Supporting Information for

"A Typology of Substitution:

Weather, Armed Conflict, and Maritime Piracy"

Kyosuke Kikuta*

* Osaka School of International Public Policy, Osaka University, 1-31 Machikaneyamacho, Toyonaka, Osaka, 560-0043, Japan. E-mail: kikuta@osipp.osaka-u.ac.jp.

Supporting Information 1. Formal Analysis

The problem is maximizing $u = (b_V - y_V)y_V - c_V y_V + (b_{\neg V} - y_{\neg V})y_{\neg V} - c_{\neg V} y_{\neg V}$ subject to a resource constraint $y_V + y_{\neg V} \leq r$ and $y_V, y_{\neg V} \geq 0$. I solve the optimization problem by using the Karush–Kuhn–Tucker (KKT) conditions (Kuhn and Tucker 1951). The Lagrangian is;

$$L = (b_V - y_V)y_V - c_V y_V + (b_{\neg V} - y_{\neg V})y_{\neg V} - c_{\neg V} y_{\neg V} - \lambda(y_V + y_{\neg V} - r).$$

Then, the KKT conditions are;

$$\begin{cases} \frac{\partial L}{\partial y_V} \leq 0,\ y_V \frac{\partial L}{\partial y_V} = 0,\ \text{and } 0 \leq y_V \leq r - y_{\neg V} \\ \frac{\partial L}{\partial y_{\neg V}} \leq 0,\ y_{\neg V} \frac{\partial L}{\partial y_{\neg V}} = 0,\ \text{and } 0 \leq y_{\neg V} \leq r - y_V. \\ \frac{\partial L}{\partial \lambda} \leq 0,\ \lambda \frac{\partial L}{\partial \lambda} = 0,\ \text{and } \lambda \geq 0 \end{cases}$$

1. Interior solutions: $\lambda = 0$

1.1. When $y_V = y_{\neg V} = 0$

The KKT condition is $y_V = y_{\neg V} = 0, c_V > b_V$, and $c_{\neg V} > b_{\neg V}$.

1.2. When $y_V > 0$ and $y_{\neg V} = 0$

The KKT condition is $y_V = \frac{b_V - c_V}{2}, y_{\neg V} = 0, b_V - 2r < c_V \leq b_V$, and $c_{\neg V} > b_{\neg V}$.

1.3. When $y_V = 0$ and $y_{\neg V} > 0$

The KKT condition is $y_V = 0, y_{\neg V} = \frac{b_{\neg V} - c_{\neg V}}{2}, c_V > b_V$, and $b_{\neg V} - 2r < c_{\neg V} \leq b_{\neg V}$.

1.4. When $y_V, y_{\neg V} > 0$

The KKT condition is $y_V = \frac{b_V - c_V}{2}, y_{\neg V} = \frac{b_{\neg V} - c_{\neg V}}{2}, c_V \leq b_V, c_{\neg V} \leq b_{\neg V}$, and $c_V + c_{\neg V} > b_V + b_{\neg V} - 2r$.

2. Boundary solutions: $\lambda > 0$

2.1. When $y_V = r$ and $y_{\neg V} = 0$

The KKT condition is $y_V = r, y_{\neg V} = 0, 0 < c_V < b_V - 2r$, and $c_V - c_{\neg V} \leq b_V - b_{\neg V} - 2r$.

2.2. When $y_V = 0$ and $y_{\neg V} = r$

The KKT condition is $y_V = 0, y_{\neg V} = r, 0 < c_{\neg V} < b_{\neg V} - 2r$, and $c_V - c_{\neg V} \geq b_V - b_{\neg V} + 2r$.

2.3. When $y_V, y_{\neg V} > 0$

The KKT condition is reduced to $y_V = \frac{b_V - b_{\neg V} - c_V + c_{\neg V} + 2r}{4}, y_{\neg V} = \frac{-b_V + b_{\neg V} + c_V - c_{\neg V} + 2r}{4}, \lambda = \frac{b_V + b_{\neg V} - c_V - c_{\neg V} - 2r}{2}$, and $x_V, x_{\neg V}, \lambda > 0$. The later inequalities give binding conditions $b_V - b_{\neg V} - 2r < c_V - c_{\neg V} < b_V - b_{\neg V} + 2r$ and $c_V + c_{\neg V} < b_V + b_{\neg V} - 2r$.

