Violence Displacement from Sea to Land: Evidence from Wind-Induced Somalian Piracy Reductions

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Abstract

Maritime piracy is a prominent form of violence in countries that face struggling institutions (e.g. Somalia), often attracting international wartime resources to combat violence on international waterways. An unintended consequence of anti-piracy operations are reduced opportunity costs of violence on land. This paper examines how reducing piracy impacts land conflict. To overcome endogeneity, we exploit variation from ocean wind speeds using two stage least squares. We find one fewer pirate attack increases conflict by 27.3% (5.9 events) and causes 9.11 more land conflict deaths. The results imply stopping piracy saves shipping companies $343,318,180 at the cost of 565 Somalian land fatalities annually.[1]

Keywords: Piracy, Somalia, Conflict, Displacement

JEL Classification: K42, H41, O10

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1 Introduction

Militaries identify success in various domains (e.g., air, sea, land, space, cyber) as critical complements.[2] Despite the large body of research on conflict, including among non-state actors, the impact of conflict in one domain on another domain has received little attention. Furthermore, intra-state actors have increasing access to other conflict domains beside land, including navies, air forces consisting of drones, and cyber attacks. The oldest non-land domain that non-state actors have access to is the sea. Maritime pirates threaten shipping (North, 1968, 1991), which prevents institutional change and economic growth (Acemoglu et al., 2005). In modern times violence against trade vessels is still widespread (Flückiger and Ludwig, 2015) and has significant costs (Besley et al., 2015). While there is research on economic and political factors that lead to piracy (Jablonski and Oliver, 2013; Axbard, 2016; Flückiger and Ludwig, 2015; Daxecker and Prins, 2016), less is known about how maritime conflict affects on land conflict.

This paper evaluates how piracy reductions off the coast of Somalia affects land conflict in Somalia. While it is clear that less piracy benefits shipping companies, reductions in piracy may have positive or negative unintended consequences for vulnerable Somalians. Economic theories of criminal actors (Polinsky and Shavell, 1979) suggest that a reduction in the optimal amount of piracy could cause these violent actors to pursue their activities elsewhere, potentially on land. In contrast, empirical work finds that piracy is positively associated with land conflict and posits that piracy funds land conflict (Daxecker and Prins, 2017; Prins et al., 2019).

By being explicit about the natural experiment underlying pirate attack assignment, this paper provides new evidence on the relationship between piracy and land conflict. Our approach exploits quasi-random variation in the optimal amount of pirate activity due to ocean wind speed, collected from remote sensors, using two stage least squares (2SLS). The negative association between Somali piracy and ocean wind speed is clearly documented (Cook and Garrett, 2013; Besley et al., 2015) and ocean wind speed helps circumvent two primary concerns in assessing the causal effects of piracy. First, many scholars and officials strongly believe that causality runs from land conflict

[2] The main conventional strategy for defending Europe during the Cold War was known as AirLand Battle, the US Navy and Air Force recently developed AirSea Battle, and the US Army is transitioning to Multi-Domain Operations as its new tactical doctrine (Feickert, 2021).

to piracy.[3] Second, man-made anti-piracy efforts from naval warships is not randomly assigned. Indeed, military forces are assigned to piracy-prone areas, which are also likely targets for development assistance and where conflict is more likely. The endogenous assignment of warships makes a direct analysis of anti-piracy efforts from warships unlikely to yield informative causal estimates. While naval warships and ocean wind speeds are not identical mechanisms for reducing the optimal amount of piracy activity, both reduce piracy.[4] Ocean wind speed passes diagnostics to be a relevant and excludable instrument in this context.

Our results find that an additional pirate attacks reduces total land conflict by 5.94 events, or about 27%. This result stands in contrast to the naïve OLS results, which find that pirate attacks increase land conflict events. Our causal estimates find that an additional pirate attack reduces land conflict fatalities by 9.11. Furthermore, one additional pirate attack also reduces institution-related conflict events by 1.68 and violence against civilians by 0.97 events.

We conclude that piracy and land-based conflict are substitutes, which stands in contrast to existing results in the literature (Daxecker and Prins, 2017; Prins et al., 2019). The reason that our results differ from previous work is likely due to our focus on an identification strategy that estimates the causal effects of piracy on land conflict. Previous research utilizes a fixed effects regression model, but does not overcome issues of reverse causality, which are undoubtedly present. The importance of a proper identification strategy is demonstrated in our analysis, as the direction of our OLS estimates flip under alternative sets of fixed effects, yet are consistently negative in our IV estimates. Another difference is that pirate attacks are self-reported, which means they are likely measured with error, our IV approach is more robust to this concern (Pischke, 2007). Impor-

[3]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 echo this 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).

