Unintentional Effects of Security Assistance on Violence: Evidence from Somali Piracy & Ocean Wind Speeds

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Abstract

Conflict harms institutions by increasing the cost of transactions and muddling investment incentives. Yet, institutions are crucial for economic growth. Maritime piracy presents one of the most prominent forms of violence in countries (e.g. Somalia) that face struggling institutions. To reduce the impact of piracy (particularly on global commerce), warships have been deployed to waters surrounding Somalia. A potential unintended consequence of piracy deterrence efforts is that they make nefarious land activities more attractive, threatening institutional development and safety. This paper examines how efforts to deter violent actors on the waterways impact land conflict. To overcome endogeneity concerns we exploit variation from ocean wind speeds, which reduce piracy for reasons not associated with dysfunctional institutions and foreign assistance, using an instrumental variables approach. We find one fewer pirate attack (1 st. dev. decrease) leads to approximately 18-30% more land violence and an additional 9.11 land conflict deaths, suggesting naval patrols harm Somalian institutions and safety. The results imply that stopping piracy saves shipping companies $343,318,180 at the cost of 565 Somalian land fatalities annually.[1]

Keywords: Piracy, Somalia, Institutions, Conflict, Displacement, Development

JEL Classification: F19, F53, K42

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"Somalia's institutions have been severely injured by prolonged conflict."

-Somalian Ambassador to U.S., 2020 (Ahmed, 2020)

1 Introduction

International trade and functioning institutions reduce transactions costs and enable secure property rights, driving economic development (Acemoglu, Johnson, & Robinson, 2005a). Increases in marine commerce lead to the economic growth and institutional development of Western Europe (Acemoglu, Johnson, & Robinson, 2005b). Two fundamental factors limiting marine commerce from facilitating economic prosperity and improvement in institutions are ocean wind speeds (Feyrer & Sacerdote, 2009; Pascali, 2017) and piracy (North, 1968, 1991).

Protecting commerce from pirates is vital, because it makes incentives for shipping companies to move goods across national boundaries in international waters stronger (Fernández & Tamayo, 2017; North, 1987) . Furthermore, violence against trade vessels has significant costs (Besley, Fetzer, & Mueller, 2015). To secure shipping lanes from piracy, naval forces patrol waters surrounding Somalia; during the peak of Somalian piracy (2008-2011), naval security cost about $2 billion dollars (Bowden, 2010; European Institute, 2011). While piracy intensity in Somalia has waned from the extremes of 2010, piracy has festered in new places (West Africa and South America) and impeded trade in Imperial China (Kung & Ma, 2014), the early Caribeean (Leeson, 2007a), modern Southeast Asia (Axbard, 2016), and contemporaneously elsewhere (Flückiger & Ludwig, 2015).

It is not surprising that aid has been provided to address populations engaging in activities detrimental to global commerce. Foreign aid falls into three categories: humanitarian, development (economic, social, or political), and security assistance (Ingram, 2019). Some find/claim foreign aid produces positive results (Civelli, Horowitz, & Teixeira, 2018; Clemens, Radelet, Bhavnani, & Bazzi, 2011; Ingram, 2019). This work notes that assistance programs promote national economic progress and stability (Ingram, 2019) and increase growth (Civelli et al., 2018; Clemens et al., 2011). Others find food aid (Nunn & Qian, 2014) and foreign aid shocks cause conflict (Crost, Felter, & Johnston, 2014; Nielsen, Findley, Davis, Candland, & Nielson, 2011), development assistance causes Dutch Disease (Rajan & Subramanian, 2011), and political assistance worsens governance (Bräutigam & Knack, 2004).[2]

Security assistance, the most fitting categorization for international warship patrols, reduces economic growth (Bove & Elia, 2018). Other findings suggest security assistance is an important complement to development assistance (Berman, Shapiro, & Felter, 2011). In addition to not promoting economic progress, security assistance could have unintended consequences. Security crack downs in regions impacting global commerce could geographically displace violent individuals (Dell, 2015). The presence of individuals with violent tendencies likely harm vulnerable populations in regions with weak institutions.[3]

Studies do not focus on piracy as an explanatory variable for economic land outcomes. Using piracy as an explanatory variable in naïve OLS regressions for land outcomes is unlikely to produce useful estimates, because the lack of a functioning state enabled piracy to flourish in Somalia.[4] Furthermore, political and development aid target areas with weak institutions; and security assistance (naval patrols) is directed toward piracy-prone areas. To provide informative estimates of the effect of piracy on land outcomes, one needs to find a piracy assignment mechanism which alleviates concerns of causality running from dysfunctional land-based institutions to piracy and the correlations between land outcomes,

[2]In contrast, De Ree and Nillesen (2009) finds aid reduces risk of civil conflict. A recent academic review on foreign aid is provided in Qian (2015).

[3]According to economic models of crime (Becker, 1968; Polinsky & Shavell, 1979), making a violent activity in one area (marine environments) more costly makes other types of activities in the same region relatively more attractive, while simultaneously encouraging violent activity in other regions (on land).

[4]The relationship between violent activities at sea and land conditions have been made by naval officials. "The causal factors remain the same: large sea spaces that defy easy application of legal restraint, favorable geography, weak or compliant states that provide sanctuary, corrupt officials and political leaders who can benefit from and protect piracy, conflict and economic disruption that open markets for stolen goods, and the promise of reward from the proceeds extracted from the sales of rich cargoes or the ransoms paid for seafarers lives. These factors, which are present today in Somalia..." (Murphy, 2009, pg. 80) Academics echoed the sentiment, noting that "while naval flotillas...play a role in safeguarding vessels -— and are probably responsible for the recent drop in hijackings off Somalia -— their presence will never act as a true deterrent for a criminal enterprise that is driven by land-based conditions" (Chalk, 2013).

piracy, development assistance, and security assistance. A solution for analyzing endogenously assigned treatments of interest, advocated for (in a general sense) by Dell, Jones, and Olken (2014), uses variation provided by weather. Specifically, ocean wind speed is a potential pseudo-random assignment mechanism for piracy, because treacherous seas make piracy less attractive (Besley et al., 2015; Cook & Garrett, 2013), but are not caused by weak institutions on land.[5]

Using ocean wind speed enables recovery of causal estimates of piracy on land conflict under plausible assumptions. One assumption is ocean wind speed only affects land conflict through its effect on piracy. While a 1-2 meter/second (m/s) change in wind speeds is unlikely to meaningfully alter on-land activities, it could impact decisions of other economic actors (e.g. fishermen), potentially leading to on land violence. To address this issue, several analyses are performed to support the exclusion restriction. First, analyses include measures of fishing conditions. Next, conflict events are subset to activities unrelated to fishermen, but related to pirates. Finally, a falsification exercise investigates ocean wind on conflict in Tanzania, a nearby region experiencing no piracy but with a strong fishing industry. Each analysis supports exclusion and subsequent causal interpretation of estimates.

The main finding concludes 1 fewer pirate attack increases on land conflict by 18-30 percent at the mean. Each additional pirate attack reduces land conflict events by 5.9, violence against civilians by nearly 1 event, institution-related conflict events by 1.68 events, and leads to 9.11 less land conflict fatalities. A pirate attacks costs shipping companies \$5,537,390, implying 1 Somalian life is worth approximately \$607,836.[6]

[5]This shares some similarity to studying conflict in Africa using rainfall (Miguel, Satyanath, & Sergenti, 2004). Somalia is not included in the sample in Miguel et al. (2004). One difference between this work and Miguel et al. (2004) is that this study has an element of displacement. Displacement leads to a more plausible exclusion restriction than rainfall, since the focus is how ocean wind speed affects land conflict.

[6]In comparison, the statistical value of prime-aged workers is \$7 million (Viscusi & Aldy, 2003), nearly 12 times higher than the value of life in Somalia

2 Background and Prior Literature

In this section, we start by distilling the events and factors that resulted in piracy becoming commonplace in Somalia. We then outline previous scholarship on the role of piracy in Somalia. Finally, this section recaps the relationship between piracy and wind speeds, as this relationship is crucial for the research design.

2.1 Somalia Before Government Dissolution in Early 1990's

The strategic location of Somalia along oil shipping routes made it an important geopolitical partner in the post World War II era. Somalia originally courted alliances with the U.S.S.R and then later the U.S. Partnering with these political superpowers allowed Somalia to build the largest army in Africa at the time (Ramsbotham & Woodhouse, 1999). As the Cold War drew to a close in the 1980's, Somalia's strategic importance was diminished, since control of oil shipping lanes was no longer necessary for the Cold War. With the reduction in Somalia's importance, The Siad Barre military dictatorship became more authoritarian, often exacerbating clan rivalries.[7] Resistance movements started to violently oppose the harsh government treatment along clan lines. In 1991, the Baare regime was toppled. The dissolution of the government increased the likelihood Somalian individuals identified with their ethnic clan (Alesina, Devleeschauwer, Easterly, Kurlat, & Wacziarg, 2003, pg. 8).[8] Somalialand (a former British protectorate) declared its autonomy and opposition groups began competing for control in the vacuum.[9]

[7]Family clans are a pervasive social structure in Somalia (Hesse, 2010).

[8]It has been found that ethnic polarization increases the incidence of civil wars (Montalvo & Reynal-Querol, 2005).

[9]Dates of when Somalia became a failed state are debated, with Menkhaus (2007), for example, arguing that elements of a failed state were present in the 1980's.

2.2 Somalia After Government Dissolution

The collapse of the government meant waters bordering Somalia were no longer patrolled by Somalian authorities. The coast of Somalia is regarded as a rich fishery and international fishing companies no longer faced enforcable regulations. In addition to illegal fishing, there are also allegations the Italian Mafia (who own waste disposal companies) negotiated with Somalian warlords to dump toxic waste along the Somalian coast in return for cash and weapons (Sorge, 2018).[10] In response to illegal fishing and toxic waste dumping, Somalians formed groups to protect their natural marine resources from outside degradation.[11]

In late 2006, internationally-backed Ethiopian troops invaded Somalia to oust the Islamic Courts Union (ICU). The operation succeeded and the U.N.-backed Transitional Federal Government (TFG) was installed.[12] The ICU splintered into different factions, including radical groups, such as Al-Shabaab. In the southern part of Somalia, Islamist insurgents waged war and often took control of towns. Anarchy in southern Somalia caused troops to be redirected away from the northern part of the country, closer to international shipping lanes (see Besley et al. (2015)), making piracy more attractive. Subsequently, piracy increased from less than 50 attacks per year in 2006 to over 200 attacks in 2009 (Do, 2013).

2.3 Organizational Structure of Piracy

Some research attempts to understand the organizations underlying piracy (Leeson, 2007a). It is unclear how these efforts contribute to reducing piracy or aiding those adversely affected. It is understood that Somalian pirate crews typically consist of three main actors: the muscle (which are often strongmen from Siad Barre's government), the financiers (warlords), and local fishermen who have knowledge of the waterways (Hunter, 2008). A fourth actor is

[10] Voice of America (2009) notes it may be as much as 100 times less expensive per ton to dump toxic waste than in the EU under EU regulations, while Monbiot (2009) puts it at 400 times less expensive.

[11] The closest term for pirate in Somali is "burcad badeed", meaning ocean robber. However, pirates refer to themselves as "badaadinta badah", meaning savior of the sea, which is sometimes translated as coastguard (Bahadur, 2011).

[12] Still, the TFG did not exercise much control over territory outside of Mogadishu and was seen as lacking legitimacy by many Somalians.

typically some type of local government officals such as a local governor or law enforcement (Daxecker & Prins, 2016).[13,14] To rule out the results conflating stopping piracy with unlucky fisherman, several robustness checks support the results being driven by pirates.

2.4 Literature on Somalian Development

Scholarly work on Somalia falls into 3 categories: qualitative (e.g. Menkhaus (2004)), comparative (Leeson, 2007b; Powell, Ford, & Nowrasteh, 2008), and causal (Maystadt & Ecker, 2014). Comparative studies examine Somalia's economic output before and after the TFG is installed. Somalia underperformed relative to neighboring countries after the installation of the U.N.-backed government (Leeson, 2007b; Powell et al., 2008). The explanation given is western-style democratic governance is not a feasible institution for clan-dominated Somalia. These studies do not have granular enough data for an explicit differencing strategy or other causal approach. There are also studies, with no data or model, offering insights into effects of violence/piracy on economic development in Somalia (Beloff, 2013; Menkhaus, 2004).

2.5 Piracy as Function of Economic Opportunity

Studies of determinants of piracy find variation in opportunity costs and benefits to piracy (Axbard, 2016; DeAngelo & Smith, 2020; Flückiger & Ludwig, 2015; Jablonski & Oliver, 2013; Kung & Ma, 2014). Axbard (2016) finds better fish nutrition leads to reductions in piracy, because individuals earn income by fishing instead.[15] Flückiger and Ludwig (2015) replicates the main results of Axbard (2016) for more countries. China enacted a trade ban in 1550 that lead to greater increases in piracy in areas more likely to trade silk with outsiders (Kung & Ma, 2014), due to the increased cost of being a merchant. DeAngelo and

[13] For information about how local officials are paid off, see: https://www.economist.com/middle-east-and-africa/2013/10/31/more-sophisticated-than-you-thought.

[14] Transparency International has ranked Somalia as the world's most corrupt country since 2007, https://www.transparency.org/cpi2019

[15] Since fishing and piracy use similar skills and equipment, an increase in fish availability and the profitability of fishing increases the opportunity costs of being a pirate.

Smith (2020) examines the introduction of private security on shipping vessels on the direct and spillover effects of pirate attacks. Piracy has rarely been an explanatory variable.

2.6 Wind Speed and Piracy

The relationship between ocean winds and piracy in Somalia is established (Besley et al., 2015; Cook & Garrett, 2013). Allowing wind to be a non-binary variable, Cook and Garrett (2013) finds a negative correlation between wind speed and pirate attacks. Additionally, there are no successful attacks after wind speeds reach 9 m/s and a stark decline in attack attempts as wind speeds increase from 8 m/s to 9 m/s. Also, wind speed reduces likelihood of success of pirate attacks, conditional on an attempt (Shortland & Vothknecht, 2011).[16] Since ocean wind affects piracy non-linearly, some specifications allow piracy to be a non-linear function of ocean wind.[17] Given prior research on wind and Somalian piracy and the usefulness for assessing first-stage relevance in a just-identified setup, the data is visually examined for a critical wind speed where piracy decreases non-linearly. Some specifications use the threshold to define "easy" and "difficult" piracy conditions.

3 Data

Our analysis makes use of three main variables: pirate attacks, on land conflict events, and ocean wind speed. Each is described below. Then, descriptive statistics and monthly variation is shown.

[16] Wind speed is also used as an instrument for drone strikes in Pakistan (Mahmood & Jetter, 2019), because accuracy and collateral damage are affected by high winds.

[17] An appealing way to do this is to use a single instrumental variable (so the equations are just-identified with 1 endogenous explanatory variable) so typical first-stage diagnostics are informative (Andrews & Stock, 2018). To use a just-identified setup requires one instrument, while prior literature suggests a non-linear break in pirate attacks occurs near 8-9 m/s, non-linearly reducing piracy-related operations.

3.1 Pirate Attacks

Pirate attack data comes from event-level data collected by the International Maritime Organization (IMO). The data includes detailed records of reported pirate attacks, date, geo-coordinates, attack descriptions, actions taken by crew, etc. The data is restricted to only geo-referenced pirate attacks that fall within a geographic region capturing pirate attacks reasonably attributed to Somalian pirates.[18] The 730 pirate attacks are shown in Figure 1a.