In summary, rebels' optimal choices are;

$$
(y_V, y_{\neg V}) = \begin{cases}
(0,0) & \text{if} \quad c_V > b_V \text{ and } c_{\neg V} > b_{\neg V} \\
\left(\frac{b_V - c_V}{2}, 0\right) & \text{if} \quad b_V - 2r < c_V \leq b_V \text{ and } c_{\neg V} > b_{\neg V} \\
\left(0, \frac{b_{\neg V} - c_{\neg V}}{2}\right) & \text{if} \quad c_V > b_V \text{ and } b_{\neg V} - 2r < c_{\neg V} \leq b_{\neg V} \\
\left(\frac{b_V - c_V}{2}, \frac{b_{\neg V} - c_{\neg V}}{2}\right) & \text{if} \quad c_V \leq b_V, c_{\neg V} \leq b_{\neg V}, \text{ and } c_V + c_{\neg V} > b_V + b_{\neg V} - 2r \\
(r, 0) & \text{if} \quad 0 < c_V < b_V - 2r \text{ and } c_V - c_{\neg V} \leq b_V - b_{\neg V} - 2r \\
(0, r) & \text{if} \quad 0 < c_{\neg V} < b_{\neg V} - 2r \text{ and } c_V - c_{\neg V} \geq b_V - b_{\neg V} + 2r \\
\left(\begin{array}{c} \frac{b_V - b_{\neg V} - c_V + c_{\neg V} + 2r}{4}, \\ \frac{-b_V + b_{\neg V} + c_V - c_{\neg V} + 2r}{4} \end{array}\right) & \text{if} \quad b_V - b_{\neg V} - 2r < c_V - c_{\neg V} < b_V - b_{\neg V} + 2r \text{ and } c_V + c_{\neg V} < b_V + b_{\neg V} - 2r.
\end{cases}
$$

The corresponding outcomes $(Y_V, Y_{\neg V}) = \left(\mathrm{I}(y_V > 0), \mathrm{I}(y_{\neg V} > 0)\right)$ are;

$$
(Y_V, Y_{\neg V}) = \begin{cases}
(0,0) & \text{if} \quad c_V > b_V \text{ and } c_{\neg V} > b_{\neg V} \\
(1,0) & \text{if} \quad c_V \leq b_V \text{ and } (c_{\neg V} > b_{\neg V} \text{ or } c_V - c_{\neg V} \leq b_V - b_{\neg V} - 2r) \\
(0,1) & \text{if} \quad (c_V > b_V \text{ or } c_V - c_{\neg V} \geq b_V - b_{\neg V} + 2r) \text{ and } c_{\neg V} \leq b_{\neg V} \\
(1,1) & \text{if} \quad c_V \leq b_V, c_{\neg V} \leq b_{\neg V}, \text{ and } b_V - b_{\neg V} - 2r < c_V - c_{\neg V} < b_V - b_{\neg V} + 2r.
\end{cases}
$$

Supporting Information 2. Descriptive Statistics

This supporting information provides basic information about the data that are used in the main analysis. The following table (Table SI-1) lists the countries and periods that are selected based on the criteria detailed in the paper.

Table SI-1. List of Countries

Country	n	Beginning	End	Country	n	Beginning	End
Algeria	5845	12/31/2000	12/31/2016	Mauritania	766	9/15/2009	10/20/2011
Angola	3288	12/31/2000	12/31/2009	Mozambique	5783	12/31/2000	10/30/2016
Bangladesh	2607	12/31/2000	12/31/2016	Myanmar	5845	12/31/2000	12/31/2016
Cameroon	5845	12/31/2000	12/31/2016	Nigeria	5845	12/31/2000	12/31/2016
Colombia	5843	12/31/2000	12/29/2016	Pakistan	5845	12/31/2000	12/31/2016
Ivory Coast	2778	9/19/2003	4/27/2011	Peru	3652	12/31/2000	12/30/2010
Egypt	5823	12/31/2000	12/31/2016	Philippines	5845	12/31/2000	12/31/2016
Georgia	2871	12/31/2000	11/9/2008	Senegal	4017	12/31/2000	12/30/2011
Haiti	1420	12/31/2000	11/19/2004	Sierra Leone	355	12/31/2000	12/20/2001
India	5845	12/31/2000	12/31/2016	Somalia	5845	12/31/2000	12/31/2016
Indonesia	1747	12/31/2000	10/12/2005	Sri Lanka	3108	12/31/2000	7/4/2009
Iran	5834	12/31/2000	12/20/2016	Sudan	5845	12/31/2000	12/31/2016
Iraq	5845	12/31/2000	12/31/2016	Thailand	5845	12/31/2000	12/31/2016
Kenya	295	3/12/2016	12/31/2016	Turkey	5845	12/31/2000	12/31/2016
Liberia	1056	12/31/2000	11/21/2003	Yemen	5845	12/31/2000	12/31/2016
Libya	1745	2/28/2012	12/7/2016				

NOTE: The table lists the countries that are selected based on the criteria detailed in the paper. The table also provides the numbers of observations, earliest dates, and last dates of the observations for the countries. If a country has multiple armed conflicts, the intermittent periods between armed conflicts are excluded.