[4]Assuming pirates are rational (Becker, 1968). There are no incapacitation effects of wind. There are also little incapacitation effects that result from naval warships. There are two reasons for this. First, nations have little incentive to undertake the costly process of prosecuting and imprisoning pirates (Kontorovich, 2010). Second, international laws and norms are often contradictory (Guilfoyle, 2012). In the pirate attack event data descriptions used in this paper, 2.6% end in pirate capture, pirate death, or destruction of pirate equipment, which demonstrates how negligible the incapacitation effects are. Often, navies respond solely with maritime aircraft such as helicopters, making capture impossible.

tantly, our results are consistent with theory (Becker, 1968; Polinsky and Shavell, 1979) and based on a natural experiment (Angrist and Pischke, 2010; Dell et al., 2014).

Given that our results find that reductions in piracy leads to geographic displacement of violence, this suggests that reducing piracy will not reduce violence and assist in the development of Somalia. As noted by Bove and Elia (2018), security assistance reduces economic growth, which appears to be the case with providing naval law enforcement. It is likely that reducing piracy, as a sole strategy for developing Somalia, will not be effective; rather, security assistance will require other developmental assistance as a complement (Berman et al., 2011). Research finds mixed effects of foreign aid. While it has been found to increase growth (Clemens et al., 2011; Civelli et al., 2018), it also causes conflict (Nielsen et al., 2011; Crost et al., 2014), Dutch Disease (Rajan and Subramanian, 2011), and worsens governance (Bräutigam and Knack, 2004).[5] Our results, that security assistance in anti-piracy efforts makes Somalians worse off, is in alignment with these findings.

These results are also important in the context of crime displacement in reaction to law enforcement in one area. Providing enforcement at sea does not eliminate criminal behavior, it only displaces it geographically. Just as geographically-oriented security crackdowns on drug cartels cause violence in neighboring areas (Dell, 2015), reductions in piracy also leads to displacement. The literature is typically concerned with ruling out geographic displacement as alternative explanations (Klick and Tabarrok, 2005; DeAngelo, 2012; Lindo et al., 2018; DeAngelo et al., 2018, 2019) and this paper demonstrates how that is an important concern. We present some of the first research that violent criminal activity can spill over across domains from marine to land areas. This agrees with the finding that broad-based deterrence is unlikely to reduce ungoverned territories (Downey, 2021).

Finally, these results are an important extension to cost-benefit analyses regarding Somalian piracy (Besley et al., 2015). While Besley et al. (2015) considers the financial cost of piracy to shipping companies, reducing piracy comes at a high cost to Somalian safety. A pirate attack costs shipping companies $5,537,390, but reduces Somalian conflict fatalities by 9.11. This implies that the value of one Somalian life is approximately $607,836, which is consistent with previous VSL

[5] In contrast, De Ree and Nillesen (2009) find that aid reduces the risk of civil conflict. A recent review on foreign aid is provided by Qian (2015).

estimates for African individuals (León and Miguel, 2017). The paper proceeds by offering a brief background on the literature and history regarding Somalia and pirates, outlining the relevant data, explaining the methods employed, and then presenting results and implications.

2 Background and Literature Related to Somalia and Piracy

We start by distilling the events and factors that resulted in piracy becoming commonplace in Somalia. We then outline previous scholarship that examines 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

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 and 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.[6] 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 et al., 2003, pg. 8).[7] Somalialand (a former British protectorate) declared its autonomy and opposition groups began competing for control in the political space, which was devoid of appointed leaders.[8]

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

[7]Ethnic polarization increases the incidence of civil wars (Montalvo and Reynal-Querol, 2005).

[8]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.

2.1.1 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).[9] In response to illegal fishing and toxic waste dumping, Somalians formed groups to protect their natural marine resources from outside degradation.

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.[10] 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, where there is a large amount of commerce shipping, (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).

Literature on Somalian Development Scholarly work on Somalia falls into 3 categories: qualitative (e.g. Menkhaus (2004)), comparative (Leeson, 2007b; Powell et al., 2008), and causal (Maystadt and 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.