3.2 Conflict Events

Event-level conflict data for Somalia were obtained from the Armed Conflict Location and Event Dataset (ACLED).[19] The data contain detailed event-level conflict events occurring in Somalia, are geo-referenced, provide full descriptions, event types, actors, fatalities, and the date of the incident. To be included, per the codebook, the event must be politically motivated armed violence or protest. Each conflict event is shown in Figure 1b.

3.3 Wind Speed

Wind speed data comes from the Jason-2 satellite hosted at the Radar Altimetry Dataset (RADS).[20] From 2008-2016, the Jason-2 satellite orbited Earth in a uniform orbit, taking readings at the same location on Earth's surface about every 9.9 days. The satellite's orbit

[18] The main areas affected by Somalian Piracy are the Gulf of Aden, the Red Sea, the Arabian Sea, and the Indian Ocean. Attacks that occurred in those ocean/sea areas and are relatively close to Somalia are included. A square was drawn that encompassed those areas. The bounding box uses maximum latitude: 18, minimum latitude: -4; maximum longitude: 66, minimum longitude: 40. Attacks far off the coast, eastward into the Indian Ocean must be included because Somalian pirates sometimes use hijacked larger ships (called motherships) to extend their range further from shore.

[19] Data is available at `https://www.acleddata.com`. The original introduction is in Raleigh, Linke, Hegre, and Karlsen (2010).

[20] These data can be accessed at `http://rads.tudelft.nl`.

dates are used as the temporal length of the sample. Two advantages of the time frame are all wind data comes from the same satellite and it is the height of Somalian piracy.[21,22,23]

Figure 1c displays all individual wind readings. There are a total of 2,372,101 readings, of which approximately 1.8 million are over water. Each individual reading has coordinates, dates, and wind readings. Wind readings (and pirate attacks) are spatially joined to ocean areas using Geographic Information Software (GIS). For example, if an ocean wind reading is inside the geographic boundaries of the Indian Ocean, then an identifier for Indian Ocean is attached.[24,25] After the region identifier is attached, it is straightforward to collapse by week-year-region to obtain a single weekly measure of wind speed for each ocean area.

3.4 Land-Ocean Region Pairing

Figure 1d shows regional assignments. Land regions are assigned to ocean areas as follows: The Gulf of Aden and Red Sea are assigned to Somalialand, the Arabian Sea is assigned to Puntland, and the Indian Ocean is assigned to the rest of Somalia.[26] Assigning land areas to separate water regions is preferred to using a single cross-sectional unit (i.e. all of Somalia)

[21] Additionally, this has the benefit of not capturing the war between Ethiopia and the Transitional Federal Government versus the Islamic Court Union (ICU), which occurred during 2005-2006.

[22] The measure of wind speed we use – altimeter wind speed – is an estimate that is predicted using a neural network algorithm (Gourrions (Gourion, Noll, Gantet, Celler, & Esquerré, 2002)), which takes wave height estimates as the primary input. The relationship between wind speed and wave height is well-established, making it possible to make good predictions of altimeter wind speed from wave heights collected by the altimeter of Jason-2. The altimeter sends out a radio wave and calculates the time it takes to bounce back. It measures the wave height by comparing the time it takes for wave to return and compares that to a reference elipsoid of Earth. More information on the details of radar altimetry can be found in Ribal and Young (2019).

[23] Satellite data is used instead of buoy or boat-collected data because pirate attacks impede collection of this data (Smith, Bourassa, & Long, 2011).

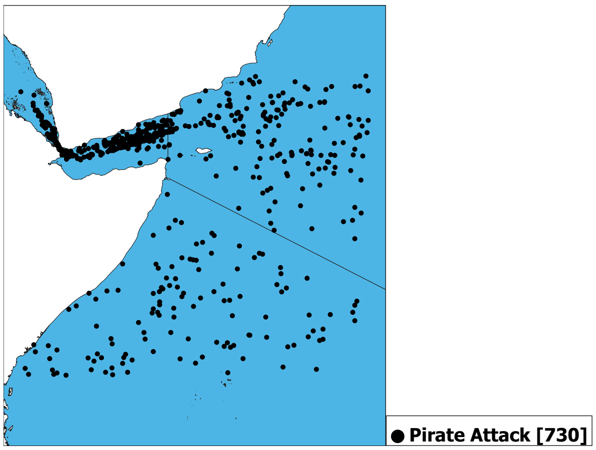
[24] Wind readings and pirate attacks are re-projected into the same coordinate reference system prior to joining, which assures they become associated with the correct ocean area.

[25] Wind measures not over land (approximately 500,000 observations) receive no ocean identifier and are dropped.

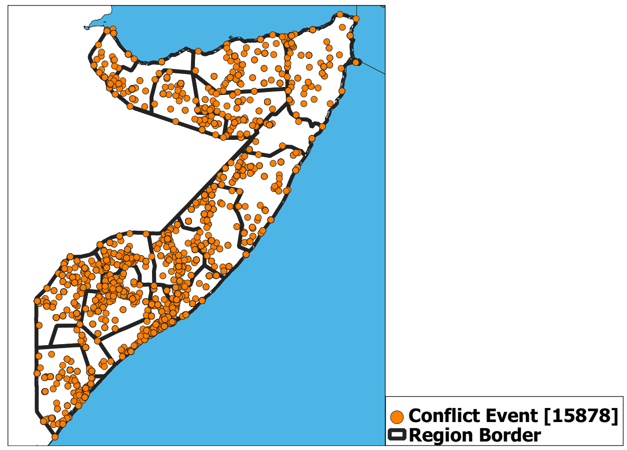
[26] Choosing the level of spatial aggregation and how regions are matched requires some discretion, the process used removes as much arbitrariness as possible. The ocean boundaries are defined by the marine regions shapefile and the land boundaries from established Somalian region boundaries, so boundaries are not arbitrarily drawn by the researchers. The northwestern most ocean areas are assigned to the northwestern most land region, the northeastern most ocean areas are assigned to the northeastern most land region, and the southernmost ocean region is assigned to the southern most land region. Robustness checks show assigning certain disputed land regions to a different ocean area does not change the results.

Figure 1: Spatial Distribution of Primary Variables and Region Definitions

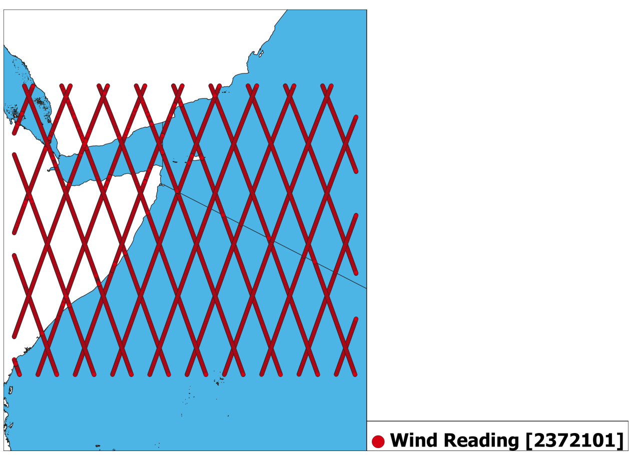
Panel A: IMO Pirate Attacks



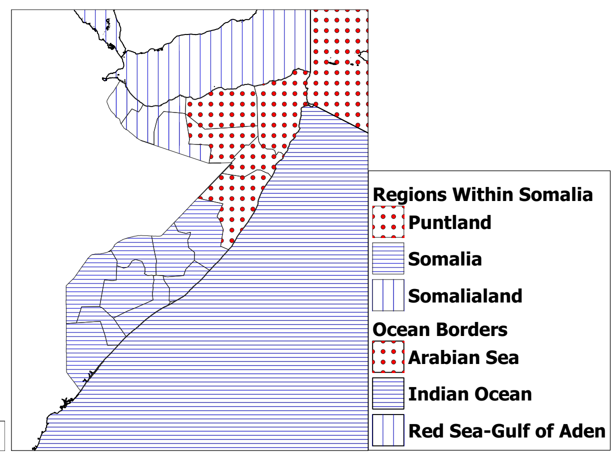
Panel B: ACLED Conflict Events



Panel C: Jason- 2 Individual Wind Readings



Panel D: Ocean-Land Region Assignment



Note: Time frame: Week 28, Year 2008 to Week 40 Year 2016. Count of dots displayed in legends. In Panel A, each black dot represents a pirate attack in the IMO data. In Panel B, each orange dot represents at least 1 conflict event. In Panel B the borders are GADM-2 recogenized borders. In Panel C, each red dot is 1 wind reading observation. The regular grid is due to regular orbit of the satellite collecting the wind readings. Panel D describes the primary assignment of ocean regions to land regions. It uses GADM-2 regions and the default ocean areas, defined by the ocean shapefile, to divide the land and ocean into northwest, northeast, and south regions.

because the data is spatially dispersed.[27,28] The panel data is formed over these geographic regions with one observation for each week.

There are two more advantages of aggregating data into relatively large spatial units. First, region fixed effects control for different legal origins.[29] In addition to established empirical importance of legal origins (Glaeser & Shleifer, 2002; La Porta, Lopez-de Silanes, & Shleifer, 2008), Draper (2009) believes differences in development across Somalia's regions can be attributed to legal system of the colonizer. Second, a disadvantage of using smaller units is spatial spillovers are highly significant in Africa using the same ACLED conflict data (Harari & Ferrara, 2018). Spillovers raises concerns that SUTVA is violated if spatial units are too small. To avoid estimating spillovers, the regional economics convention is followed by aggregating to large spatial units (Baum-Snow & Ferreira, 2015).[30]

3.5 Summary Statistics

Table 1 displays descriptive statistics of the sample of 1,548 weekly, region-level observations. The preferred aggregation method to calculate a single wind speed across multiple wind readings per unit of observation is to take the median of the multiple wind speed readings. By using the median, the wind measurement is less vulnerable to outliers.[31]

Panel A describes the aggregate sample. The average wind speed is 5.43 m/s, the standard deviation is 2.14. Standard deviation is nearly 2/5 of the mean, showing considerable variation for a regression analysis. There are 28 observations with missing wind speed (1519 compared to 1548 expected observations for 3 regions over 516 possible weeks), because wind speed can be missing due to the Jason-2 satellite not taking any over-water readings in a

[27]Piracy in the northeast of the Indian ocean is unlikely to be related to land conflict in the most south-western land area of Somalia.

[28]Follow-up analyses also exploit the spatial detail in the conflict data by subsetting conflict by closer to and farther from the coast.

[29]Somalialand was settled by the British and the other two regions were settled by Italy who ruled differently and had different legal systems.

[30]An example of this approach is Duranton and Turner (2011).

[31]This is preferred because ocean wind speed altimeter readings close to land masses are often recorded with greater error. Being close to land masses affects the recording of oceanographic variables such as wave height and wind speed.

region during a specific week-year. There is an average of 0.46 pirate attacks per region-week-year and the median of pirate attacks (1.12) is twice as large, indicating piracy data is skewed towards 0. Conflict data has a mean of 10.42 and standard deviation of 14.53, meaning there is ample variation in conflict also. The median is twice the mean, indicating a right skew to the conflict data and several specific categories of conflict are also right-skewed.

Panels B and C subsample to observations above and below the mean of (ocean-week-year median) wind speed. In Panel B, when wind speed is greater than the sample mean wind speed, mean pirate attacks are 0.16. In contrast, Panel C shows when wind speed is less than the mean, there is an average of 0.69 pirate attacks. When wind speed is high (and pirate attacks are low), an average of 12.85 conflict events occur, compared to only 8.47 conflict events when wind speed is below the median wind speed. When wind speed is greater than the mean, there are 21.8 land conflict fatalities, in contrast to the 13.37 fatalities when wind speed is lower than median. Similar conclusions can be drawn from variable medians.

3.6 Monthly Ocean Wind Speed, Pirate Attacks, and Conflict

Figure 2 shows monthly totals of piracy and conflict, alongside monthly mean ocean wind speed. Wind speed peaks in the summer and winter monsoon seasons and pirate attacks are inversely related to wind speed. As ocean wind speeds slow down between monsoon seasons, pirate attacks increase and there are less land conflict events.

4 Model

The analysis aims to identify how eradicating piracy affects safety of communities on land. Specifically, we aim to understand how deterring piracy via international aid and displace-

Table 1: Descriptive Statistics

Panel A: Aggregate

	Mean	Median	SD	Min	Max	Count
Median Wind Speed	5.43	5.13	2.14	0.1	13.4	1519
Median Wind Speed (Winsor 5%)	5.41	5.13	1.95	2.6	9.9	1519
Pirate Attacks	0.46	0.00	1.12	0.0	14.0	1548
Total Conflict Events	10.42	4.00	14.53	0.0	80.0	1548
Chlorophyll	0.29	0.22	0.83	0.1	30.0	1455
Land Conflict Fatalities	17.14	2.00	31.54	0.0	309.0	1548
Land Conflict, No Unlikely Events	8.90	2.00	13.55	0.0	79.0	1548
Land Conflict, No Unlikely Subevents	8.19	3.00	11.89	0.0	70.0	1548
Land Conflict, Pirate Weapons	2.65	1.00	4.91	0.0	35.0	1548
Land Conflict, No Unlikely Actors	9.23	3.00	13.42	0.0	76.0	1548
Land Conflict, At Least 1 Communal Militia	1.10	0.00	1.61	0.0	12.0	1548
Land Conflict, Grenades	0.62	0.00	1.61	0.0	15.0	1548
Land Conflict, Poor Institution Subevents	0.26	0.00	0.64	0.0	5.0	1548

Panel B: Wind Speed > Mean

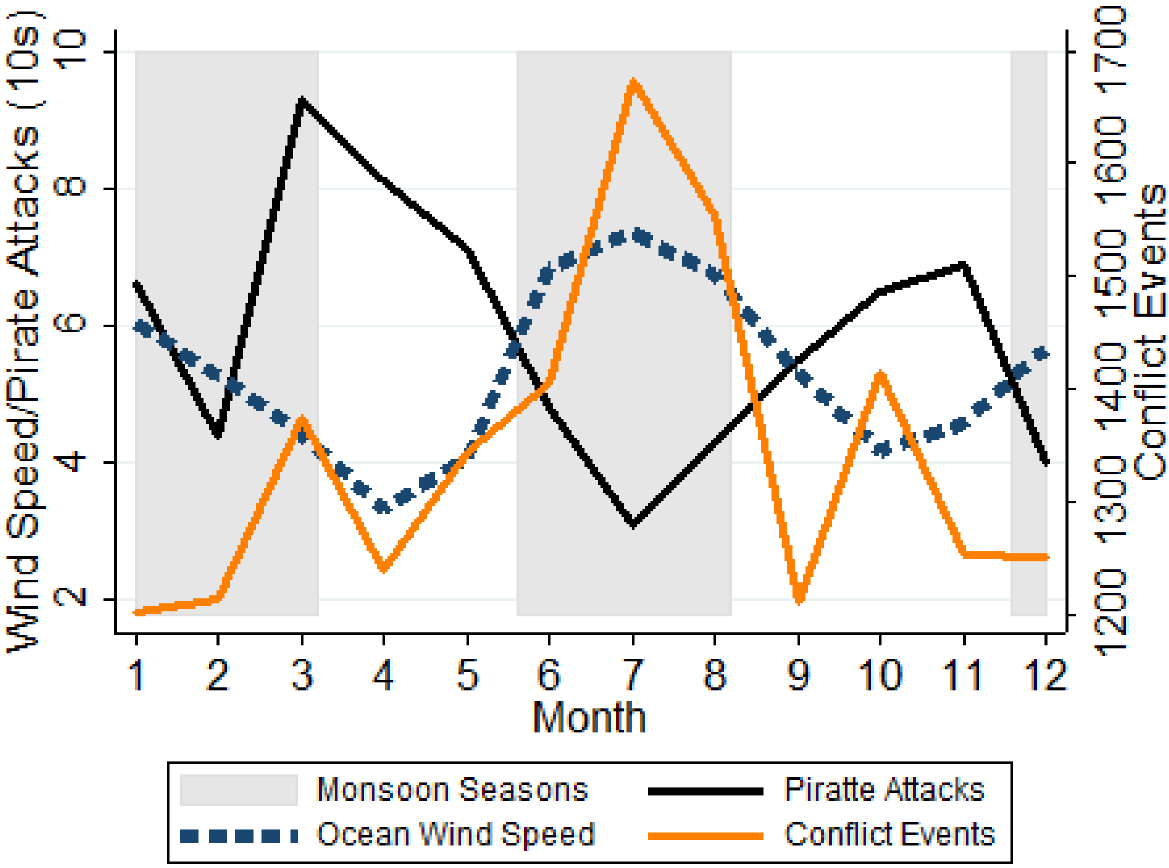
	Mean	Median	SD	Min	Max	Count
Pirate Attacks	0.16	0.00	0.55	0.0	6.0	691
Total Conflict Events	12.85	5.00	16.14	0.0	80.0	691
Median Wind Speed	7.34	6.84	1.69	5.4	13.4	662
Chlorophyll	0.27	0.25	0.18	0.1	3.4	667
Land Conflict Fatalities	21.80	4.00	36.52	0.0	309.0	691
Land Conflict, No Unlikely Events	11.09	4.00	15.17	0.0	79.0	691
Land Conflict, No Unlikely Subevents	10.10	4.00	13.27	0.0	70.0	691
Land Conflict, Pirate Weapons	3.33	1.00	5.61	0.0	33.0	691
Land Conflict, No Unlikely Actors	11.44	5.00	15.03	0.0	76.0	691
Land Conflict, At Least 1 Communal Militia	1.36	1.00	1.83	0.0	12.0	691
Land Conflict, Grenades	0.77	0.00	1.85	0.0	15.0	691
Land Conflict, Poor Institution Subevents	0.32	0.00	0.72	0.0	5.0	691