The following table (Table SI-2) shows the summary statistics of the explanatory, outcome, and control variables.

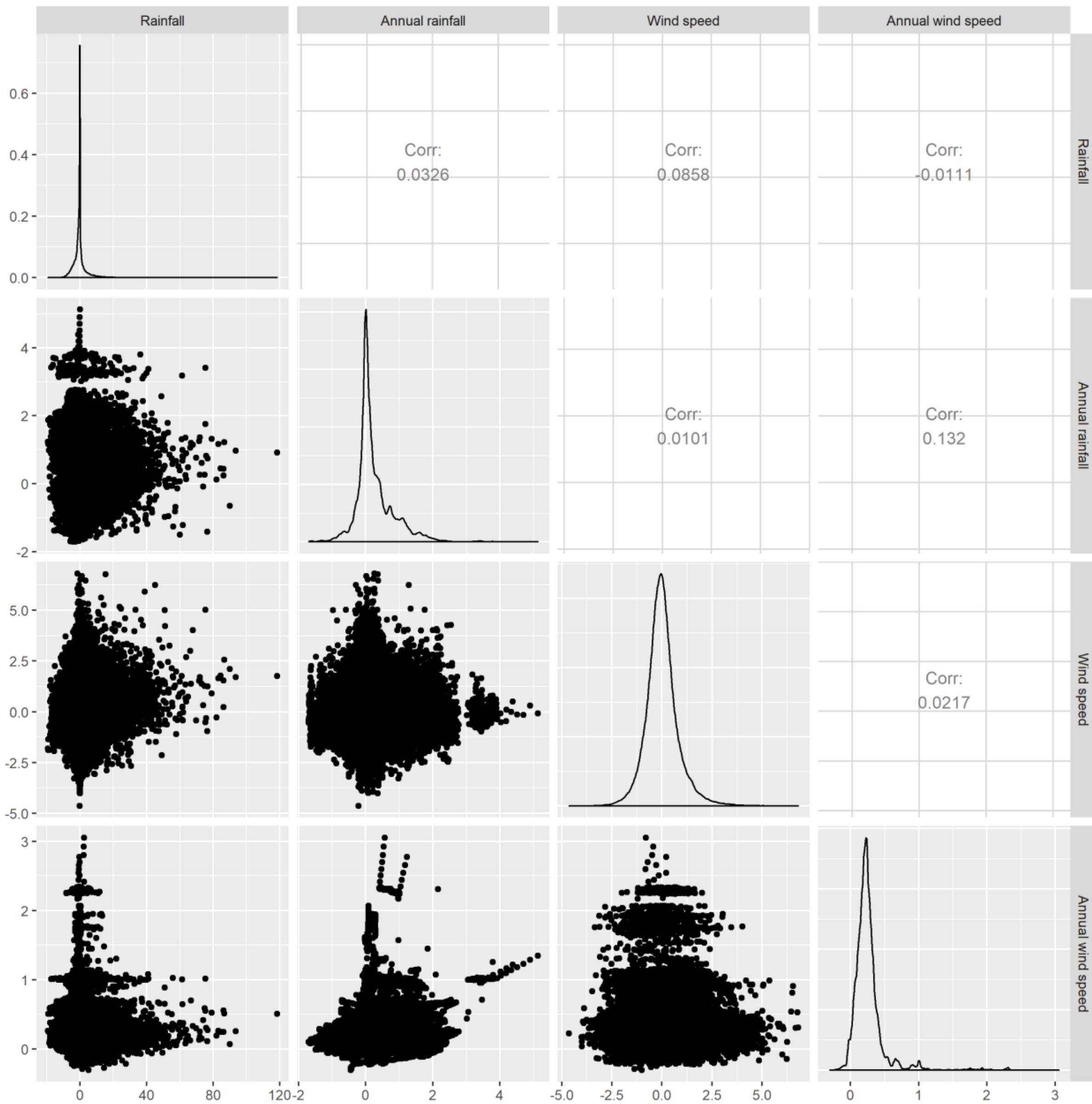
Table SI-2. Summary Statistics

	Mean	S.D.	Min	Max
$violence_{it}$	0.0955	0.2939	0	1
$piracy_{it}$	0.0235	0.1516	0	1
$rain_{it}$	-0.0067	4.7812	-19.307	118.40
$wind_{it}$	0.0047	0.8158	-4.6356	6.8102
$\mathrm{E}_{t'\in\{t-1,\ldots,t-365\}}(rain_{it'})$	0.2518	0.5605	-1.7071	5.1257
$\mathrm{E}_{t'\in\{t-1,\ldots,t-365\}}(wind_{it'})$	0.2543	0.2276	-0.3043	3.0538