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

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

2.2 Piracy

Previous research has attempted to understand the organization of piracy enterprises (Leeson, 2007a). 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 typically some type of local government official, such as a local governor or law enforcement (Daxecker and Prins, 2016).[11]

Piracy as Function of Economic Opportunity Studies on the determinants of piracy find variation in opportunity costs and benefits to piracy (Flückiger and Ludwig, 2015; Axbard, 2016; Kung and Ma, 2014; Jablonski and Oliver, 2013; DeAngelo and Smith, 2020). Axbard (2016) finds better fish nutrition leads to reductions in piracy because individuals earn income by fishing instead (see also Flückiger and Ludwig (2015)). China enacted a trade ban in 1550 that lead to greater increases in piracy in areas more likely to trade silk with outsiders (Kung and Ma, 2014), due to the increased cost of being a merchant. DeAngelo and Smith (2020) examine the introduction of private security on shipping vessels on the direct and spillover effects of pirate attacks. Piracy has rarely been an explanatory variable, despite the way piracy interferes with commerce and safety.

Ocean Wind Speed and Somali Piracy The relationship between ocean wind speed and piracy in Somalia is well established (Cook and Garrett, 2013; Besley et al., 2015). For example, Cook and Garrett (2013) finds a negative correlation between wind speed and pirate attacks. There are no successful documented attacks when wind speeds reach or exceed 9 m/s.

3 Data

We aim to determine how reducing maritime piracy impacts conflict on land. At a minimum this requires data on both piracy and land conflict at granular temporal and spatial frequencies. With these data in hand, one could estimate the associations between piracy and land conflict.

[11]For information about how local officials are paid off, see The Economist (2013). *Transparency International* has ranked Somalia as the world's most corrupt country since 2007.

However, there are two main issues with this regression: piracy is not randomly assigned and is likely influenced by land conflict (reverse causality) and incident-level data on piracy is self-reported and likely undercounted (measurement error). Our approach overcomes these limitations by incorporating additional data on ocean wind speed from the Jason-2 satellite which provides plausibly exogenous, high frequency variation in piracy across space and time.

Pirate Attacks Pirate attack data are sourced 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.[12] The 730 pirate attacks are shown in Figure 1a. Importantly, pirate attacks are self-reported by the attacked ship which means that piracy is measured with error.

Conflict Events Event-level conflict data for Somalia were obtained from the Armed Conflict Location and Event Dataset (ACLED).[13] 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. The 15,878 conflict events are shown in Figure 1b.

3.1 Ocean Wind Speed

Ocean wind speed data are sourced from the Jason-2 satellite hosted at the Radar Altimetry Dataset (RADS).[14] From 2008-2016, the Jason-2 satellite orbited Earth in a uniform orbit, taking readings at the same location of the Earth's surface about every 9.9 days. The satellite's orbit dates are used as the temporal length of the sample. Two advantages of the time frame are that all wind data come

[12]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 a maximum latitude of 18, a minimum latitude of -4, a maximum longitude of 66, and a minimum longitude of 40. Attacks far off the coast, eastward into the Indian Ocean must be included because Somalian pirates sometimes use hijacked ships to attack farther from shore.

