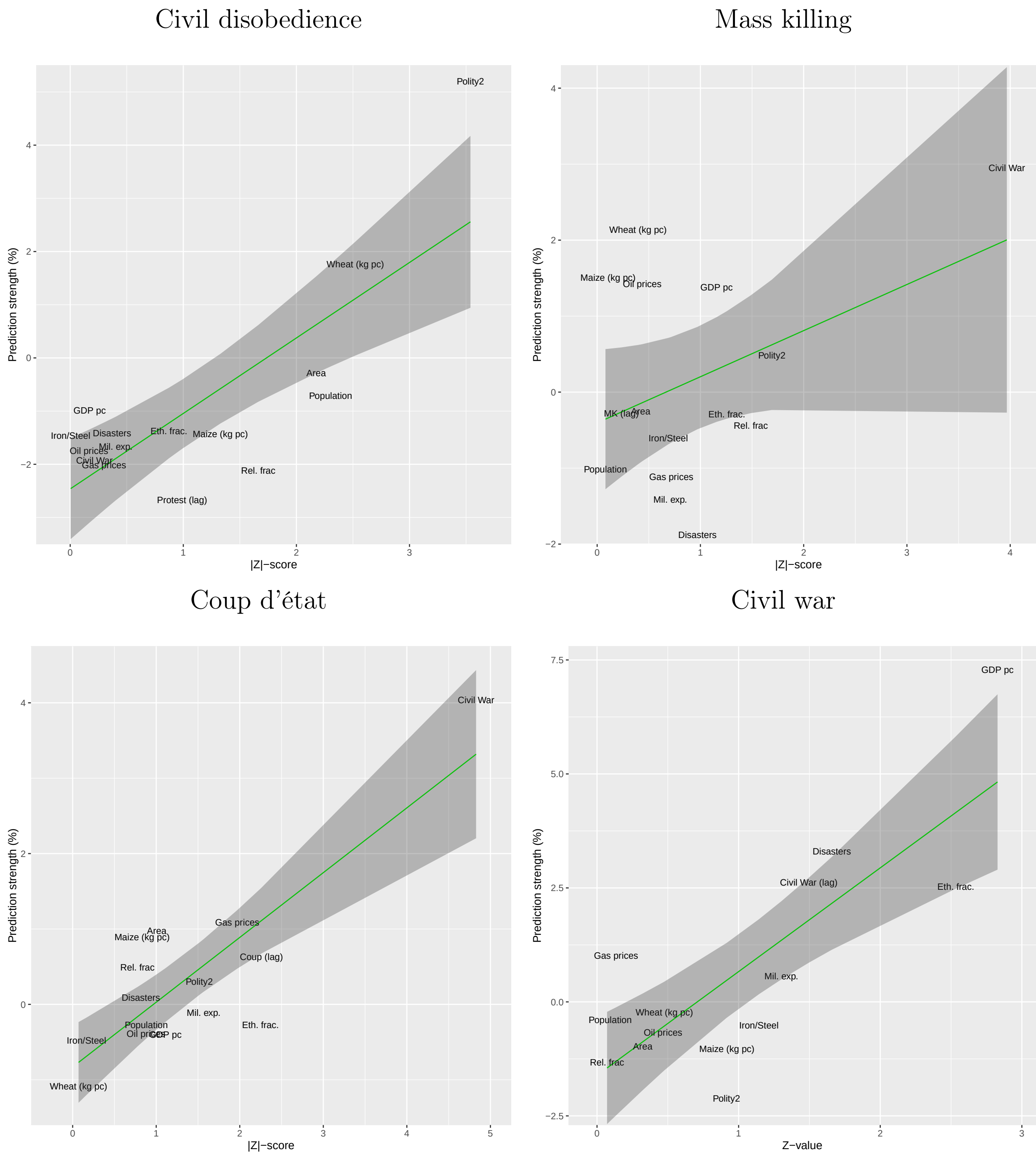

Table A5: Percent Change in Predictor Strength in Models of Social Conflict, 1961–2011 – High Density Sample

	Nonviolent civil disobedience$_t$	***Coups d'état$_t$***	***Mass killing$_t$***	***Civil war$_t$***
DV_{t-1}	-2.666%	0.634%	-0.277%	2.622%
	(0.990)	(2.260)	(0.235)	(1.496)
Civil war$_t$	-1.921%	4.041%	2.952%	–
	(0.215)	(4.829)	(3.967)	
Polity2$_t$	5.204%	0.302%	0.486%	-2.113%
	(3.539)	(1.516)	(1.692)	(0.914)
Population$_t$[1]	-0.709%	-0.273%	-1.013%	-0.389%
	(2.303)	(0.882)	(0.081)	(0.093)
GDP pc$_t$[1]	-0.982%	-0.400%	1.381%	7.285%
	(0.172)	(1.111)	(1.157)	(2.828)
Country area[1]	-0.278%	0.977%	-0.249%	-0.974%
	(2.175)	(1.006)	(0.422)	(0.323)
Military exp.$_t$[1]	-1.661%	-0.106%	-1.412%	0.569%
	(0.403)	(1.568)	(0.709)	(1.302)
Iron/steel$_t$[1]	-1.462%	-0.477%	-0.602%	-0.508%
	(0.004)	(0.166)	(0.689)	(1.143)
Oil prices$_t$	-1.745%	-0.386%	1.427%	-0.665%
	(0.166)	(0.877)	(0.437)	(0.466)
Gas prices$_t$	-2.010%	1.088%	-1.113%	1.020%
	(0.300)	(1.970)	(0.718)	(0.135)
Natural disasters$_t$	-1.408%	0.089%	-1.876%	3.310%
	(0.370)	(0.817)	(0.972)	(1.658)
Eth. fractionalization	-1.375%	-0.270%	-0.290%	2.534%
	(0.873)	(2.248)	(1.256)	(2.534)
Rel. fractionalization	-2.115%	0.494%	-0.439%	-1.320%
	(1.663)	(0.776)	(1.488)	(0.071)
Maize (kg pc)$_t$[1]	-1.428%	0.895%	1.512%	-1.024%
	(1.328)	(0.831)	(0.106)	(0.917)
Wheat (kg pc)$_t$[1]	1.765%	-1.083%	2.138%	-0.228%
	(2.521)	(0.070)	(0.396)	(0.476)

Note: The change in the fully specified model's predictive power when the variable is removed (in percents). Values in parentheses are $|Z|$ scores of each variable in the fully specified model.

[1] In natural log form.

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