NOTE: The table shows the summary statistics of the variables. The variable $rain_{it}$ is the deviation in rainfall on the ground (millimeter per hour), and $wind_{it}$ is the deviation in ocean wind speed (meter per second). $n = 128{,}973$.

The following figure (Figure SI-1) graphically shows the weather variables. As seen in Figure SI-1, the weather variables tend to have skewed distributions, and a few variables have weak correlations (e.g. annual rainfall and annual wind speed).

Figure SI-1. Descriptive Statistics



NOTE: The figure shows the density plots and scatter plots of the weather variables. The diagonal panes are density plots of the variables. The panes in the lower corner are bivariate scatter plots of the variables. The panes in the upper corner show the correlation coefficients of the variables.

Finally, the following table (Table SI-3) is a contingency table of violence and piracy. As seen in the table, although there is a fair number of violent and piracy events, it is extremely rare to have both violence and piracy on a single day. This confirms the notion that unless a group were to have infinite resources and time, they need to substitute a choice over another in the short term (Most and Starr 1984).

Table SI-3. Contingency Table

		$piracy_{it}$	
		0	1
$violence_{it}$	0	114,038 (88.42%)	2,623 (2.03%)
	1	11,900 (9.23%)	412 (0.32%)

NOTE: The table is a contingency table of $violence_{it}$ and $piracy_{it}$. The parentheses are proportions in the sample

Supporting Information 3. Description of the Coastal Areas

In the main analysis, I examine coastal areas. However, one may wonder how the costal areas are different from the inland areas. In Table SI-4, I compare the basic characteristics available in PRIOGRID (Tollefsen, Strand, and Buhaug 2012) of coastal and remaining inland areas in the 31 countries. The coastal areas are more densely populated with more concentrations of both urban and agricultural sectors. In the developing countries, coastal areas tend to be economic centers, and also the rivers flowing into ocean make the coastal lands appropriate for agriculture. Moreover, coastal lands are wet and hence have richer vegitations than drier inland areas (especially in Africa). These facts suggest that the coastal and inland areas are heterogenous, and hence that our findings about coastal areas cannot be easily extended to inland areas (even without saying that maritime piracy is not feasible in inland areas).

Table SI-4. Coastal and Inland Areas

	Coastal areas	Inland areas
Urban areas (%)	0.2840	0.1185
Agricultural areas (%)	35.50	24.20
Forest areas (%)	23.42	20.98
Gross cell product (USD)	0.4461	0.1315
Nightlight (0-1)	0.0679	0.0504
Population (thousands)	397.3	187.0

NOTE: The table shows the basic characteristics of the coastal and inland areas in the 31 coastal countries.

Supporting Information 4. Different Thresholds of Coastal Distances

In the paper, I use 100 kilometers as a threshold for determining the coastal land and sea areas. In this robustness check, I conduct additional analyses with two different thresholds: 50 and 200 kilometers. The following table (Table SI-5) shows the results of the analyses. In both cases, the main results are supported.

Table SI-5. Results with Different Thresholds of Coastal Distances

	50-kilometer threshold		200-kilometer threshold	
Outcome	$violence_{it}$	$piracy_{it}$	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0196	0.0160	-0.0300	0.0141
	(0.0172)	(0.0101)	(0.0276)	(0.0111)
$wind_{it}$	-0.0883	-0.1246	-0.1569	-0.1598
	(0.0805)	$(0.0614)^{\dagger}$	(0.1463)	$(0.0779)^{*}$
$rain_{it}wind_{it}$	-0.0196	0.0076	-0.0214	0.0052
	$(0.0091)^{*}$	(0.0074)	$(0.0102)^{*}$	(0.0088)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

Supporting Information 5. Results with the UCDP GED and MPD

Although I use the GTD and MPELD as main data sources of violence and piracy in the main analysis, it is also useful to check the robustness of the findings with different datasets. To this end, I present the results with the UCDP GED (Sundberg, Lindgren, and Padskocimaite 2010) and the MPD (Coggins 2012) in this supporting information. As seen in Table SI-6, the main results hold even with the alternative measures.