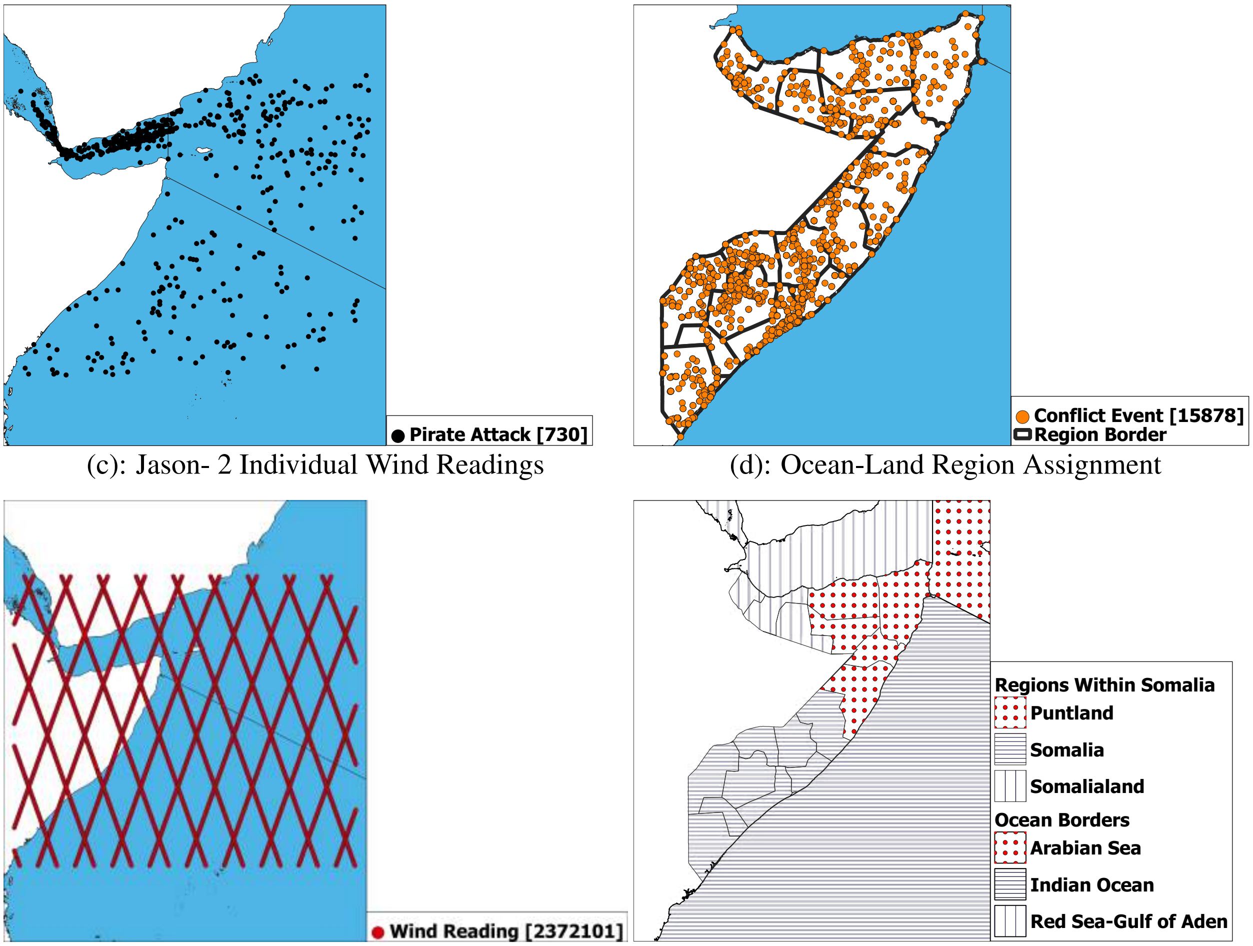
[13]Data is available at https://www.acleddata.com. An introduction is found in Raleigh et al. (2010).

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

Figure 1: Spatial Distribution of Primary Variables and Region Definitions

(a): IMO Pirate Attacks (b): ACLED Conflict Events

(c): Jason- 2 Individual Wind Readings (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 at least 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 marine gazetter shapefile, to divide the land and ocean into northwest, northeast, and south regions. This division removes discretion from the researcher to define regions and allows the region fixed effects in the regression models to be interpreted as controlling for alternative legal origins since Somalialand was settled by the British and the other regions by the Italians. Also large spatial units are most consistent with the SUTVA assumption which is required for estimates to represent heterogeneous local average treatment effects. We show alternative mappings in Figure A.7 and the corresponding regressions in Tables A.6, A.10, and A.11.

from the same satellite and it is the height of Somalian piracy.[15,16,17]

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, a date, and an altimeter wind speed. Wind readings (and pirate attacks) are spatially joined to ocean areas using Geographic Information Software (GIS). For example, if an ocean wind speed reading is inside the geographic boundaries of the Indian Ocean, then an identifier for Indian Ocean is attached.[18]

With the ocean identifier attached, we create a single weekly measure of wind speed for each ocean area. The preferred aggregation method to calculate a single wind speed across multiple wind readings per region-week is to use the median of the wind speed readings. By using the median, the wind measurement is less vulnerable to being skewed by outliers.[19]

3.2 Regional Match

Our research question requires pairing land areas (for conflict) to ocean areas (for piracy). Figure 1d displays how ocean areas are paired with land areas. 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.This specific mapping is preferred because it removes discretion since the boundaries were defined by separate entities for both the land and ocean. The results are robust to alternative land-ocean matches.[20] The naval boundaries seem to roughly correspond with clusters of piracy activity with piracy being dense in the Gulf of Aden, dispersed in the Arabian Sea, and sparse in the Indian Ocean.