Panel C: Wind Speed < Mean

	Mean	Median	SD	Min	Max	Count
Pirate Attacks	0.69	0.00	1.38	0.0	14.0	857
Total Conflict Events	8.47	3.00	12.76	0.0	68.0	857
Median Wind Speed	3.96	4.09	0.97	0.1	5.4	857
Chlorophyll	0.29	0.19	1.12	0.1	30.0	788
Land Conflict Fatalities	13.37	1.00	26.28	0.0	208.0	857
Land Conflict, No Unlikely Events	7.13	2.00	11.81	0.0	64.0	857
Land Conflict, No Unlikely Subevents	6.65	2.00	10.40	0.0	56.0	857
Land Conflict, Pirate Weapons	2.10	0.00	4.19	0.0	35.0	857
Land Conflict, No Unlikely Actors	7.44	2.00	11.67	0.0	60.0	857
Land Conflict, At Least 1 Communal Militia	0.89	0.00	1.37	0.0	9.0	857
Land Conflict, Grenades	0.50	0.00	1.37	0.0	11.0	857
Land Conflict, Poor Institution Subevents	0.21	0.00	0.57	0.0	5.0	857

Notes: Panel A reports summary statistics for all crimes in entire sample. Panel B subsamples to only weeks where the wind speed was greater than the aggregate median wind speed. Panel C subsamples to only weeks where the wind speed is less than the median.

Figure 2: Monthly Wind Speed, Pirate Attacks, and Land Conflict



Note: N= 1519. Time frame is 2008-2016. Conflict events and pirate attacks are summed within months. Wind speeds' median is used. Monsoon season defined according to Shortland and Vothknecht (2011).

ment of violent actors on shore impacts land violence. The data measures ocean wind, aggregated piracy and conflict events within year-week-region. The naïve model is:

$$Land\ Conflict_{ryw} = \alpha + \beta_1 Pirate\ Attacks_{ryw} + \gamma_T + \mu_R + u_{ryw}, \tag{1}$$

where subscript r represents the region, subscript y stands for year, and subscript w stands for week. Time (γ_T) and region (μ_R) fixed effects are also included.

In Equation 1, β_1 is an unreliable estimate of the causal effect of an additional pirate attack on land conflict for at least two reasons: omitted variables correlated with the outcome and explanatory variable and endogenously assigned piracy. A common hypothesis is land conflict causes conditions to be ripe for pirates to thrive (Murphy, 2009), making pirate attacks endogenously assigned with respect to land conflict due to simultaneity. Simultaneity violates OLS assumptions and leads to incorrect standard errors. Due to non-random assignment, estimates of β_1 cannot be interpreted causally without (conditional) independence.

It is unlikely independent assignment of piracy can be achieved by conditioning on covariates. For example, one unobservable in u_{ryw} is legal institutions. Legal institutions are correlated with both piracy and land conflict. Region fixed effects only control for time-invariant characteristics of the regions; if institutions are time variant, then omitting legal institutions biases β_1 in Equation 1. Obtaining sub-national, weekly-varying information on legal institutions in Somalia is impossible.[32] Pirate attacks are also influenced by other factors likely correlated with land conflict, such as shipping vessel decisions, international navies, or whatever legal enforcement exists on land in Somalia. It is difficult, if not impossible, to obtain data at a weekly frequency for these important factors so they cannot reasonably be included in Equation 1, which makes β_1 uninformative (in terms of magnitude, sign, and statistical significance). To obtain useful estimates of the effect of pirate activity on

[32] Another factor in u_{ryw} is risk-taking preferences, which have been shown to be higher in areas with more conflict (Voors et al., 2012).

land conflict, a mechanism for isolating "as-if" random variation in pirate attacks is required to circumvent the issues of omitted variables and endogenous assignment of pirate attacks.

4.1 Theoretical Predictions

The research design uses quasi-random assignment of piracy from variation in ocean wind speed. Wind is connected to two basic economic frameworks to derive testable predictions. Both models illustrate high ocean wind speeds make piracy less attractive at the margin.

Higher wind speeds reduce piracy, because higher wind speeds increase risk associated with engaging in piracy activities (e.g. attempting to board another moving vessel) making likelihood of reward lower. High wind speeds are problematic for pirates due to the type of boat commonly used in Somalian piracy, a small wooden "skiff".[33] Skiffs are incapable of operating in environments with high wind, because they are slower and/or difficult to handle in ways that hinder successful piracy attempts. Larger, more expensive vessels would be capable of piracy in high wind speed environments and are uncommon in Somalian piracy operations. The increase in risk of injury or death associated with higher wind speeds result in either (a) fewer individuals being willing to engage in piracy or (b) a higher compensating differential for those willing to engage. Either case predicts a reduction in overall piracy.

Consider a potential Somalian pirate maximizing utility between activities, piracy and other,

$$U = f(Piracy,\ Other\ Activities).$$

When choosing the optimal amount of piracy activity to engage in the pirate considers both the marginal benefit of piracy and the marginal cost of piracy. Wind speed reduces the expected marginal benefits of piracy, because wind speed makes boarding, and thus being rewarded, far less likely. High wind speeds are a negative shock to the marginal benefit of piracy causing potential pirates to substitute time towards other activities which have

[33] IMO reports often discuss Somalian pirate attacks that involve motherships, which are sometimes hijacked boats, to launch skiffs.

relatively higher returns. High ocean wind speed reduces the attractiveness of piracy, like naval warships, displacing violent individuals onto land (Axe, 2009).

Other Activities includes land conflict, as Somalian pirates possess the capital inputs for piracy (guns, ammo, and explosives) that also could produce land conflict. Labor inputs for piracy can also be substituted towards nefarious acts on land. Someone willing to shoot, abduct, and loot at sea is likely to be willing to engage in violent behavior on land.[34,35] Table A.1 shows examples from the data demonstrating how pirates hijack on land and at sea (rows 1 and 2, respectively) and utilize the same weapons (rows 3 and 4).

A money in utility (MIU) model (Sidrauski, 1967) enables a concise explanation of the exact mechanism through which ocean wind speed affects piracy and land conflict. Utility is rewritten as a function of money from piracy and money from other activities:

$$U = f(m_P, m_O).$$

For simplicity, we assume money from pirate activities and money from other activities are perfect substitutes:[36]

$$U = m_P + m_O.$$

Money received from piracy activities, m_P, depends on both the time spent pursuing pirate activities, t_P, which is a choice variable, and the wage rate per unit of time, W_P:

$$m_P = g(t_P; W_P).$$

Pirates are time constrained, causing a trade-off between pirating and other activities:

$$T = t_p + t_o.$$

[34] Anecdotal support that pirates turn to land conflict when navies intervene exists (Coker & Paris, 2013).

[35] Somalian nationals pursuing piracy implies the return is higher at sea compared to land activities.

[36] Note that this implicitly assumes that money from pirate activities are equally good at facilitating transactions, a motivation of the money in utility model. This is likely an unnecessarily strong assumption, but it is a useful abstraction that facilitates interpretation of the trade-offs involved.

The expected wage rate, $E[W_P]$, depends on the probability of boarding, b $\in$ (0,1), the loot on board, L, and the expected ransom money from holding hostages, R,[37]

$$E[W_P] = b(L + E[R]).$$

High wind speed reduces the expected marginal benefit of piracy by causing negative exogenous shocks to the expected wage rate, $E[W_P]$, causing it to fall to $\overline{E[W_P]}$,

$$E[W_P] = b_c(L + E[R]) > \overline{E[W_P]} = b_h(L + E[R]).$$

This occurs because the probability of boarding in calm conditions, b_c, is greater than the probability of boarding in windy conditions, b_h. Existing studies suggest b = 0 if wind speed exceeds 9 m/s (Cook & Garrett, 2013). High wind speeds cause m_p to decrease to $\overline{m_p}$ and U drops to $\overline{U}$, *ceteris paribus*. This causes marginal units of time spent on pirate activities to be substituted towards other activities, as the marginal benefits of piracy are reduced by high wind speed. To summarize, higher wind speeds are similar to warships for pirates, because high wind speed and naval patrols make piracy less attractive at the margin.

4.2 Two Stage Least Squares

To leverage variation in the marginal benefit of piracy from ocean wind speed, two-stage least squares (2SLS) is used. The first-stage regression is,

$$Pirate\ Attacks_{ryw} = \alpha + \phi_1 Median\ Wind\ Speed_{ryw} + \gamma_T + \mu_R + \epsilon_{ryw}, \tag{2}$$

[37]This is a simplification, because not all boardings result in successful looting or ransoms. Sometimes pirates are deterred by crew responses after the pirates board or ransoms are not paid. It is a useful abstraction, because when b = 0, the wage rate is at most 0 for pirates and it is so in the model. This assumes payment upon boarding.

in which all subscripts and fixed effects are identical to Equation 1. Prior literature (Besley et al., 2015; Cook & Garrett, 2013) and Section 4.1 predicts $\phi_1 < 0$. Next, do reductions in the marginal benefit of piracy have adverse effects on Somalia? The second stage is

$$Land\ Conflict\ Events_{ryw} = \theta + \beta_1 \widehat{Pirate\ Attacks}_{ryw} + \gamma_T + \mu_R + u_{ryw}, \tag{3}$$

$\widehat{Pirate\ Attack}_{ryw}$ are fitted values from Equation 2. Section 4.1 predicts $\beta_1 < 0$.

4.3 Relevance

Causal identification of β_1 requires wind speed is a relevant instrument for pirate attacks, meaning wind speed explains an adequate amount of variation in pirate activity. Studies show high wind speeds reduce pirate attacks (Cook & Garrett, 2013), because pirates use small skiffs that are difficult to use in windy conditions (Ellerman, Forbes, & Rosenberg, 2010). Relevance is tested using the Kleibergen-Paap F-statistic for $\phi_1 = 0$ (Kleibergen & Paap, 2006).[38]

4.4 Exclusion Restriction

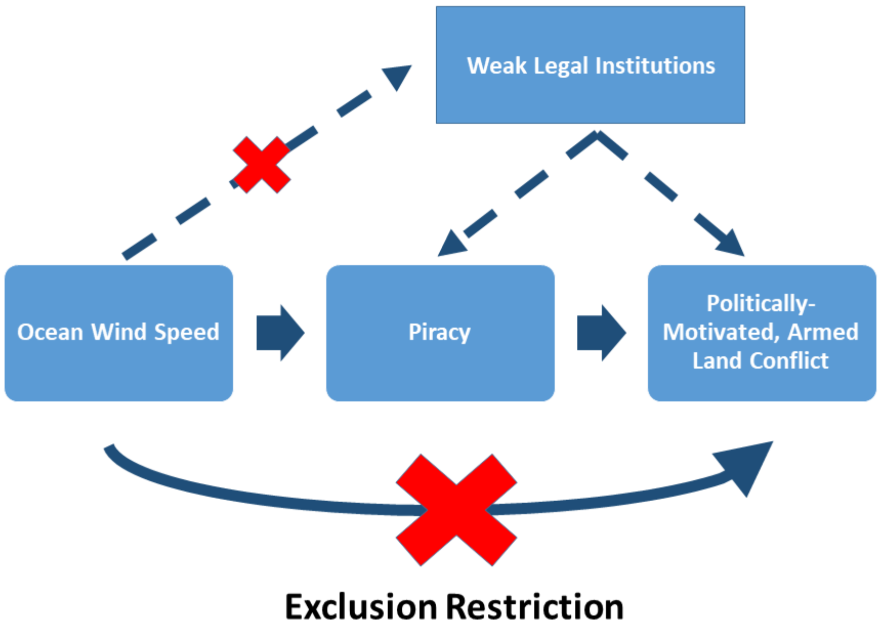
Causal identification of β_1 assumes ocean wind speed is excludable from Equation 3, meaning ocean wind speed affects land conflict events only through its effect on pirate attacks. Panel A of Figure 3 illustrates the exclusion restriction that must be satisfied for estimates to have a causal interpretation. It is plausible ocean wind speed effects land conflict only through its effect on pirate attacks and results support validity of exclusion in three ways.[39]

[38] Kleibergen-Paap F is more appropriate for heteroskedastic errors (Andrews & Stock, 2018).

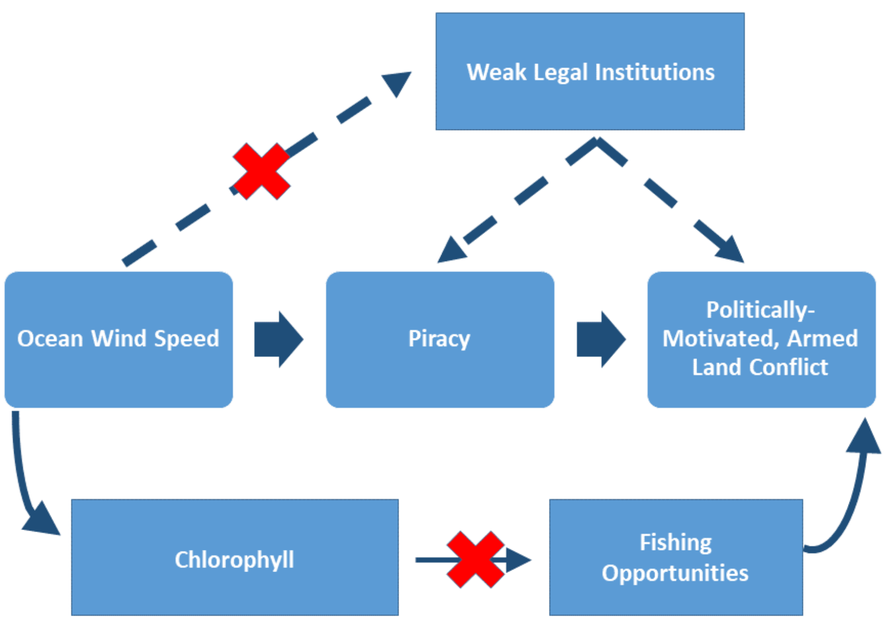
[39] Alternatively, we believe ocean wind speed does not affect land conflict through the institutions of Somalia in any way except for through exogenously altering the cost to pirates of engaging in attacks.