Table SI-6. Results with Alternative Measures of Violence and Piracy

Outcome	$violence_{it}$ (UCDP GED)	$piracy_{it}$ (MPD)
$rain_{it}$	-0.0233	0.0081
	(0.0140)	(0.0068)
$wind_{it}$	-0.1331	-0.0796
	(0.1067)	$(0.0453)^{\dagger}$
$rain_{it}wind_{it}$	-0.0280	0.0117
	$(0.0109)^{*}$	(0.0073)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

Supporting Information 6. Controlling for Temperature

In the paper, I do not include temperature as a control variable, as rainfall can causally affect temperature and hence controlling for temperature can cause a bias due to the posttreatment control. In addition, the temperature data are based on weather-station observations, which can be subject to reporting biases (Schultz and Mankin Forthcoming). Nonetheless, I control for daily minimum and maximum temperatures below. The temperature data come from the NOAA Climate Prediction Center (CPC) Global Temperature Monitoring dataset, which is available daily at a spatial resolution of 0.5-degree by 0.5-degree grid cells (NOAA 2018). As seen in Table SI-7, controlling for temperature does not alter my findings.

Table SI-7. Results with Controlling for Temperature

Outcome	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0192 (0.0204)	0.0136 (0.0108)
$wind_{it}$	-0.0363 (0.1018)	-0.1534 $(0.0776)^{\dagger}$
$rain_{it}wind_{it}$	-0.0200 $(0.0068)^{*}$	0.0057 (0.0078)
$temperature_{\min,\, it}$	-0.0487 (0.0355)	-0.0069 (0.0260)
$temperature_{\max,\, it}$	0.1285 $(0.0455)^{*}$	-0.0340 (0.0304)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

Supporting Information 7. Different Moving Averages of Weather Variables

In the paper, I control for past-one-year averages of rainfall and ocean wind speed to account for the effect of long-term weather conditions, such as those on crop production and economic growth (Miguel, Satyanath, and Sergenti 2004). Controlling for long-term weather conditions is useful to limit the focus to day-to-day tactical variation. I use the one-year-averages as they always include every season in a year regardless of countries. However, it is useful to show the results with different moving averages of the weather variables. The following table (Table SI-8) shows the results with controls for past-one-month or past-one-week averages of the rainfall and ocean wind speed. As seen in the table, the main results hold even with these controls.

Table SI-8. Control for Past-one-month or Past-one-week Mean of Rainfall and Wind

	Past-one-month Averages		Past-one-week Averages	
Outcome	$violence_{it}$	$piracy_{it}$	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0234	0.0137	-0.0184	0.0117
	(0.0214)	(0.0104)	(0.0204)	(0.0104)
$wind_{it}$	-0.1240	-0.1437	-0.1485	-0.1386
	(0.1016)	$(0.0733)^{\dagger}$	(0.1029)	$(0.0736)^{\dagger}$
$rain_{it}wind_{it}$	-0.0183	0.0057	-0.0192	0.0046
	$(0.0069)^{*}$	(0.0078)	$(0.0065)^{*}$	(0.0067)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-month or past-one-week averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

Supporting Information 8. Country-year-month Fixed Effects

In this supporting information, I present the results with controls for the country-year-month fixed effects, which can account for unobserved confounders that can change from one month to another. The following table (Table SI-9) indicates that this does not change the results.

Table SI-9. Results with Controlling for Country-specific Trends

Outcome	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0117	0.0121
	(0.0158)	(0.0093)
$wind_{it}$	-0.1980	-0.1358
	$(0.0974)^{\dagger}$	$(0.0727)^{\dagger}$
$rain_{it}wind_{it}$	-0.0154	0.0016
	$(0.0064)^{*}$	(0.0049)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year-month fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

Supporting Information 9. Inclusion of Zero-Variance Countries

In the main analysis, I exclude the 10 coastal conflict countries that have zero variance in $violence_{it}$ or $piracy_{it}$ in the main analysis.[1] As I detail in footnote 17 in the manuscript, piracy or rebels' violence is nearly impossible in these countries, and these cases do not fit well with my theoretical argument. Nonetheless, it is useful to check the robustness of the findings to the inclusion of those cases. As seen in Table SI-10, the main results hold.