There are two more advantages of aggregating data into relatively large spatial units. First, re-

[15] 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.

[16] The measure of wind speed we use – altimeter wind speed – is an estimate that is predicted using a neural network algorithm (Gourion et al., 2002), which takes wave height estimates as the primary input. 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 the wave to return and compares that to a reference ellipsoid of Earth. Details about radar altimetry can be found in Ribal and Young (2019). The relationship between wind speed and wave height is well-established, making it possible to make good predictions of wind speed from wave heights collected by the altimeter of Jason-2.

[17] Satellite data is used because pirate attacks do not impede collection of the data (Smith et al., 2011).

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

[19] This is preferred because ocean wind speed altimeter readings close to land masses are often recorded with greater error. Regardless, summary statistics and results are similar when the mean is used instead of the median.

[20] The alternative mappings of ocean area to land regions are shown in Figure A.7.

gion fixed effects control for different legal origins.[21] In addition to the established importance of legal origins (Glaeser and Shleifer, 2002; La Porta et al., 2008), Draper (2009) believes differences in development across Somalia's regions can be attributed to the legal system of the colonizer. Second, a disadvantage of using smaller units is spatial spillovers. These are significant in Africa using the same ACLED conflict data (Harari and Ferrara, 2018). Spillovers raise concerns that SUTVA is violated if spatial units are too small. The aggregation described above is more consistent than using a greater number of smaller units, with the SUTVA assumption necessary to interpret estimates as causal effects.[22] It is technically possible to assign attacks to the nearest land point using GIS, but this overassigns piracy to regions that have landmasses that protrude into the bodies of water.[23]

3.3 Summary Statistics

The panel data is formed over these regions with one observation for each week from week 28 of 2008 to week 40 of 2016. Table 1 displays descriptive statistics of the balanced panel (516 weeks X 3 regions) of 1,548 weekly, region-level observations. Panel A describes the aggregate sample. The average wind speed is 5.43 m/s, with a standard deviation of 2.14. Given that the standard deviation is nearly 40% of the mean, there is considerable variation for analysis.[24]

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 zero. There is an average of 10.42 conflict events and a standard deviation of 14.53, which provides ample variation in conflict for our analysis. The average number of conflict fatalities is 17.14 with up to 309 individuals killed in conflict in a given region-year-week.

[21] Somalialand was settled by the United Kingdom and the other two regions were settled by Italy, which had a different legal system.

[22] This is a standard approach to causal inference with 2SLS in the regional economics, see (Baum-Snow and Ferreira, 2015; Duranton and Turner, 2011).

[23] It also ignores an important aspect of piracy operations, which requires them to have permissive land areas of operations which cannot be dealt with well using this approach.

[24] There are 28 observations with missing wind speed because wind speed can be missing due to the Jason-2 satellite not taking any over-water readings in a region-week-year.

Table 1: Summary Statistics

Panel A: Aggregate

	Mean	Median	SD	Min	Max	Count
Median Wind Speed	5.43	5.13	2.14	0.1	13.4	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 the 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.

4 Method

The analysis aims to identify how reducing piracy affects safety of communities on land. Specifically, we aim to understand how reducing piracy via international aid and displacement of violent actors on shore impacts land violence. A naïve model that one might consider is:

$$Land\ Conflict_{ryw} = \beta_1 Pirate\ Attack_{ryw} + \mu_r + \gamma_y + \eta_m + u_{ryw}, \tag{1}$$

in which *r* represents the region, *y* is the year, *m* denotes the month, and *w* indicates the week.

Table 2 presents estimates of the conditional associations between piracy and land conflict. Pirate attacks always have a statistically significant association with land conflict, but the sign switches from negative to positive when time fixed effects are added in columns 2 and 3. While Panel A uses aggregated Somalia, Panel B disaggregates to 3 separate regions to control for region-level heterogeneity. Region fixed effects do not alleviate the sign switching due to time fixed effects.[25] This contrasts Daxecker and Prins (2017) in which only positive effects are reported.