Figure 3: Identification

Panel A: Ocean Wind Speed Only Affects Land Conflict Through Piracy



Panel B: Exclusion, Conditional on Chlorophyll



Note: Directed Acyclic Graphs (DAG) of identification strategy (Pearl, 1998).

4.5 Conditions For β_1 to be Heterogeneous LATE

Three conditions are required to interpret β_1 as the heterogeneous local average treatment effect (LATE). One, wind speed must be independent [OF? WRT?](as good as randomly assigned), which is satisfied. Second, monotonicity (Imbens & Angrist, 1994) requires increases in wind speed do not reduce piracy. The monotonicity assumption is supported by Figure 4a, where increasing wind speeds are associated with reductions in pirate attacks. Finally, the Stable Unit Treatment Value Assumption (SUTVA) requires potential outcomes of treated units to not affect untreated units. As noted in Section 3.4, broad spatial units are used to minimize likelihood of SUTVA violations (Baum-Snow & Ferreira, 2015).

5 Results

This section begins by showing unreliability of OLS and verifying 2SLS predictions. Next, exclusion is supported and results are insensitive to various robustness checks. The section concludes with considering consequences of piracy eradication for Somalians' safety.

5.1 Reduced Form and First Stage Binned Scatter Plots

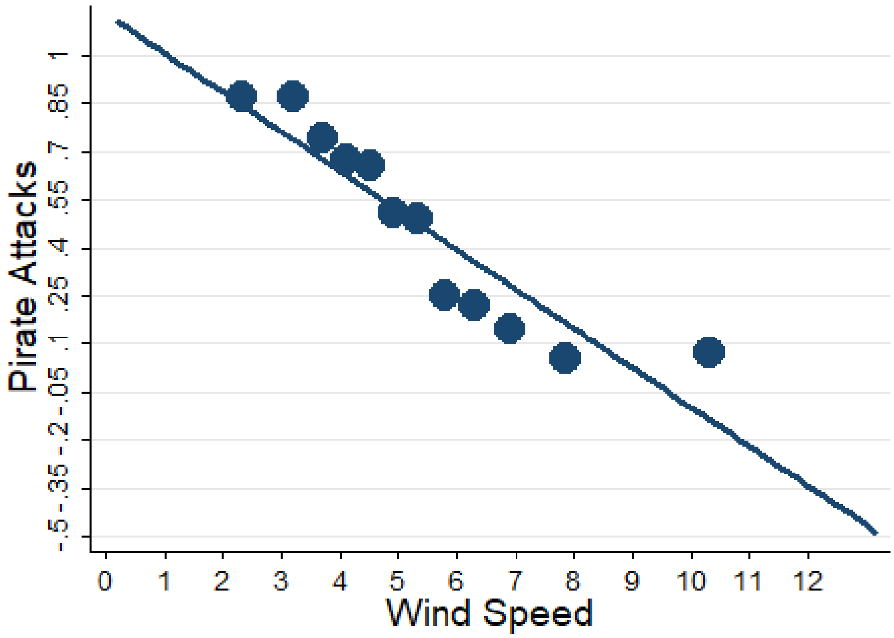
Figure 4 plots piracy attacks and land conflict, conditional on ocean wind speed. No functional form is assumed and number of bins minimizes a bias-variance trade-off (Cattaneo et al., 2019).[40,41] Figure 4a shows an approximately linear, negative association between wind speed and piracy. However, the linear fit is not equally accurate at each x-axis increment in Figure 4a, showing observable non-linearity. At wind speeds less than 5 m/s (near the average wind speed), the average number of piracy attacks is between 0.7-0.85. At wind

[40] The linear fit is shown because the primary model assumes linearity, in accordance with most applied two stage least squares research designs (Lochner & Moretti, 2015).

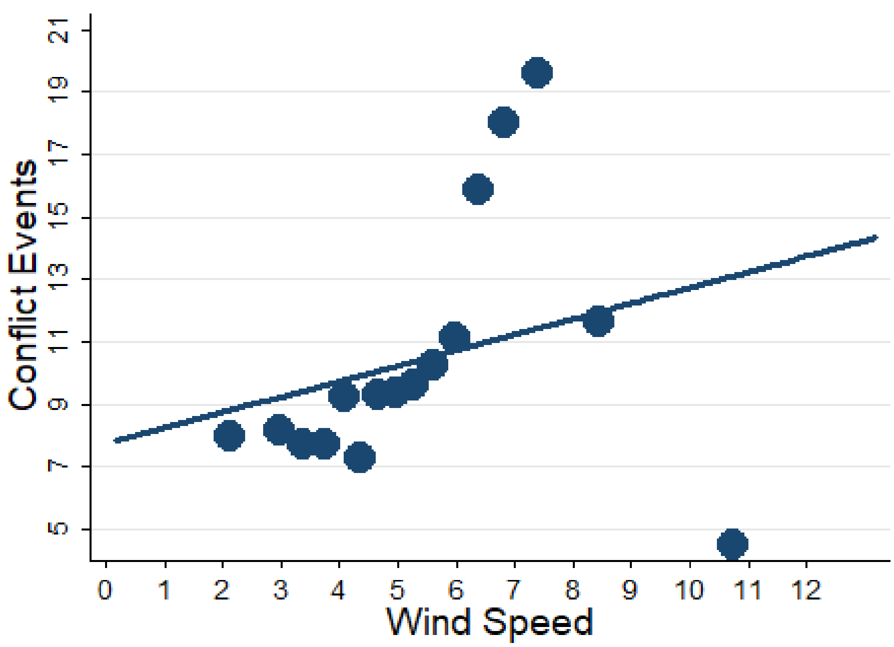
[41] Prior literature (Cook & Garrett, 2013) finds non-linearities in the effect of ocean wind speed on piracy, which we also observe in Figure 4a.

Figure 4: Binned Scatterplots of Piracy and Conflict by Wind Speed

Panel A: Piracy, Conditional on Wind Speed



Panel B: Conflict, Conditional on Wind Speed



Note: Binsreg (Cattaneo, Crump, Farrell, & Feng, 2019) used. Procedure selects number of bins to optimize a bias-variance tradeoff. Equal number of observations in each bin. No covariates controlled for.

speeds greater than 5 m/s the averages are below the linear fit and the average of pirate attacks is in the range of 0.1-0.25. There is a change in slope near wind speeds of 6 m/s.[42]

Figure 4b examines the reduced form, ocean wind on land conflict. Similar to Figure 4a, the right most wind speed bin is a clear outlier. The error becomes larger near wind speeds of 6 m/s. At 6 m/s, this is the same wind speed where piracy decreases non-linearly, suggesting a non-linearity in the relationship between ocean wind and land conflict almost exactly where there is a non-linearity between ocean wind and piracy.[43]

5.2 Pirate Attacks and Land Conflict by Ocean Wind Quartiles

The primary regression results impose linear functional forms, which Figure 4b shows may not fit the data well. To examine the relationship between ocean wind speed, piracy, and land conflict without imposing linearity, Figure A.4 presents the distributions of piracy and land conflict, conditional on wind speed quartiles. Figure A.4 shows the effect of wind speed on piracy and land conflict is not solely due to linear functional form assumptions.

5.3 OLS

Table 2 presents estimates of the naïve relationship between piracy and land conflict. The coefficient on pirate attacks always has a statistically significant impact on land conflict, but the sign switches when time fixed effects are added. Panel B drops observations with missing wind speed, like the 2SLS approach, and time fixed effects switch the sign. Panel C uses Poisson regression because conflict events are discrete; time fixed effects switch the sign.

One possible explanation for pirate attacks' sign switching with time fixed effects is endogenously assigned piracy. There is also omitted variable bias when not controlling for factors potentially correlated with both the treatment (pirate attacks) and the outcome

[42] Prior work (Cook & Garrett, 2013) suggests this point is 8 m/s. There are 3 possible reasons for this data suggesting 6 instead of 8 m/s is critical. 1) Cook and Garrett (2013) uses a different time period. 2) Cook and Garrett (2013) uses a different study region- all of Somalia's bordering waters. 3) Cook and Garrett (2013) might use a different aggregation like mean instead of median.

[43] Similar conclusions about ocean wind, piracy, and land conflict can be drawn from Figures A.1 and A.2.

Table 2: Naïve Estimates of the Effect of Pirate Attacks on Land Conflict

	(1)	(2)	(3)
Panel A: OLS, All Observations			
Pirate Attacks	-0.74***	0.87***	0.46***
	(0.13)	(0.14)	(0.12)
Observations	1548	1548	1548
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X
Panel B: OLS, No Missing Wind Observations			
Pirate Attacks	-0.75***	0.88***	0.46***
	(0.13)	(0.14)	(0.12)
Observations	1519	1519	1519
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X
Panel C: Poisson, All Observations			
Pirate Attacks	-0.19***	0.07***	0.15***
	(0.03)	(0.02)	(0.03)
Observations	1548	1548	1548
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Heteroskedasticity robust standard errors in parentheses. All regressions show regressions of pirate attacks on total land conflict. Panel A and B use OLS. Panel B drops observations where wind speed is missing. Panel C uses Poisson regression. Column 1 includes only region fixed effects. Column 2 includes region fixed effects, year fixed effects, and month fixed effects. Column 3 includes region X year X month fixed effects.

(on-land conflict events), such as legal institutions (see Figure 3). There are some maritime piracy events reported in the conflict data, which could lead to a pirate attack being recorded as a conflict event. Using wind speed assuages concerns about the effect of measurement error in the dependent variable on instrumental variable estimates, because it is unlikely pirate attacks are more/less likely to be recorded as conflict based on ocean wind speed.[44]

The strong influence of region and time fixed effects are clearly important. First, region fixed effects control for time-invariant differences across regions. Second, Somalian piracy had an important time component, as attention to piracy grew over time. Controlling for year fixed effects should account for the variation in awareness and responses to piracy over time. Month fixed effects are included to account for wind changes during monsoon seasons.

5.4 2SLS

Following Equations 2 and 3, Table 3 presents 2SLS results. Each panel uses different fixed effects, and Panel E adds a region-specific linear time trend. Relevance is tested using the Kleibergen-Paap F-statistic.[45] The F-statistic is above 30 in panels A-C and above 15 in Panels D and E., indicating wind speed adequately predicts piracy (Stock & Yogo, 2002).

In each panel, one additional pirate attack reduces land conflict events by between 2.7 (Panel C) and 5.94 (Panel E) weekly events. All second stage coefficients are statistically significant at 5%.[46] Point estimates are similar to the difference in mean conflict events observed in Table 1 when data is segregated by mean wind speed. A 1 standard deviation increase in pirate attacks (1.12) increases conflict by between 0.186 and 0.409 standard deviations. The standard deviation interpretation suggests stopping piracy results in economically significant

[44] Assuming $Cor(Measurement\ Error_{Conflict}, Ocean\ Wind\ Speed) = 0$ is reasonable. One would need to believe that wind speed is somehow correlated with the maritime piracy events that are present in the land conflict data, which seems unlikely. Results are unchanged when dropping marine incidents from the conflict data.

[45] Andrews and Stock (2018) suggests using the Kleibergen-Paap F when 2SLS is just-identified and errors are non-homoskedastic.

[46] There are some areas where discretion is required. Table A.3 examines a limited set of these areas. First, there is some discretion required in assigning land areas to ocean areas. Panel A re-assigns some disputed territories to a different ocean and the results are unchanged. Panel B drops incidents that are potentially considered marine incidents and the results are also unchanged.

Table 3: 2SLS Estimates of Piracy on Land Conflict

Dep. Variable	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Single Independent Variable			
Median Wind Speed	0.50***	-0.12***	
	(0.16)	(0.01)	
Pirate Attacks			-4.08***
			(1.25)
Kleibergen-Paap F			111.8
Panel B: Region, Year, Month FE's			
Median Wind Speed	0.28**	-0.09***	
	(0.11)	(0.02)	
Pirate Attacks			-2.96**
			(1.32)
Kleibergen-Paap F			35.46
Panel C: RegionXYear, Month FE's			
Median Wind Speed	0.25***	-0.09***	
	(0.09)	(0.02)	
Pirate Attacks			-2.70**
			(1.09)
Kleibergen-Paap F			36.70
Panel D: RegionXYearXMonth FE's			
Median Wind Speed	0.50***	-0.08***	
	(0.17)	(0.02)	
Pirate Attacks			-5.90**
			(2.35)
Kleibergen-Paap F			16.00
Panel E: RegionXYearXMonth, Linear Time Trend			
Median Wind Speed	0.50***	-0.08***	
	(0.17)	(0.02)	
Pirate Attacks			-5.94**
			(2.35)
Kleibergen-Paap F			15.94

Note: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. The table displays 2SLS regressions of pirate attacks on land conflict events, using ocean wind speed as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. In Panel A, no fixed effects (time, cross-sectional unit) are used. In Panel B, region fixed effects, month fixed effects, and year fixed effects are included. Region effects are the combination of a specific ocean area and a federal "region", defined by governing body, in Somalia. In Panel C, RegionXYear interacted, and month fixed effects are included. In Panel D, RegionXYearXMonth interacted fixed effects are included. In Panel E, RegionXYearXMonth interacted fixed effects and a region-specific linear time trends are included.

increases in conflict. Table 2 showed the importance of time and region fixed effects, making including region, month, and year fixed effects preferable. Using 2SLS, the sign on pirate attacks does not hinge on fixed effects and supports theoretical predictions.

The preferred fixed effects are RegionXYearXMonth (Panel D) for two reasons. First, there is substantial month to month variation in wind speed due to monsoon seasons, which is different depending on the severity of monsoons by year. Different regions are differentially exposed to this variability. Second, Dell et al. (2014) suggests, when weather is used to identify the effects of an endogenous treatment, the cross-sectional unit (in this case, region) fixed effects should be interacted with time fixed effects so the effects are identified by within-unit weather shocks at a certain time.[47]

5.5 Excluding Land Conflict Close to Coast

Since transportation costs are non-zero, it is likely pirates have a larger effect on land conflict events near the coast. Table 4 presents the second stage of 2SLS regressions which only count land conflict events increasingly farther from the coast. Column 1 only includes conflict events at least 10 miles away from the coast and the estimated effect of pirate attacks falls from 5.94 to 3.37, suggesting attacks close to the coast are driving the results. Column 2 includes conflict events at least 25 miles away from the coast and the magnitude of the effect of piracy drops to 2.97. Column 3 includes conflict events at least 75 miles away from the coast and the estimated effect falls to 2.51, less than half the magnitude of estimates including conflict closer to the coastline. The majority of pirates likely live near the coast which is where the largest effects are found. Violent actors exist throughout the country, so it is unsurprising effects can be found for areas distant from the coast.[48]

[47]While the F-statistic is smaller with interacted fixed effects, the instrument remains adequately strong. Since, interacted fixed effects, region-by-year-by-month fixed effects, are the preferred specification going forward, Figure A.3 repeats the binned scatter plots, including these fixed effects.

[48]Many Somalians are nomadic and the unit of analysis is a week which gives enough time to travel inland.

Table 4: Excluding Land Conflict Events Closer To Coast

	(1) >10 Miles Only	(2) >25 Miles Only	(3) >75 Miles Only
$\widehat{Pirate\ Attacks}$	-3.37**	-2.97**	-2.51***
	(1.33)	(1.16)	(0.97)

Note: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Standard errors robust to heteroskedasticity shown in parentheses. Distances are measured in miles. Column 1 includes only conflict events at least 10 miles away from the coast. Column 2 includes only conflict events at least 25 miles away from the coast. Column 3 includes only conflict events at least 75 miles away from the coast. All fixed effects are partialled out.