Table SI-10. Results with All Coastal Conflict Countries

Outcome	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0243	0.0116
	(0.0182)	(0.0084)
$wind_{it}$	-0.1286	-0.1137
	(0.0879)	$(0.0555)^{*}$
$rain_{it}wind_{it}$	-0.0180	0.0054
	$(0.0058)^{*}$	(0.0066)

NOTE: The table shows the OLS estimates of the coefficients at a percentage scale. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 167{,}251$ with 41 coastal conflict countries for 2001–2016. $*\ p < 0.05$, $\dagger\ p < 0.10$.

[1] China, the Republic of the Congo, the Democratic Republic of the Congo, Eritrea, Israel, Lebanon, Russia, Syria, UK, and USA.

Supporting Information 10. Count Variables

In the main analysis, I use the dichotomized outcomes of rebels' violence and piracy attacks. As I mentioned in the theory section, the dichotomization is useful for developing a *typology* of substitution. Furthermore, because the continuous effort levels y_G and y_M are complicated non-linear functions of c_G and c_M, we can only weakly identify the continuous functions in an empirical analysis. In addition, the counts of violent and piracy events have skewed distributions, which make the estimation of the interaction models sensitive to outliers. Despite these facts, it is still useful to provide the results with the count variables. The following table (Table SI-11) shows the estimates coefficient values when I use the counts of rebels' violence and piracy attacks.

Table SI-11. Results with Count Variables

Outcome	$violence_{count,it}$	$piracy_{count,it}$
$rain_{it}$	-0.0006	0.0002
	(0.0005)	(0.0002)
$wind_{it}$	-0.0011	-0.0026
	(0.0018)	$(0.0015)^{\dagger}$
$rain_{it}wind_{it}$	0.0001	0.0001
	(0.0003)	(0.0001)

NOTE: The table shows the OLS estimates of the coefficients. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 128{,}973$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

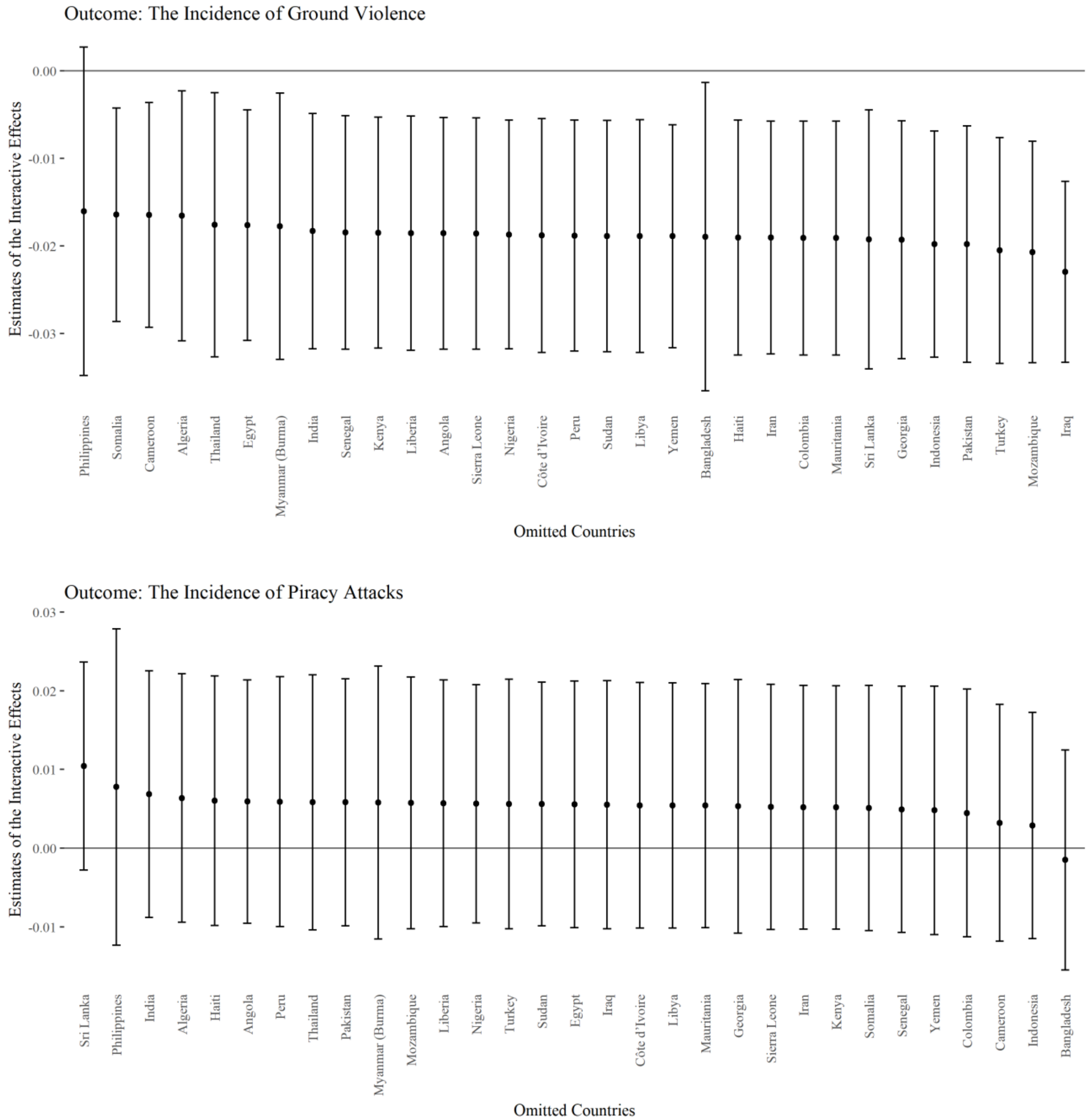
Consistent with my expectation, these results suggest that the conditional effects might exist but it is difficult to empirically detect the conditional effects. These are not surprising given the potentially complicated functional forms of the conditional effects and the skewness of the count variables.