There are three leading explanations for why the sign switches under alternative fixed effects. First, there are omitted variable bias issues when not controlling for factors potentially correlated with both the treatment (pirate attacks) and the outcome (on-land conflict events), such as legal institutions.[26] 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. Second, fixed effects are not an adequate identification strategy to overcome omitted variable bias and the reverse causality from land conflict to piracy. A common hypothesis is that 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. Third, there is measurement error in pirate attacks since they are self-reported by attacked crews. Any of these could explain why signs switch under alternative fixed effects when estimating naïve associations.

[25] Table A.1 shows that dropping missing wind or using Poisson estimation do not alleviate the sign flipping.

[26] Legal institutions are correlated with both piracy and land conflict. Region fixed effects only control for time-invariant characteristics of 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 diffuclt, if not impossible.

Table 2: Conditional Associations Between Piracy and Land Conflict Estimated by OLS

Panel A: Aggregate Somalia			
	(1)	(2)	(3)
Pirate Attack	-2.81***	0.77***	1.50***
	(0.30)	(0.29)	(0.30)
Observations	516	516	516
Year FEs	-	X	-
Month FEs	-	X	-
MonthXYear FEs	-	-	X
Panel B: 3 Somalian Regions			
	(1)	(2)	(3)
Pirate Attack	-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

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Heteroskedasticity robust standard errors in parentheses. The table displays OLS regressions of land conflict events on pirate attacks. In Panel A, Somalia is not disaggregated into constituent regions. In Panel B, three regions are used. Table A.1 shows regressions that use Poisson and drop missing wind observations and the conclusions are similar.

4.1 Two Stage Least Squares

To overcome the issues outlined with using Equation 1 for estimating the impact of piracy reduction measures, our approach relies on weather-induced variation in piracy. We employ two-stage least squares (2SLS) in which the first-stage regression is:

$$Pirate\ Attacks_{ryw} = \phi_1 Ocean\ Wind\ Speed_{ryw} + \beta_2 X_O + \mathbf{X_L}\beta + \mu_r + \gamma_y + \eta_m + \epsilon_{ryw}, \quad (2)$$

in which all subscripts and fixed effects are identical to Equation 1. Ocean wind speed alters the expected marginal benefits of piracy, because higher wind speed makes it difficult to board vessels (Cook and Garrett, 2013; Besley et al., 2015). Assuming pirates are rational actors (Leeson, 2009), a lower expected marginal benefit of piracy leads to a reduction in the optimal amount of piracy activity which means that we expect $\phi_1 < 0$.[27] Both equations include additional covariates (X_O and X_L) which will be explained in Section 4.2.

Descriptive statistics in our data support our hypothesis about high ocean wind speeds reducing piracy. Panels B and C of Table 1 subsample to observations above and below the average (ocean-week-year median) wind speed, respectively. In Panel B, when wind speed is greater than the sample average wind speed, average pirate attacks are 0.16. In contrast, Panel C shows when wind speed is less than the average, there is an average of 0.69 pirate attacks. Figure 2 displays 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.