5.6 Examining Consistency of Results with Exclusion Restriction

The primary threat to interpreting second stage estimates as causal is potential violations of exclusion. Exclusion is violated if ocean wind speed affects land conflict by inducing fisherman to commit violent acts on land.[49] The next analyses suggest exclusion is viable.

The objective of the next set of results is to suggest ocean wind speed affects land conflict only through piracy. To do this, one strategy is to show that fishing conditions do not affect land conflict, so fishermen are unlikely driving the relationship between ocean wind and land conflict. For this analysis, a control for fishing conditions is included. Second, it is examined whether ocean wind speed affects land conflict that is more likely to be associated with pirates and less likely to be associated with fishermen. Finally, a neighboring country, Tanzania, is examined because it also has fishermen but drastically less piracy. If ocean wind speed does not affect land conflict in a country without piracy, it supports the exclusion restriction.

[49]Since the outcome is politically-motivated armed conflict, the estimates would not capture the effect of domestic violence that results from wind speeds impacting fishing conditions. To think wind speed affecting fishing would violate the exclusion restriction is hypothesizing that fishermen come home after having a tough week due to wind and participate in armed conflict. Nevertheless, it is impossible to rule out this possibility a priori.

5.6.1 Satisfying Conditional Exclusion By Controlling for Fishing Conditions

By definition, a violation of the exclusion restriction means:

$$Cov(Ocean\ Wind\ Speed_{ryw}, u_{ryw} \mid \mathbf{R}, \mathbf{T}) \neq 0. \tag{4}$$

A violation of exclusion is ocean wind speed affecting returns to fishing, and distraught fishermen committing violent acts on land as a result. Exclusion is violated if ocean wind is correlated with unobservables related to fishing (contained in u_{ryw}) that are time-variant (not controlled for by region fixed effects, $\mathbf{R}$) and affect conflict.[50] A straightforward way to regain the plausibility of the exclusion restriction, enabling causal claims, is appealing to conditional exclusion. Conditional exclusion means any way ocean wind speed (the instrument) could affect conflict (the outcome) are included in the regression as control variables. By including them, it blocks "backdoor paths" from ocean wind to conflict.[51]

By definition, satisfying conditional exclusion means:

$$Cov(Ocean\ Wind\ Speed_{ryw}, \widetilde{u}_{ryw} \mid \mathbf{R}, \mathbf{T}, \mathbf{X}_{ryw}) = 0,\text{[52]} \tag{5}$$

in which $\mathbf{X}_{ryw}$ are variables contained in u_{ryw} in Equation 4 and that ocean wind speed and land conflict are both correlated with; $\widetilde{u}_{ryw} = f(u_{ryw}, \mathbf{X}_{ryw})$.[53] If one believes wind speeds push fishermen and pirates to commit violent acts on land, then good candidate variables for X_{ryw} are variables affecting fishermen temperament and potentially affected by ocean wind.

One variable affecting fish markets, is associated with piracy, and could affect fisherman temperament is chlorophyll concentration (Axbard, 2016). Chlorophyll is a nutrient in the fish food chain, meaning higher concentrations leads to better fishing conditions. Fishing

[50] If the outcome was domestic violence this would be even more concerning, but the dependent variable is politically-motivated armed conflict. Since the outcome is politically-motivated armed conflict, the estimates do not capture the effect of domestic violence that results from wind speeds impacting fishing conditions, which could result in domestic violence.

[51] This strategy is shown in Figure 3b.

[52] $\mathbf{R}$ and $\mathbf{T}$ are region and time fixed effects in any form.

[53] With an additive functional form assumption, could be represented $\widetilde{u}_{ryw} = u_{ryw} - f(\mathbf{X}_{ryw})$.

conditions are likely to have a noticeable impact on the economic opportunity from fishing, as shown in Axbard (2016) and Flückiger and Ludwig (2015), and therefore the attitudes of fishermen. Also, certain monsoon season winds bring in higher amounts of chlorophyll with ocean swells (Chatterjee, Kumar, Prakash, & Singh, 2019; McClanahan, 1988).[54]

Chlorophyll concentration data comes from satellite data on the NASA Ocean Color website. Table 1, Panel A shows 120 chlorophyll observations missing from the "full" sample and 91 from the wind sample used in the 2SLS regressions.[55] Descriptive statistics show (Table 1, Panels B and C) average chlorophyll does not differ by average ocean wind speed.

Table 5, Panel A includes a linear measure of chlorophyll in the reduced form, first stage, and second stage as a control variable.[56] Including chlorophyll makes Equation 5 the required assumption to gives estimates a causal interpretation. Fishing conditions are not statistically significant in any regression in Table 5, Panel A. The F-stat drops from 16 to 14.86, further suggesting chlorophyll is negligible when included in a regression of piracy on wind speed. Also, better fishing has a positive point estimate, contradicting expectations, although this estimate is not statistically different from zero. Finally, the second stage estimate is nearly unaffected by including chlorophyll; the statistical significance is the same and the magnitude barely changes (5.94 to 6.09). This analysis suggests fishing conditions do not impact the estimates of piracy on land conflict, implying the exclusion restriction holds.[57]

5.6.2 Land Conflict Outcomes Reducing Likelihood of Exclusion Violations

A different approach for examining plausibility of exclusion as it relates to fishermen is considering dependent variables more likely associated with pirates and less likely associated with fishermen. This assumes likelihood of fishermen involvement is not homogeneous across

[54]There are potentially other aspects of fishing conditions that may better control for fishing conditions. The difficulty is that this control variable must be observed weekly at a sub-national level.

[55]It is reasonable to believe that these chlorophyll observations are missing at random, particularly conditional on the fixed effects.

[56]Chlorophyll is arguably not endogeneous, which would make it a suitable control variable.

[57]Due to the negligible impact of including chlorophyll concentration for the main estimates and the missing chlorophyll for 91/1519 (6%) of observations, chlorophyll concentration is omitted in most subsequent regressions.

Table 5: 2SLS Estimates of Pirate Attacks on Conflict, Verifying Consistency With Exclusion Restriction

Dep. Variable	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Conditioning on Fish Nutrition			
Median Wind Speed	0.52***	-0.09***	
	(0.19)	(0.02)	
Good Fishing	-0.02	0.07	0.40
	(0.02)	(0.05)	(0.33)
Pirate Attacks			-6.09**
			(2.50)
Kleibergen-Paap F			14.86
Observations	1428	1428	1428
Panel B: Only Conflict w/ Actors Less Likely to Fish			
Median Wind Speed	0.43***	-0.08***	
	(0.16)	(0.02)	
Pirate Attacks			-5.09**
			(2.12)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519
Obs. Where Y = 0			333
Panel C: Subset Conflict to Events w/ Pirate Weapons			
Median Wind Speed	0.18***	-0.08***	
	(0.06)	(0.02)	
Pirate Attacks			-2.12***
			(0.80)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519
Obs. Where Y = 0			768
Panel D: Conflict Sub-Events Not Fishermen-Associated			
Median Wind Speed	0.38***	-0.08***	
	(0.14)	(0.02)	
Pirate Attacks			-4.51**
			(1.86)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519
Obs. Where Y = 0			355

Note: * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. The table displays 2SLS regressions of pirate attacks on land conflict events, using ocean wind speed as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes a linear measure of chlorophyll concentration, an important source of fish nutrition (Axbard, 2016). Higher values of chlorophyll imply better fishing conditions. Panel B drops actors that are less likely to be fishermen or related to piracy including: a sole military actor, military on military, sole rebel action, rebel vs rebel, sole protestor, sole protestors vs civilians, or other sole actions. Panel C only considers conflict events where a pirate weapon was used such as a gun, rocket-propelled grenade, or grenade. Panel D considers a subset of conflict events based on sub-event type. The dropped sub-event types are: air/drone strikes, change to group/activity, disrupted weapons use, excessive force against protesters, government regains control of territory, mob violence, non-violent transfer of territory, other, peaceful protest, remote explosion, suicide bomb. See Table A.4 for more information on the hierarchy of events.

specific features of the conflict data. The data is subset by actors involved in the events, the types of weapons used, and the (sub-)event type classification given by ACLED.[58]

Actors Section 5.6 seeks to both falsify the link between fishermen and land conflict and strengthen the relationship of wind speed to land conflict, through piracy. Dropping military and rebel actions strengthens the relationship of wind speed on conflict, through piracy. Dropping protesters and sole actors falsifies the link between wind speed and conflict through fishermen, because fishermen are likely classified as these actor types. Table 5, Panel B drops interactions between actors not clearly related to pirates.[59] The coefficient drops from 5.9 to 5.09 and remains statistically significant at the 5% level. The same significance and size suggest effects are due to actors likely to be considered pirates, not fishermen, consistent with exclusion.

Weapons Pirates use specific weapons, like guns, grenades, rocket-propelled grenades, pipes, and knives, that are not critical for fishing.[60] In Panel C of Table 5 only conflict events in which weapons associated with pirates are included in the dependent variable.[61] Panel C finds 1 additional pirate attack leads to 2.12 less events with pirate weapons on land and the effect is statistically significant at the 1% level.[62] This strong relationship between at-sea pirate attacks and on-land events with pirate weapons supports exclusion.

Event Types Individuals who engage in piracy are more likely to participate in some types of conflict and less likely to engage in others. Similarly, fishermen are more likely to engage

[58] For example, fishermen are more likely to protest than to initiate a drone airstrike, more likely to be involved as a protester than as a state military combatant, and less likely to use a rocket-propelled grenade.

[59] The dropped interactions between parties are: sole military actor, state military versus state military, sole rebel action, rebel versus rebel, sole protestors, protestors versus civilians, and other sole actions.

[60] Aside from anecdotes, reading event descriptions from the IMO pirate data can make this obvious.

[61] To find land conflict events where pirate attacks are used, the description of the event is searched for keywords that identify pirate weapons. The keywords are: "AK-47", "AK- 47", "AK47", "Ak47", "ak47", "Ak-47", "AK 47", "Kalashnikov", "gunfire", "gunmen", "gunman", "gun", "rifle", "RPG", "bazooka", "grenade". Also, sub-events, labeled "Grenade" are used.

[62] There are, at least, two reasons this estimate is not closer to the 5.94 estimate. First, increases in conflict can also come from pirates not using these specific weapons. Second, not all cases of pirate weapon use may be reported in the data.

in some types of conflict. Table 5, Panel D excludes event types in which fishermen are likely to participate and which are unlikely perpetuated by actors who engage in piracy.[63] In Panel D, the second stage coefficient is 4.51, which is close to 5.94, and statistically significant. It is not concerning the magnitudes are not exactly the same, due to imperfect selection and recording of event types. Excluding specific sub-event types supports exclusion.

5.6.3 Reduced Form Analysis in Tanzania, A Pirateless Country

Next, does ocean wind affect land conflict when there are no pirates? To investigate, the analysis uses a country near Somalia with little to no piracy - Tanzania.[64] Tanzania's population includes fishermen, making it suitable to perform falsification here. Land conflict also occurs in Tanzania, making it possible to measure the effect of wind speed on land violence in a country with no pirates.[65] Regional assignments for Tanzania are shown in Figure A.5.

Table 6 presents estimates of ocean wind on land conflict. Panel A presents OLS estimates with varying fixed effects. In columns 1 and 2, the estimated effect is near zero and not statistically significant. In column 3, the estimated effect of wind on land conflict is statistically significant at the 10% level and negative in sign, which is opposite from the effect of wind on conflict in Somalia. While suggestive, this estimate is based on relatively sparse conflict in Tanzania (883 out of 982 observations have no conflict) and the preferred fixed effects for Somalia may not make sense in Tanzania due to the sparseness. Table 6, Using Poisson, under all three specifications, ocean wind does not affect land conflict.

[63] The excluded sub-event types are: air/drone strikes, change to group/activity, disrupted weapons use (bomb defusals), excessive force against protesters, government regains control of territory, mob violence, non-violent transfers of territory, other, peaceful protests, remote explosions, and suicide bombs. The sub-events are nested within the event categories of battles, explosions/remote violence, violence against civilians, protests, riots, and strategic developments. See Table A.1 for details.

[64] Nigeria borders Somalia on the south. Tanzania is on Nigeria's southern border.

[65] Indeed, a differences-in-differences analysis utilizing Somalia and Tanzania is possible, but pirate attacks are endogenous due to Somalia's failed state.

Table 6: Estimates of the Effect of Wind Speed on Land Conflict in Tanzania

	(1)	(2)	(3)
Panel A: OLS, Up to 3 Countries in Land			
Wind Speed	-0.01	-0.00	-0.02*
	(0.01)	(0.01)	(0.01)
Observations	982	982	982
Obs. Where Y = 0			883
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X
Panel B: Poisson, Up to 3 Countries in Land			
Wind Speed	-0.08	-0.08	-0.14
	(0.08)	(0.09)	(0.10)
Observations	982	982	982
Obs. Where Y = 0			883
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X
Panel C: OLS, Coastal Only			
Wind Speed	-0.00	0.00	-0.01
	(0.01)	(0.01)	(0.01)
Observations	982	982	982
Obs. Where Y = 0			902
Region FEs	X	X	
Year FEs		X	
Month FEs		X	
RegionXYearXMonth FEs			X

Note: * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. All regressions show regressions of wind speed on total land conflict. Panel A and B use up to 3 countries in land which are shown in Figure A.5. Panel B uses Poisson models. Panel C uses only the coastal sample of countries. Column 1 includes only region fixed effects. Column 2 includes region fixed effects, year fixed effects, and month fixed effects. Column 3 includes region X year X month fixed effects.

It is unlikely coastal fishermen cause violence in the interior of Tanzania.[66] When dropping all non-coastal regions, there are no statistically significant effects. When there are no pirates, ocean wind does not affect conflict, supporting exclusion.

5.7 Alternative Specifications

Tables 7 and 8 investigate the sensitivity of the results to different specifications. In all 5 panels of Table 7 the first stage F-statistic remains above 10, suggesting no panel suffers from weak instrument problems under alternative specifications or different samples. The specification differences for each panel are discussed next.

5.7.1 Week of Year Fixed Effects

Panel A includes week fixed effects (1-52), so effects of piracy on land conflict are estimated within each week of the year during a specific region-month-year. If within region-year-month is not small enough unit to be consistent with Dell et al. (2014)'s suggestion to use weather *shocks*, this specification is as saturated as possible.[67] Column 3, Panel A shows the estimated effect of piracy on conflict is 45% smaller in magnitude and statistically significant.

5.7.2 Single Wind Dummy as Instrument

Panel B uses a single dummy variable which takes on a value of one if there are fast winds. As Figure 4a suggests, there is a non-linear reduction in piracy at a high enough wind speed, specifically when wind speeds reach 6 m/s (mean wind speed = 5.43). A single dummy approach is preferred, because the equation remains just-identified.[68]

The F-stat remains large enough to consider the instrument relevant. One additional pirate attack reduces land conflict by 9.01. All estimates are statistically significant at 1%.

[66] Indeed, the only reason land-locked regions are included is to reduce sparseness of conflict, which could lead to less variance if the decrease in sparseness is not accompanied by a larger increase in variance due to using a less (coastal) homogeneous sample.

[67] This would be most concerning if there was substantial week to week variation.

[68] Just-identified facilitates the straightforward application of using the first-stage F-stat from the test that the instrument is not zero as a relevance diagnostic.