Supporting Information 11. Leave-one-country-out Tests

One may be concerned about whether a few outliers, such as Somalia and Nigeria, drive the empirical findings. I address this concern by conducting leave-one-country tests, in which I drop each country and re-estimate the regression models. The following figures (Figure SI-2) show the estimates of the coefficients for the interaction terms (β_3 and γ_3 in the equation in the main paper) when each country on the horizontal axis is omitted from the sample. With only one exception, which is not surprising given the multiple hypotheses testing ($31 * 0.05 = 1.55$ results should be statistically significant), ground and ocean weather conditions affect the incidence of rebels' violence. By contrast, none of the conditional effects on maritime piracy are statistically significant.

The omission of the Phillippines results in a statistically non-significant result, probably due to the reduced variances of the explanatory and outcome variables (in fact, the point estimate is similar to that in the main analysis). The standard deviation of the outcome variable is 0.4795 in the Phippinnes, which is nearly two times larger that in the remaining countries (0.2759). Similarly, the standard deviation of rainfall deviation is 6.5367 in the Phillippines, which is larger than the standatd deviation in the other countries (4.6816). These facts suggest that the omission of the Philippines reduces the variances of the outcome and explanatory variables, which in turn makes the estimate less precise (while not changing the point estimate).

Figure SI-2. Leave-one-country-out Tests



NOTE: The figures show the estimates of the coefficients for the interaction terms when each country in the horizontal axis is omitted from the sample. In the first and second figures, the outcome variables are the incidences of ground violence and maritime piracy attacks respectively. The point estimates and corresponding 95% confidence intervals are the dots and error bars.

Supporting Information 12. Mechanism: Fishing

As I discuss in the manuscript, a possible alternative explanation of my findings is fisheries; rainfall decreases rebel violence especially when the ocean is windy, for rough seas may limit opportunities for fishery industries and people might therefore alternatively engage in violence. Although I am skeptical of this view as switching from non-violent (fishing) to violent activities (violence) is usually more difficult than switching between violent activities (piracy and violence), I also conduct an additional analysis to test this possibility. I collect data on the phytoplankton absorption coefficient, which is a measure of phytoplankton abundance in the ocean (Flückiger and Ludwig 2015). Because phytoplankton abundance is a predictor of fish abundance and does not affect operational costs of piracy activities, I can exclude the alternative explanation if the results hold even after controlling for phytoplankton abundance. Note that this analysis can suffer from posttreatment control bias as ocean wind can affect phytoplankton abundance.

The phytoplankton data are derived from the MODIS Aqua products. I calculate the average phytoplankton absorption coefficients within 100 kilometers from coastal lines. Due to the MODIS's limited coverage, the values of the phytoplankton variable are missing for 38,220 observations (29.63% of the sample). Because the missing values are due to almost random variation in the satellite orbits, the missing-completely-at-random assumption is not so implausible,[2] and hence I drop those observations of missing values. In the following analysis, the

[2] In fact, even with list-wise deletion, the estimates of the regression models are very similar to the main results.

phytoplankton variable and its interaction with ground rainfall are added to the regression model.[3] As seen in Table SI-12, even when I account for the effect of phytoplankton abundance, it does not change the main findings.