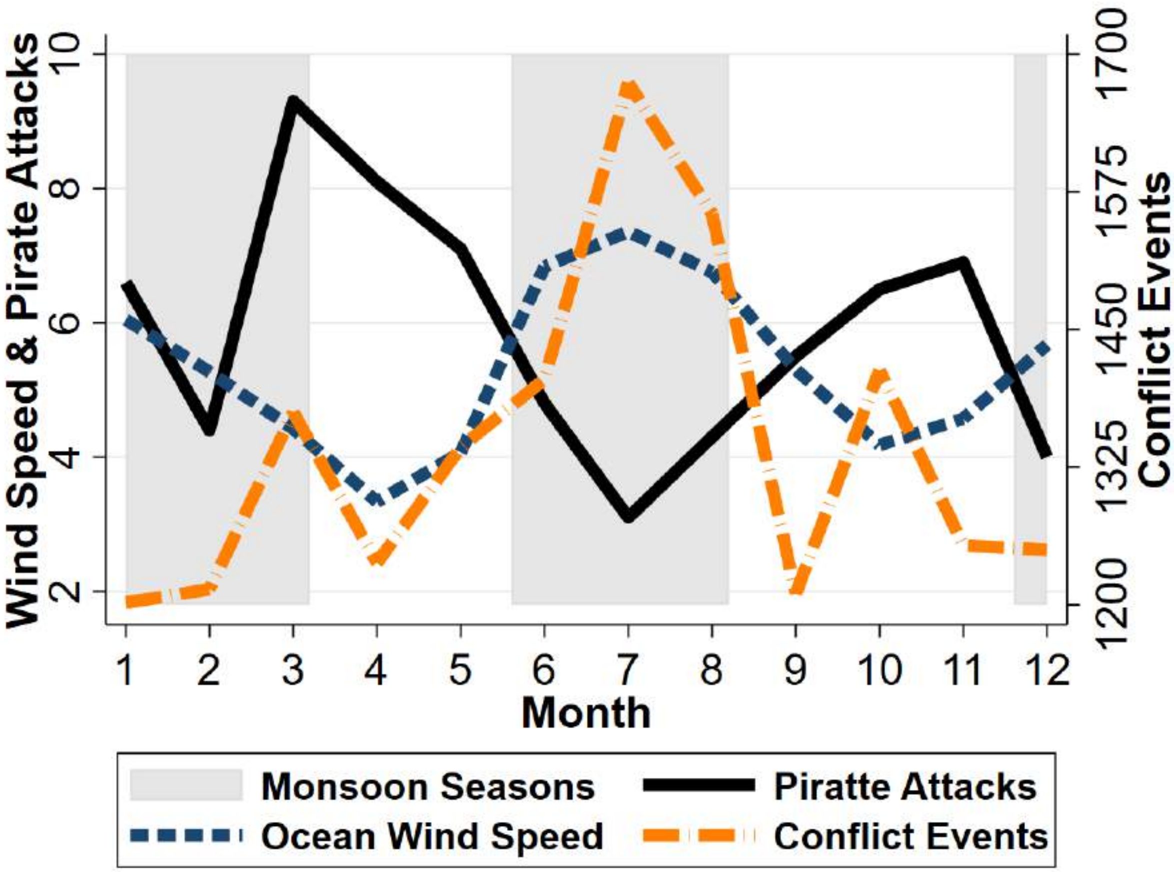
We then examine whether the reduction in piracy has adverse effects on Somalian land violence. The second stage regression is:

$$Land\ Conflict_{ryw} = \beta_1 \widehat{Pirate\ Attacks}_{ryw} + \beta_4 X_O + \mathbf{X_L}\delta + \mu_r + \gamma_y + \eta_m + u_{ryw}, \quad (3)$$

in which $\widehat{Pirate\ Attack}_{ryw}$ are fitted values from Equation 2. Below, the assumptions required to interpret β_1 as a local average treatment effect are discussed. Even with non-classical measurement error in piracy, as long as wind speed is uncorrelated with measurement error in piracy, this

[27] We outline some of the relevant theoretical considerations in Section B. Typically deterrence, in this case warships, relies on raising the expected marginal cost to criminal activity. Regardless, raising the cost or reducing the benefit will reduce the optimal amount of that activity.

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



Note: Time frame is 2008-2016. Conflict events and pirate attacks are totals within months. Conflict events are a long dash with a small dot between dashes. Pirate attacks are a solid line. Wind speeds' median is used. Ocean wind speed is the dashed line. Monsoon season defined according to Shortland and Vothknecht (2011). Pirate attacks are in 10s. The equivalent weekly-level is shown in Figure A.1.

approach yields consistent estimates (Pischke, 2007, pg. 8). We consider several types of standard errors. Our preferred estimates use heteroskedasticity robust standard errors.[28] The main result is the same using wild-cluster bootstrapped standard errors.

Panels B and C of Table 1 show that 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 average wind speed. When wind speed is greater than average, there are 21.8 land conflict fatalities, in contrast to the 13.37 fatalities when wind speed is lower than average. Figure 2 shows that as ocean wind speeds slow between monsoon seasons, pirate attacks increase and there are fewer land conflict events.[29]

Fixed Effects When using weather to identify causal effects in panel data, Dell et al. (2014) recommends interacting the cross-sectional unit with time fixed effects. This enables identification to come from weather shocks within a particular place at a particular time. Regions are the cross-sectional unit and the available time fixed effects include year, month, and week of the year. One cannot interact region with year, month, and week because that is the unit of analysis. Therefore, the most temporally saturated the specification, while also being interacted with region fixed effects (as recommended by Dell et al. (2014)), can be is region X year X month.[30]

4.2 Identification

Identification of causal effects, using the 2SLS approach outlined above, requires several assumptions. First, ocean wind speed must be a relevant first stage, requiring ocean wind speed to be correlated with pirate attacks (i.e. $\phi_1 \neq 0$). The binned scatterplots, that are presented in Figure 3, further expands on how the data is consistent with this narrative.[31] As shown in Figure 3a, there is a clear negative association between ocean wind speed and pirate attacks. When ocean wind speed is slow (around 2.5 m/s), the number of pirate attacks averages nearly 1 per week; however, when ocean wind speed is fast (around 7.5 m/s), the average number of pirate attacks drops to nearly 0.