Table 7: 2SLS Alternative Specifications

Dependent Variable:	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: RegionXYearXMonth, Week FE			
Median Wind Speed	0.31*	-0.09***	
	(0.17)	(0.02)	
Pirate Attacks			-3.25*
			(1.72)
Kleibergen-Paap F			17.17
Observations	1519	1519	1519
Panel B: RegXYrXMth FEs, Wind > 6 Dummy			
Wind Speed > 6	2.14***	-0.24***	
	(0.62)	(0.06)	
Pirate Attacks			-9.01***
			(3.31)
Kleibergen-Paap F			13.72
Observations	1519	1519	1519
Panel C: RegXYrXMth FEs, Wind < 5 Dummy			
Wind Speed < 5	-1.34**	0.28***	
	(0.59)	(0.08)	
Pirate Attacks			-4.89**
			(2.38)
Kleibergen-Paap F			11.76
Observations	1519	1519	1519
Panel D: Log Conflict			
Median Wind Speed	0.05***	-0.07***	
	(0.02)	(0.02)	
Pirate Attacks			-0.83**
			(0.35)
Kleibergen-Paap F			13.66
Observations	1253	1253	1253
Panel E: Inverse Hyperbolic Sine Conflict			
Median Wind Speed	0.05***	-0.08***	
	(0.02)	(0.02)	
Pirate Attacks			-0.60**
			(0.26)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519
Semi-Elasticity at Mean			-0.273

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Heteroskedasticity robust standard errors in parentheses. The table displays 2SLS regressions of pirate attacks on land conflict events, using (sometimes transformed) ocean wind speed as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All panels include region X month X year interacted fixed effects. In Panel A, week of the year (1-52) fixed effects are included. In Panel B, wind speed is transformed to a binary variable = 1 if wind ≥ 6. In Panel C, wind speed is transformed to a binary variable = 1 if wind ≤ 5. In Panel D, the dependent variable is ln(conflict). In Panel E, an inverse hyperbolic sine transformation is applied to land conflict. The coefficient requires re-transforming to be interpreted as a semi-elasticity, which is presented, for details on how, see Bellemare and Wichman (2020).

The growth in statistical significance comes with reduced likelihood the exclusion restriction is viable. The reason for this, as shown in Figure 4b, is very high ocean wind (indicating a monsoon) leads to less conflict than any other wind speed. This likely reflects monsoon weather makes it difficult to engage in any land activities, including conflict.

Alternatively, the analysis could focus on low wind, because low wind makes piracy more attractive. Low wind deals with exclusion, which could be violated by monsoon strength winds. For Panel C, ocean wind speeds less than 5 m/s are used as the instrument since using less wind < 6 would only flip the sign. Panel C, column 1 shows lower wind speeds reduce land conflict. In the first stage results of Panel C, column 2, lower wind speeds increase piracy. Additionally, the F-stat is still above 10, suggesting low wind speed is an adequately strong instrument. Panel C, column 3 shows the second stage estimate of an additional pirate attack (4.89) is close to the magnitude in the preferred specification (5.94).

5.7.3 Conflict Transformations

Panels D and E consider transformations of land conflict to investigate whether potentially non-normal (for example conflict outliers or highly skewed) distributions of the dependent variable are driving the results. First, Panel D uses the log transformation, finding an additional pirate attack reduces land conflict by about 83 percent and is statistically significant at the 5% level. However, the log of conflict is not defined if conflict equals 0, resulting in 266 (17.5% of the "full sample") observations where conflict is undefined in Panel D.

Dropping zero-valued observations is not desirable and may be why the estimate of piracy attacks on conflict in Panel D is large in magnitude compared to prior results. To retain zero-valued dependent variable observations, Panel E transforms conflict using the inverse hyperbolic sine (IHS) transformation. The IHS transformation is defined at 0, meaning zero-valued dependent variable observations are included. Additionally, the second stage coefficient can be interpreted as a 1 unit increase in piracy leads to a $(\beta_1 * 100)\%$ change in conflict. β_1 is transformed to be relevant at the means of piracy and conflict (Bellemare &

Wichman, 2020). After transforming the estimated effect, an additional pirate attack leads to a 27.3 percent reduction in land conflict at the mean (10.42).

Outliers or other distributional issues in conflict do not appear to be driving the estimated effects, since Panel D and E are also statistically significant with reasonable magnitudes. If anything, using the IHS transformation seems to be consistent with the bottom range of the magnitude of the estimated effects, because a 27.3 percent conflict reduction is equivalent to 2.74 fewer conflict events. The magnitude of 2.74 is close to the reported results in Table 3 that do not use region-by-year-by-month fixed effects.[69]

5.7.4 Second Stage Modeled as Poisson

Estimates so far assume conflict is continuous which could be problematic if conflict is sparse or highly skewed. Also, log or IHS transformations may have limited effects on conflict, because of the limited range and discreteness. An alternative way to address discrete dependent variables is modeling the second stage as Poisson (Mullahy, 1997).[70] Table 8 models conflict as a Poisson process using GMM (Angrist, 2001; Mullahy, 1997) to examine if this continuous assumption for a discrete dependent variable drives the results.[71] The generalized method of moments approach, multiplicative errors and a log-link function used in Mullahy (1997) are deployed. In all 3 columns of Table 8, there is a same-signed effect that is statistically significant. In line with prior estimates, the table suggests an 18 to 30 percent reduction in land conflict due to 1 additional pirate attack. [72] Tables 7 and 8 suggest estimation method and assumptions about conflicts' distribution are not driving the results.

5.8 Consequences of Stopping Piracy for Civilians

Table 9 investigates if piracy affects land conflict consequential for safety. The effect of additional pirate attacks on fatalities and violence against civilians is estimated, because

[69] Although Panel D and E of Table 7 uses region-year-month interacted fixed effects in all specifications.
[70] For a similar empirical application see Dube and Vargas (2013).
[71] The model does not converge if region-by-year-by-month fixed effects are included.
[72] Since Table 8 presents Poisson coefficients, they are interpreted: $(e^{\beta_1} - 1) * 100 \approx x\%$.

Table 8: GMM Estimates of Effect of Pirate Attacks on Land Conflict

	(1)	(2)	(3)
Pirate Attacks	-0.30***	-0.30***	-0.18*
	(0.09)	(0.09)	(0.10)
Region FEs	X	-	-
Year FEs	X	-	-
Month FEs	X	X	X
RegionXYear FEs	-	X	X
Week FEs	-	-	X

Note: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. Second stage modeled as a Poisson count model. Multiplicative errors assumed. General method of moments used, with a log link function. Command from Stata used: ivpoisson gmm.

violence is associated with shocks that reduce aid and wages if political institutions are non-cohesive (Besley & Persson, 2011). Then, fatalities from events classified as violence against civilians is used as the dependent variable.

5.8.1 Fatalities

In Table 9, Panel A the dependent variable is the number of land casualties from all conflict events. Piracy on fatalities is statistically significant at the 5% level. A 1 pirate attack increase reduces land conflict fatalities by 9.11 ($\approx 1/3$ of a standard deviation) This magnitude is similar to the effects of piracy on overall conflict events. Reducing piracy to reduce shipping rates (Besley et al., 2015) harms Somalians.

5.8.2 Violence Against Civilians

Table 9, Panel B presents estimates of the effect of additional pirate attacks on ACLED-defined violence against civilians events. These events include: sexual violence, attacks, and abduction/forced disappearances. Column 3 shows that there is a 0.97 event reduction in conflict events, which is statistically significant at the 10% level, classified as violence against

Table 9: 2SLS Estimates of Pirate Attacks on Fatalities and Violence Against Civilians

Dep. Variable	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Number of Fatalities			
Median Wind Speed	0.77**	-0.08***	
	(0.38)	(0.02)	
Pirate Attacks			-9.11**
			(4.62)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			589
Panel B: Violence Against Civilians			
Median Wind Speed	0.08*	-0.08***	
	(0.04)	(0.02)	
Pirate Attacks			-0.97*
			(0.54)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			673
Panel C: Fatalities, Violence Towards Civilian Events			
Median Wind Speed	0.11*	-0.08***	
	(0.06)	(0.02)	
Pirate Attacks			-1.28*
			(0.73)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			837

Notes: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. The table displays 2SLS regressions. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All models include regionXyearXmonth fixed effects. Panel A uses fatalities as the dependent variable, taken from the fatalities column in the data. Panel B uses all events where the type of event was violence against civilians. Panel C uses the number of fatakities from events in which the type of event is violence against civilians.

civilians with each additional pirate attack. This implies that of the decrease in conflict due to additional piracy (5.9), about 16.3 percent is driven by conflict events involving civilians.

Fatalities and violence against civilians begs the question, how many additional fatalities are civilians? The conflict data is imperfect for the question, because fatalities are not disaggregated by actor. To answer this question, fatalities during events classified as violence against civilians is examined. Panel C shows an additional pirate attack reduces fatalities during violence against civilians events by 1.28. Reducing piracy increases civilian fatalities.

5.9 Institution-Related Conflict Consequences of Stopping Piracy

Table 10 examines institution-related conflict. The effect of piracy is estimated on the amount of conflict involving communal militias, the most likely classification for a Somalian clan. This is important, because part of the reason Somalia is currently stateless is the Siad Barre regime stoking clan tensions. Naturally, less clan conflict is a channel through which a functioning national government could be restored in Somalia (Alesina et al., 2003; Montalvo & Reynal-Querol, 2005). If stopping piracy exacerbates clan-level violence, then it directly contributes to continued statelessness and lack of functioning institutions. Finally, it concludes by examining conflict events that are directly related to institutions.

5.9.1 Clan-Related Violence

Panels A-D of Table 10 investigates the effect how stopping piracy affects clan violence. Panel A specifies linear wind and the reduced form effect, column 1, is small and insignificant. A possible reason is clan violence is a rare event, there are 797 out of 1,519 observations where there are no conflict events with at least 1 communal militia in a week. Correspondingly, the second stage coefficient is statistically insignificant ($p<0.18$) in Panel A, column 3. To adjust for potentially mis-specified linear functional form, Panel B of Table 10 uses wind speed > 6 as the instrument. In Panel B, the reduced form effect in column 1 is larger and

Table 10: 2SLS Estimates of Pirate Attacks on Institution-Related Conflict

Dep. Variable	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Conflict w/ At Least 1 Communal Militia			
Median Wind Speed	0.04	-0.08***	
	(0.03)	(0.02)	
Pirate Attacks			-0.47
			(0.35)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			797
Panel B: At Least 1 Communal Militia, Wind > 6			
Wind > 6	0.22**	-0.24***	
	(0.10)	(0.06)	
Pirate Attacks			-0.93**
			(0.46)
Kleibergen-Paap F			13.92
Obs. Where Y = 0			797
Panel C: Conflict w/ 2 Communal Militias			
Median Wind Speed	0.02	-0.08***	
	(0.02)	(0.02)	
Pirate Attacks			-0.29
			(0.18)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			1132
Panel D: 2 Communal Militias, Wind > 6			
Wind > 6	0.10*	-0.24***	
	(0.06)	(0.06)	
Pirate Attacks			-0.44*
			(0.26)
Kleibergen-Paap F			13.92
Obs. Where Y = 0			1132
Panel E: Institution-Related Conflict			
Median Wind Speed	0.14**	-0.08***	
	(0.06)	(0.02)	
Pirate Attacks			-1.68**
			(0.78)
Kleibergen-Paap F			16.00
Obs. Where Y = 0			714

Notes: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. The table displays 2SLS regressions. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All models include regionXyearXmonth fixed effects. Panels A and B use a dummy variable for whether wind is above 6 as the instrument. Panel C uses linear wind as the instrument. Panel A uses conflict events in which at least 1 communal militia is involved. Panel B uses conflict events in which 2 communal militias are involved. Panel C uses institution-related sub-events and event descriptions. Sub-events include: abduction/forced disappearance (), government regains territory (monopoly on violence), grenade (property rights), headquarters or base established (monopoly on violence), looting/property destruction (property rights), non-state actor overtakes territory (monopoly on violence), remote explosive/landmine/IED (transactions costs), shelling/artillery/missile attack (property rights), or suicide bomb (transactions costs). Additionally events are included if they have certain words in their description: “checkpoint”, “toll”, “tax”, “ngo”, “official”, “roadblock”.

statistically significant above 95% confidence. Correspondingly, the second stage effect is statistically significant above 95% and a larger magnitude.

Panel C of Table 10 uses conflict between 2 communal militias as the outcome. In column 1, the reduced form is small and insignificant and the second stage is also insignificant ($p<0.108$). Two reasons for insignificance are 1) conflict between 2 communal militias is rare (1132/1519 weeks have 0 conflict) and mis-specified functional forms. To deal with potentially mis-specificied linear wind, Panel D of Table 10 instead uses wind > 6 as the instrument. In Panel D, column 1 the reduced form of wind is statistically significant. Correspondingly, the second-stage is also statistically significant above 90% confidence.

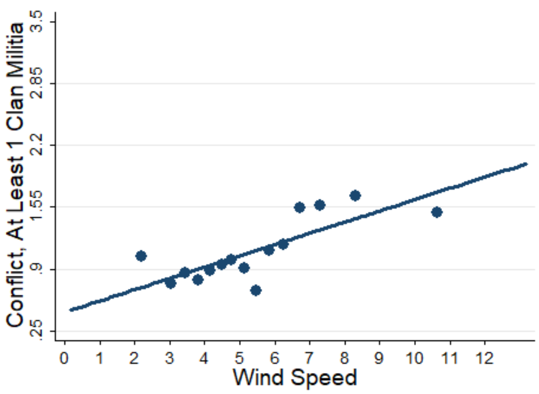
Figure 5 investigates conclusions of Panels A-D of Table 10 by showing reduced form binned scatter plots with and without fixed effects.[73] Figure 5a shows conflict involving 1 communal militia is increasing in ocean wind speed without fixed effects and the global, linear line of best fit is steep. Part of the steepness is due to the monsoon season extreme winds not reducing conflict like Figure 4b. When fixed effects are added in Figure 5c, monsoon winds are a bad leverage point again causing the slope to flatten.[74] Figure 5b repeats the analysis using conflict between 2 communal militias as the outcome. Even when no fixed effects are included, monsoon winds are a bad leverage point, causing slope to remain similar when fixed effects are added in Figure 5d. Despite the inclusion of fixed effects causing points to be more dispersed (greater error), clan-related conflict still increases with wind speed.

[73] Assuming independence of wind, the reduced form can be considered an intent to treat effect.

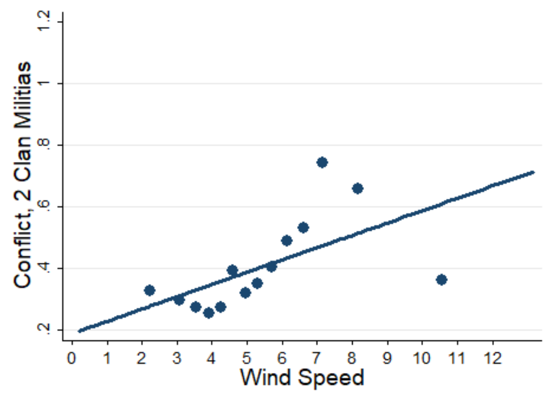
[74] Bad leverage point: Far from x-mean and far from the fit. For details see Verardi and Croux (2009).