Table SI-12. Results with Phytoplankton Abundance

Outcome	$violence_{it}$	$piracy_{it}$
$rain_{it}$	-0.0476 (0.0266)	0.0221 (0.0149)
$wind_{it}$	-0.1869 (0.1463)	-0.1685 (0.0884)†
$plankton_{it}$	-0.0448 (0.0358)	0.0292 (0.0270)
$rain_{it}wind_{it}$	-0.0405 (0.0124)*	-0.0030 (0.0135)
$rain_{it}plankton_{it}$	-0.0006 (0.0034)	0.0043 (0.0030)

NOTE: The table shows the OLS estimates of the coefficients. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 90{,}753$ with 31 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

[3] Due to missing values, I cannot calculate the past-one-year average of the phytoplankton variable without massive interpolation, hence I do not include the variable.

Supporting Information 13. Mechanism: Cross-area Correlations

Another alternative explanation is that ocean wind correlates with strong wind on the ground, which in turn makes it difficult for rebels to conduct violent activities. This might explain the finding that rebels conduct violence when both ocean and ground weathers are favorable. Although satellite data of ground wind speed is not available and hence I cannot control for ground wind speed, a possible approach is a placebo test with countries where maritime piracy is nearly impossible regardless of weather conditions. In my analysis, these are the countries that are excluded from the main analysis: Israel, Lebanon, Russia, Syria, and Ukraine, all of which did not experience even a single piracy event for the entire period of analysis (see footnote 17 in the manuscript).[4] Because the costs for piracy should be prohibitively high in these countries, my model expects that ocean wind speed does not change rebels' choices, and thus that ocean wind speed does not affect violence or condition the effect of ground rainfall on violence. By contrast, if ocean wind speed would affect violence through its correlation with ground wind speed, ocean wind should affect violence even in those countries. The following table (Table SI-13) indicates that ocean wind speed has no significant effect on violent activities when it is nearly impossible to conduct piracy, and that the coefficient for the interaction term is also not statistically significant.

[4] I do not conduct an equivalent analysis for maritime piracy, because the countries that did not experience any violence in the coastal areas are very limited (the Republic of the Congo and the Democratic Republic of the Congo) and hence the clustered standard errors cannot be computed.

Table SI-13. Placebo Test with Countries of No Piracy Event

Outcome	$violence_{it}$
$rain_{it}$	-0.1366 $(0.0341)^{*}$
$wind_{it}$	-0.2900 (0.2120)
$rain_{it}wind_{it}$	-0.0062 (0.0251)

NOTE: The table shows the OLS estimates of the coefficients. The standard errors clustered for countries are in parentheses. The models include the country fixed effects, date fixed effects, and country-year fixed effects. The control variables are the past-one-year averages of ground rainfall and ocean wind speed, and their interaction. $n = 17{,}632$ with 5 coastal conflict countries for 2001–2016. $*\ p < 0.05, \dagger\ p < 0.10$.

References

Coggins, Bridget L. 2012. "Global Patterns of Maritime Piracy, 2000–09: Introducing a New Dataset." *Journal of Peace Research* 49 (4): 605–17.

Flückiger, Matthias, and Markus Ludwig. 2015. "Economic Shocks in the Fisheries Sector and Maritime Piracy." *Journal of Development Economics* 114 (May): 107–25.

Kuhn, H. W., and A. W. Tucker. 1951. "Nonlinear Programming." https://projecteuclid.org/euclid.bsmsp/1200500249 (accessed on 24 November, 2020).

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112 (4): 725–53.

Most, Benjamin A., and Harvey Starr. 1984. "International Relations Theory, Foreign Policy Substitutability, and 'Nice' Laws." *World Politics* 36 (3): 383–406.

NOAA. 2018. "Global Temperature Time Series." 2018. https://www.cpc.ncep.noaa.gov/products/global_monitoring/temperature/global_temp_accum.shtml (accessed on 24 November, 2020).

Schultz, Kenneth A., and Justin S. Mankin. Forthcoming. "Is Temperature Exogenous? The Impact of Civil Conflict on the Instrumental Climate Record in Sub-Saharan Africa." *American Journal of Political Science*.

Sundberg, Ralph, Mathilda Lindgren, and Ausra Padskocimaite. 2010. "UCDP GED Codebook Version 1.0." http://ucdp.uu.se/downloads/ged/ucdp-ged-polygons-v-1-1-codebook.pdf (accessed on 24 ovember, 2020).

Tollefsen, Andreas Forø; Håvard Strand & Halvard Buhaug. 2012. "PRIO-GRID: A unified spatial data structure." *Journal of Peace Research*, 49(2): 363-374.