Figure 5: Reduced Form Effect of Wind Speed on Clan-Related Conflict

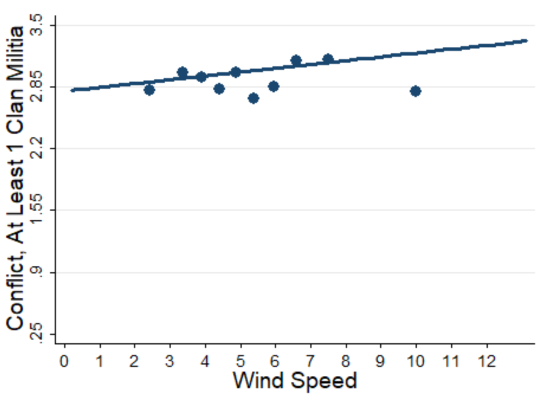
Panel A: At Least 1 Communal Militia, No Fixed Effects



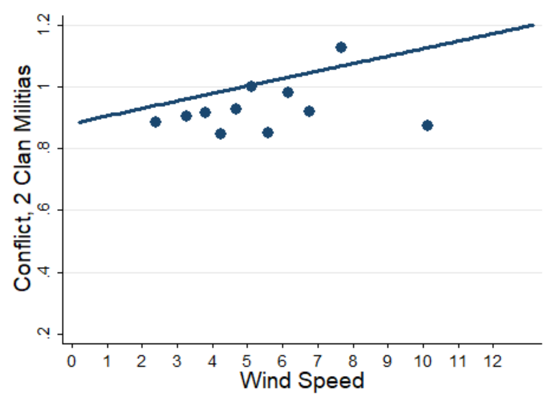
Panel B: Only 2 Communal Militias, No Fixed Effects



Panel C: At Least 1 Communal Militia, Region-by-Year-by-Month Fixed Effects



Panel D: Only 2 Communal Militias, Region-by-Year-by-Month Fixed Effects



Note: Optimal number of bins calculated using Cattaneo et al. (2019). Covariate exclusion uses semi-parametric measures, not residualization. This is due to Frisch-Waugh relying on linear regression being correct enough functional form.

5.9.2 Miscellaneous Institutional Impacts

Table 10, Panel C investigates the impact of pirate attacks on conflict events related to quality of institutions.[75] This analysis is important when viewed in the context of the Somalian ambassadors' claim that: " prolonged conflict has severely damaged Somalia's institutions." However, without random assignment of conflict, it could be weak institutions have caused conflict. Panel C finds an additional, pirate attack leads to 1.68 fewer institution-damaging conflict events, which is statistically significant above 95 percent. While this analysis cannot provide direct evidence on the effect of conflict on institutions, it is causal evidence that displacing violent individuals onto land leads to more conflict which is bad for institutions.

6 Welfare Analysis

Piracy has significant impacts on shipping rates (Besley et al., 2015), impacting an important link in global trade. Due to this impact, there is pressure to eradicate piracy. The 2008 upsurge in Somalian piracy lead to an approximately 8.2-12.3 percent increase in shipping rates (Besley et al., 2015). To calculate the cost of piracy, Besley et al. (2015) uses

$$Cost_{Piracy} = Deadweight\ Tons\ (DWT)/Day * (Pirate)\ Rate\ Increase * Days * Total\ DWT.$$

To put the estimates reported in Section 5 in the context of Besley et al. (2015), it is necessary to put Besley et al. (2015) in terms of 1 additional pirate attack. The 8.2 percent increase in shipping rates due to piracy was calculated from May 2008-December 2010, a period of 31 months. In the data used in this paper, there are 181 attacks over this period. In the 31 months prior to May 2008, there are 44 attacks. The 8.2 percent increase in shipping

[75] The analysis uses events that have either an institution-related keyword or institution-related sub-event type. Institution-related means an event deals with property rights, transactions costs, changes in the party with a monopoly on violence (Olson, 1993), The sub-events that are considered are: abduction/forced disappearance, government regains territory (violence monopoly), grenade (property rights), headquarters or base established (violence monopoly), looting/property destruction (property rights), non-state actor overtakes territory (violence monopoly), remote explosive/landmine/IED (transactions costs), shelling/artillery/missile attack (property rights), or suicide bomb (transactions costs). The institution-related words are: checkpoint, toll, tax, ngo, official, roadblock.

rates is due to 137 more attacks in the post-period compared to the pre-period. Assuming a linear effect, one additional pirate attack increases shipping rates by $\approx 0.05\%$.

The trade-off to reducing piracy is it leads to violent activities occurring on land; the estimates show additional pirate attacks reduce land conflict. It is reasonable to give estimates a causal interpretation, since analyses investigating the plausibility of exclusion return results consistent with ocean wind speed affecting land conflict only through piracy. An additional pirate attack leads to less weapons on land, conflict between clan militias, violence against civilians and is not sensitive to functional form assumptions, model types, or considering coastal conflict. An additional pirate attack leads to about 9.11 fewer fatalities on land in Somalia. Upcoming calculations of shipping company savings compared to lives of Somalians lost discards costs of clan-based conflict and other institutional woes; making calculations conservative for the total cost of piracy.

Stopping piracy reduces shipping company's costs by reducing shipping rates. The total cost of 1 pirate attack is calculated as:

$$C_{Gulf\ of\ Aden,\ Lower\ Rate\ Increase} = 0.476 * 0.0005 * 30.3 * 646,064,000.^{76} \tag{6}$$

Thus, preventing 1 pirate attack benefits shipping companies by saving them $5,537,390. This benefit to shipping companies comes at the cost of 9.11 Somalian lives, implying Somalian lives are valued at $607,836. These estimates are an important extension to understanding the costs and benefits of eradicating piracy in Besley et al. (2015).

For comparison, a U.S. life in 2020 is valued at approximately $10 million (Gonzalez, 2020; Viscusi & Aldy, 2003). This estimate provides perspective on the safety trade-off of eradicating piracy which is borne by a vulnerable population to benefit international shipping companies. Prior academic and public press have focused only on the financial cost of piracy

[76] This formula is used in Besley et al. (2015). The only difference is this formula calculates the cost of 1 piracy attack, so the rate increase due to 1 attack (0.0005) is used instead of the increase due to all attacks.

(e.g. to taxpayers supporting naval warships) (Bowden, 2010), leaving out this relevant negative safety externality.

6.1 Assuming Higher Piracy Costs to Shipping

Equation 6 is the lowest cost equation used in Besley et al. (2015), meaning it implies the lowest value on Somalian lives. However, there are also estimates that use higher estimates of piracy cost (0.123 instead of 0.082) and an additional ocean area (the Indian Ocean). The cost calculations, for 1 pirate attack and a higher rate increase estimate due to piracy, for the Gulf of Aden and Indian Ocean respectively are

$$C_{Gulf\ of\ Aden,\ High\ Rate\ Increase} = 0.0009 * .4726 * 30.3 * 646064000, \text{ and}$$
$$C_{Indian\ Ocean,\ High\ Rate\ Increase} = 0.0009 * .4648 * 20.67 * 578000000.$$

These high estimates suggest that stopping 1 pirate attack saves shipping companies \$13,291,703.92. Combined with the estimates in this paper that an additional pirate attack reduces land fatalities by 9.11, these estimates using higher costs of piracy suggest a Somalian life is valued at \$1,459,023.48. In comparison to the \$10 million value of a U.S. life (Gonzalez, 2020; Viscusi & Aldy, 2003), this is still only approximately 14.59% of the value of a US life.

7 Conclusion

The main finding is a 1 standard deviation reduction in piracy increases land conflict by between 18 and 30 percent. Interpreting these estimates as causal is supported by 3 exclusion restriction falsification exercises, which would show evidence that ocean wind affects land conflict through reducing fishermen opportunities. First, the effect is unchanged when including chlorophyll concentration, an important measure of fish nutrition. Second, the effect of wind on conflict appears to be strongly related to pirate-related events, actors, and weapons. Third, there is no reduced form relationship between wind and land conflict in

Tanzania, a nearby country with fishermen but no pirates. Additional robustness finds the results are not sensitive to distributional assumptions, functional form, or driven by conflict which is far from the coastline.

The final set of results show the reduction in piracy is detrimental to Somalian safety and institutions. Stopping a pirate attack results in an additional 9.11 conflict events. However, piracy also leads to an 8.2% increase in shipping rates (Besley et al., 2015), which under plausible assumptions implies 1 attack increases shipping rates by 0.005%. Combining this information with the estimates reported in this study implies that saving shipping companies $5,537,390-13,291,703.92 costs 9.11 Somalian lives. The calculations imply, for an upper bound on the value of a Somalian life, between 607,000 and 1.459 million.

The first contribution is studying the safety and institutional outcomes of stopping piracy. This is done by using ocean wind speed as plausibly exogenous variation in piracy in Somalia. To investigate these outcomes of piracy, ACLED conflict data, which has not yet been examined in the context of piracy, is used to derive outcomes of interest such as conflict, civilian safety, and institution-related woes.

The second contribution is studying the displacement of violent actors on institutions using a causal strategy. Prior approaches (Leeson, 2007b; Powell et al., 2008) have had difficulty making causal quantitative insights regarding Somalia. Furthermore, this study takes place in Somalia where there is a noticable lack of institutions and the ambassador notes prolonged conflict has severely harmed institutions (Ahmed, 2020).

The third contribution is using estimates to quantify the safety trade-off to eradicating piracy. The economic benefits to shipping companies have already been calculated by Besley et al. (2015) and the analysis is extended to consider the safety and institutional development of Somalians, an under-developed country. While institutional damage is difficult to quantify, estimates suggest preventing one pirate attack results in 9.11 Somalian land fatalities.

There are limitations of this study that could be addressed with future work. First, it would be straightforward to see if pirates have an impact in other geographic areas besides

Somalia. Second, there may be better measures of institutional functionality that would be interesting as a different dependent variable, measuring similar outcomes. Finally, displaced violent individuals may also have other measurable effects, for instance leading to low birth-weight babies in utero during unattractive times to be a pirate or new business formation that future research could examine.

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A Online Appendix

Table A.1: Descriptions of Events

Row	Event	Description
1	Ocean Hijacking	Non-violent activity: Somali gunmen have hijacked a freighter ship off the coast of El-Maan.
2	Land Hijacking	A truck carrying goods from Bargal to Bosasso and belonging to a member of the Siwaqron subclan was reportedly hijacked by pirates from the Ali Saleban sub-clan of Majerteen. The truck is said to have been taken to Balidhidin in Bari Region. Perpetrators are believed to have retaliated after one of their cars had been hijacked by other pirates from the Siwaqron sub-clan.
3	Ocean Weapons	Seven pirates, in two speedboats, armed with guns and rocket propelled grenade launchers chased and fired upon the ship underway. The Master contacted the IMB Piracy Reporting Centre for assistance. The coalition Navy dispatched one warship to assist the ship. The constant manoeuvring of the ship prevented the boarding of the pirates. On seeing the coalition warship, the pirate boats aborted their attempt and moved away. However an unexploded grenade was found on the bridge wing
4	Land Weapons	2 pirates killed a police officer at a check point in Garsoor. Police managed to arrest the 2 and seized bazookas, 6 AK 47 rifles and 5 thousand dollars from their vehicle.

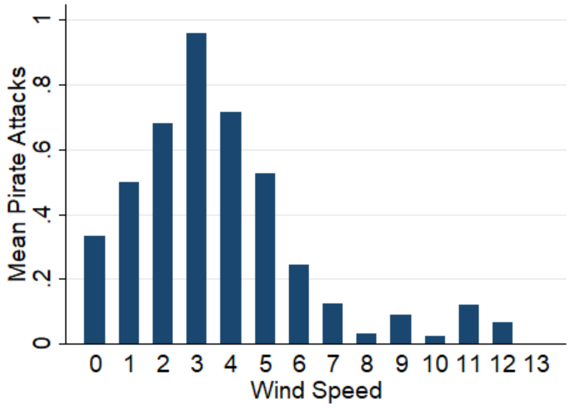
Table A.2: Wind Statistics By Month

	Mean	Median	SD	Min	Max
Panel A: January					
Median Wind Speed	5.94	6.05	1.04	3.2	8.0
Panel B: February					
Median Wind Speed	5.42	5.27	1.09	2.7	8.2
Panel C: March					
Median Wind Speed	4.44	4.42	1.07	1.9	6.8
Panel D: April					
Median Wind Speed	3.53	3.33	1.36	0.1	7.6
Panel E: May					
Median Wind Speed	4.50	4.07	1.72	1.5	9.8
Panel F: June					
Median Wind Speed	6.82	6.84	2.80	1.7	13.4
Panel G: July					
Median Wind Speed	7.57	7.36	2.66	2.3	12.9
Panel H: August					
Median Wind Speed	6.61	6.76	2.36	2.1	12.1
Panel I: September					
Median Wind Speed	5.48	5.31	1.95	1.4	11.4
Panel J: October					
Median Wind Speed	4.24	4.18	1.25	1.1	8.3
Panel K: November					
Median Wind Speed	4.52	4.57	1.23	0.4	7.4
Panel L: December					
Median Wind Speed	5.70	5.67	1.34	1.6	8.9

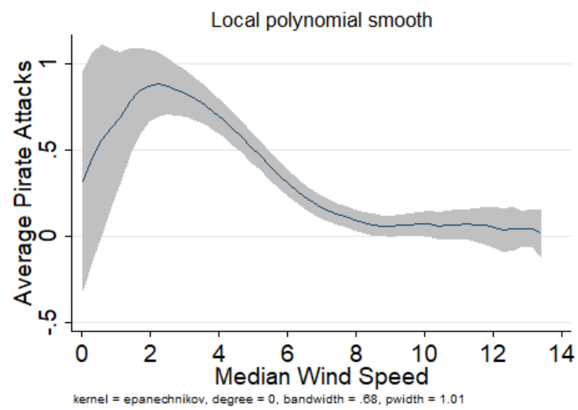
Notes:

Figure A.1: Mean Pirate Attacks and Mean Land Conflict by Median Wind Speed

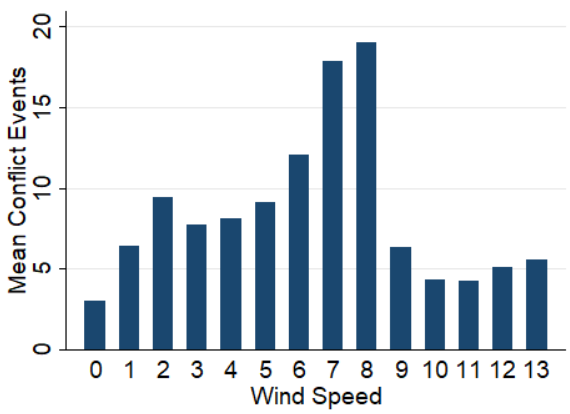
Panel A: Wind Speed, Pirate Attacks



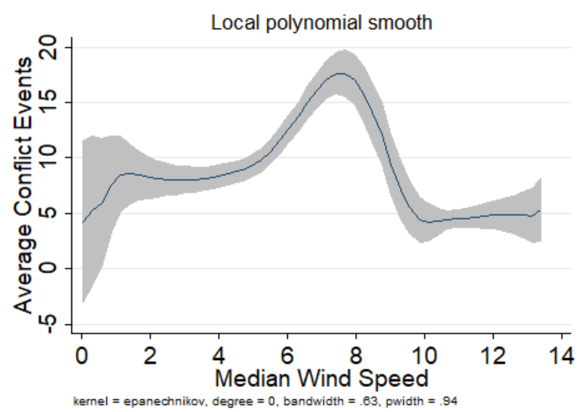
Panel B: Wind, Pirate Attacks, Local Polynomial



Panel C: Wind Speed, Conflict



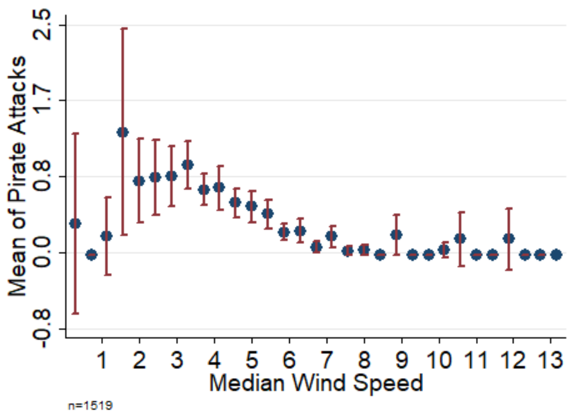
Panel D: Wind, Conflict, Local Polynomial



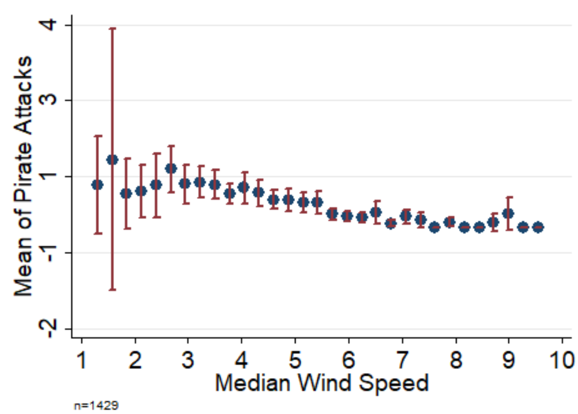
Note: N = 1,519 Region-Year-Week Level Observations. Panel A and C round wind speed to nearest whole number. Panel B and D are local polynomial regressions with an epanechnikov kernel.

Figure A.2: Mean Land Conflict by Median Wind Speed, Conditional on Wind Speed

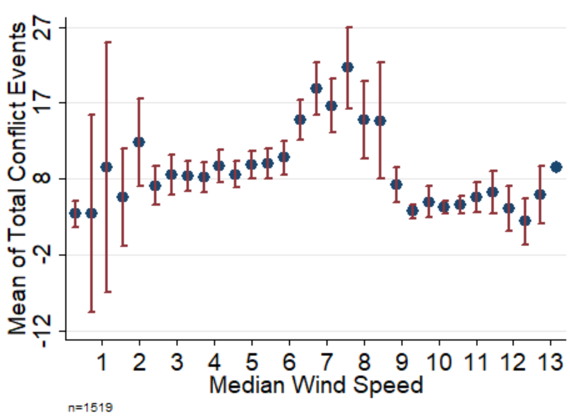
Panel A: Wind Speed, Pirate Attacks



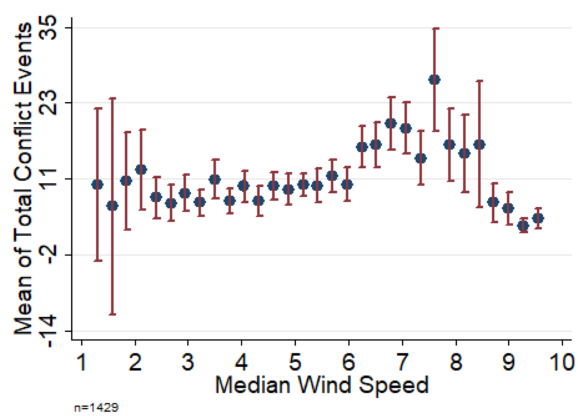
Panel B: Wind, Piracy (Outliers Dropped)



Panel C: Wind Speed, Conflict



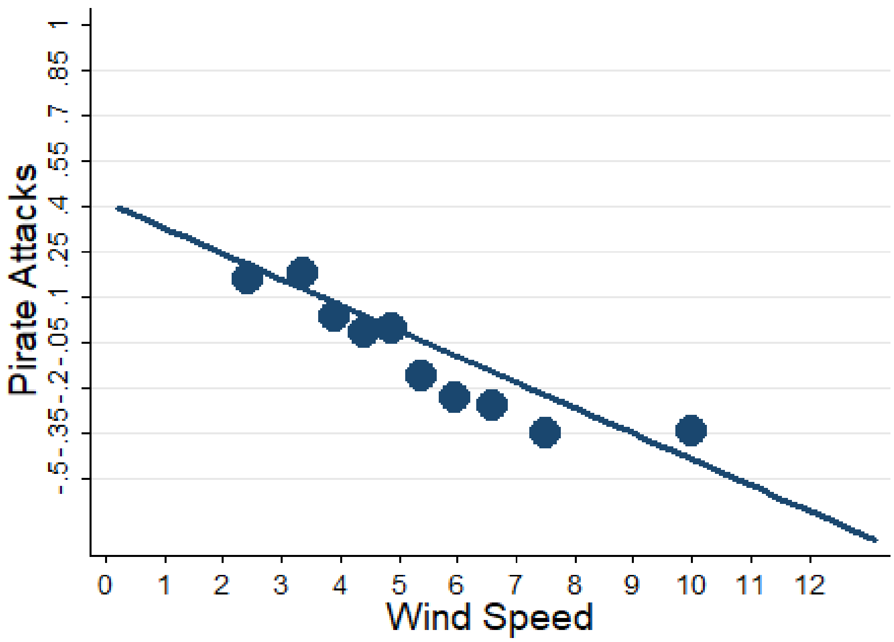
Panel D: Wind, Conflict (Outliers Dropped)



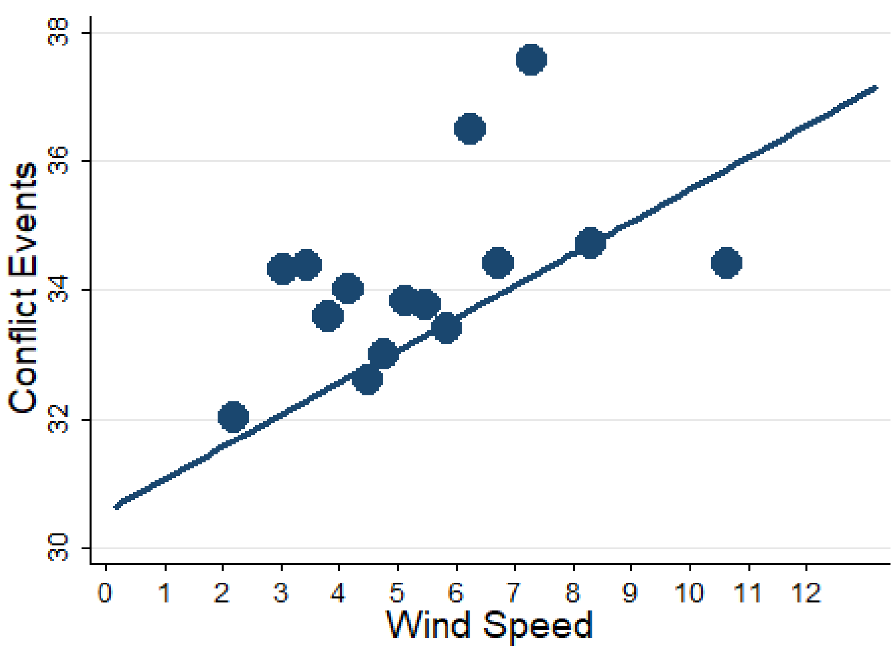
Note: 90% confidence intervals shown. Points show mean of pirate attacks or conflict events, conditional on wind being in certain bin of wind speed values. Number of bins is Stata default histogram option. Number of bins = $\min\{\sqrt{N}, 10ln(N)/ln(10)\}$, where N is the number of observations

Figure A.3: Binned Scatterplots of Piracy and Conflict by Wind Speed, Fixed Effects

Panel A: Piracy, Conditional on Wind Speed, FE



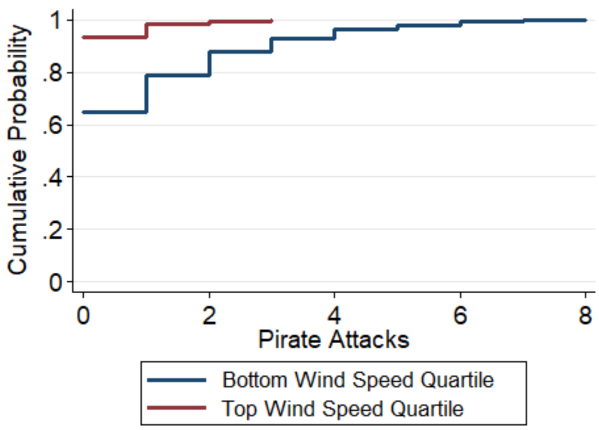
Panel B: Conflict, Conditional on Wind Speed, FE



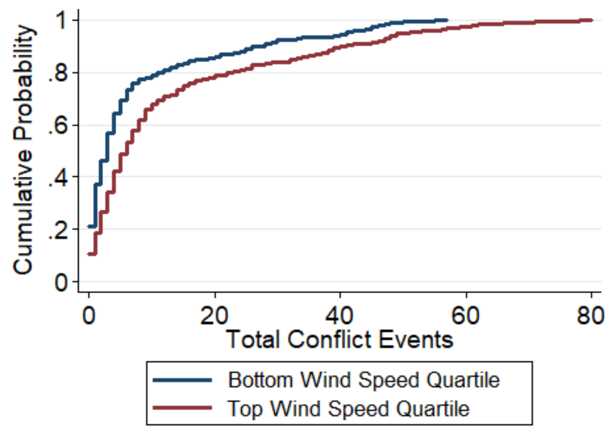
Note: Binsreg (Cattaneo et al., 2019) used. Procedure selects number of bins to optimize a bias-variance tradeoff. Equal number of observations in each bin. No covariates controlled for.

Figure A.4: Distributional Shifts

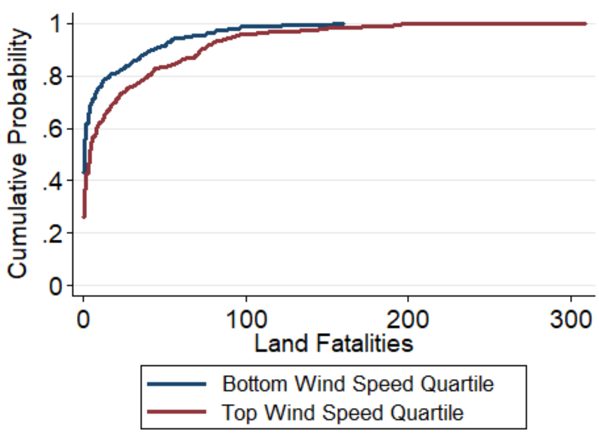
Panel A: Wind Shifts Distribution of Pirate Attacks



Panel B: Wind Shifts Distribution of Conflict Events



Panel C: Wind Shifts Distribution of Land Fatalities



Note: Distributions of pirate attacks and land conflict events by ocean wind speed. In all 3 figures the Kolmgorov-Smirnoff (K-S) tests reject equality of distributions with a p-value < 0.000.

Table A.3: 2SLS Robustness to Different Areas of Discretion

	(1)	(2)	(3)
	Reduced Form	First Stage	Second Stage
Dependent Variable	Conflict	Pirate Attacks	Conflict
Panel A: Drop Marine Incidents from Conflict			
Median Wind Speed	0.49***	-0.08***	
	(0.17)	(0.02)	
Pirate Attacks			-5.78**
			(2.33)
Kleibergen-Paap F			16.00
Panel B: Reassign Disputed Territories			
Median Wind Speed	0.50***	-0.08***	
	(0.17)	(0.02)	
Pirate Attacks			-5.91**
			(2.33)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519

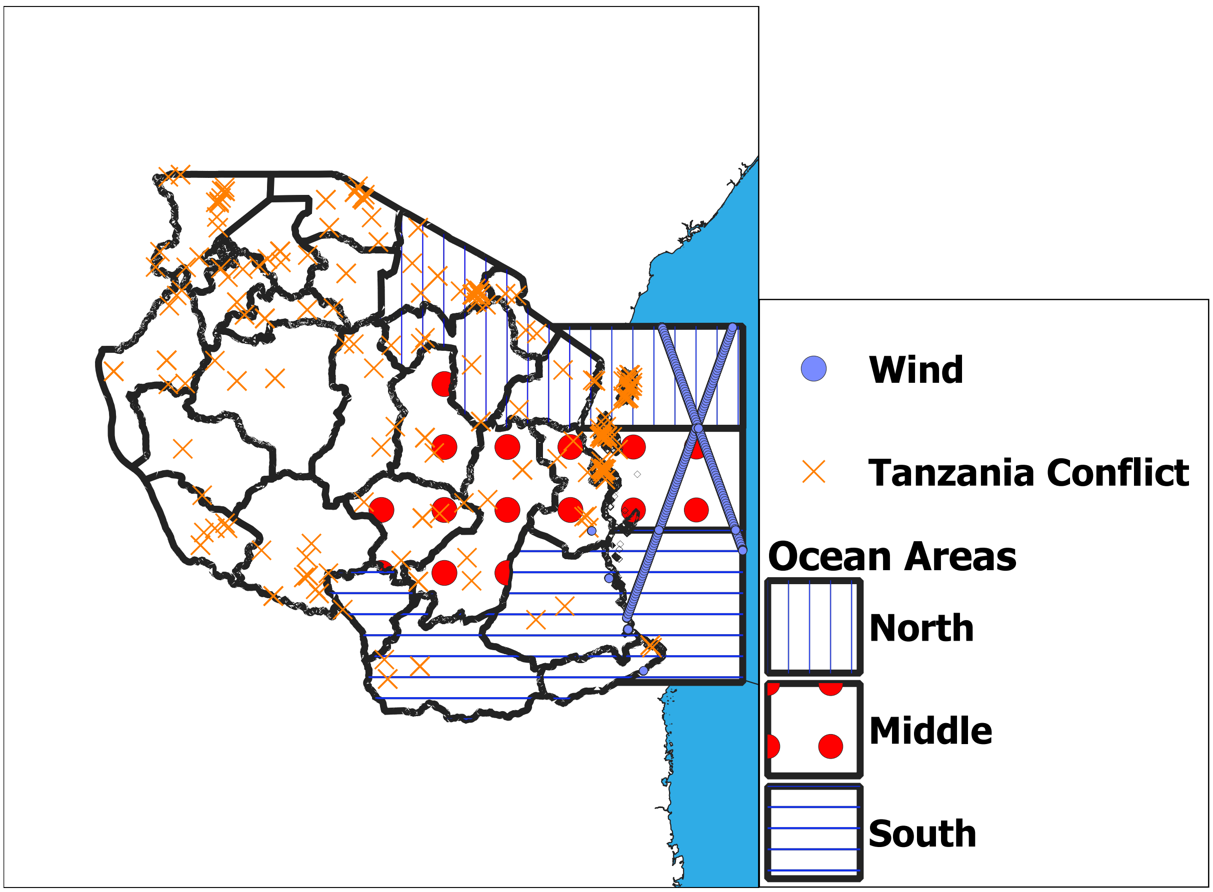
Notes: * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. This table displays robustness tests to the baseline findings in Table **??**. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All regressions include region fixed effects, month fixed effects, and year fixed effects. Panel A uses non-transformed wind speed. Panel B drops pirate-marine incidents which are coded in the ACLED data from the conflict dependent variable. Panel C reassigns disputed sub-regions, , to the other regions. Panel D includes a linear measure of chlorophyll concentration. Panel E includes a linear time trend.

Table A.4: ACLED Event Hierarchy

General	Event Type	Sub-Event Type
Violent events	Battles	Armed clash Government regains territory Non-state actor overtakes territory
	Explosions/ Remote violence	Chemical weapon Air/drone strike Suicide bomb Shelling/artillery/missile attack Remote explosive/landmine/IED Grenade
	Violence Towards Civilians	Sexual violence Attack Abduction/forced disappearance
Demonstrations	Protests	Peaceful protest Protest with intervention Excessive force against protesters
	Riots	Violent Demonstration Mob violence
Non-violent actions	Strategic Developments	Agreement Arrests Change to group/activity Disrupted weapons use Headquarters or base established Looting/property destruction Non-violent transfer of territory Other

Note: Events hieracrchy comes from ACLED codebook.

Figure A.5: Tanzania Map



Note: Ocean areas align with latitutde and longitude 1 degree lines that were super-imposed. They are drawn to most closely align spatially with the coastal country it is near.