[28] There are few clusters, so even though errors are possibly correlated within regions, there are only 3 clusters which makes appeals to asymptotic theory and clustered standard errors likely inappropriate.

[29] Similar conclusions can be drawn from Figure A.1, which is the weekly equivalent of the same figure.

[30] When using region X year X month, week of year fixed effects (1-52) can also be included, but they must not be included in the interaction.

[31] No functional form is assumed and the number of bins minimizes a bias-variance trade-off (Cattaneo et al., 2019).

As shown in Figure 3b, adjusting for region-year-month fixed effects does not significantly alter this relationship.

Furthermore, all of the points are near the linear fit which means the relationship is precisely estimated and suggests the first-stage F-test will be adequately strong. Our regression results find large and statistically significant estimates for ocean wind speed's association with piracy which suggests minimally biased second stage estimates (Stock and Yogo, 2002). We also show that our results are at least as statistically significant when using Anderson-Rubin (AR) confidence sets which are efficient for just-identified two stage estimates with potentially weak instruments and typically produce more conservative inference than valid t-ratio inference (Lee et al., 2022). Young (2022) finds that highly leveraged first stages lead to misleading inference, but this first stage does not appear to be the result of single high leverage points. The strong and precise first stage requirement is met.

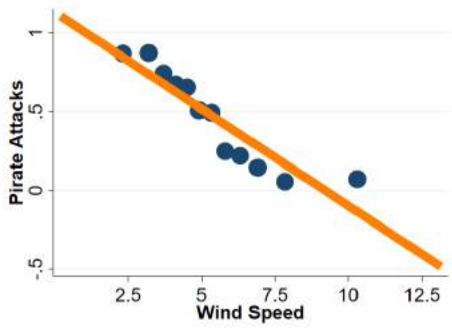
The estimates are valid for region-weeks in which ocean wind speed causes variation in piracy, otherwise known as compliers. To interpret the estimates as causal for compliers requires a weakly monotonic relationship between ocean wind speed and pirate attacks (Angrist et al., 1996; Imbens and Angrist, 1994). As shown in Figures 3a and 3b, pirate attacks are weakly monotonically decreasing in ocean wind speed (i.e. an increase in ocean wind speed is never associated with an increase in pirate attacks). Thus, regardless of which fixed effects are included, this weakly monotonic relationship between instrument and treatment requirement is satisfied.

Second, ocean wind speed must be independent of land conflict. Since there is no way for land conflicts to influence ocean wind speeds, we believe that this assumption is satisfied and that it is better than using fixed effects to overcome reverse causality from conflict to piracy.[32] Section 4.2.2 will conduct balance tests that support that ocean wind speed is as good as random. Under this independence assumption, the reduced form effect of ocean wind speed on land conflict can be interpreted as an intent-to-treat effect. Figures 3c and 3d examine the reduced form estimation of ocean wind speed on land conflict and find a positive association between ocean wind speed and land conflict. Since the first stage association is negative regardless of fixed effects, these results suggest the IV estimates will be negative and that fixed effects will not be detrimental to the sign.

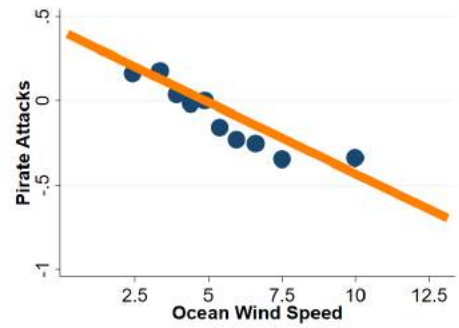
[32] Over a longer time period, land conflict could influence ocean wind speed if it leads to more or less climate change, but this is not an issue over the 8 year period that we examine.

Figure 3: Binned Scatter Plots of the Effect of Ocean Wind on Piracy, Land Conflict, Land Conflict Fatalities, and Institution-Related Conflict

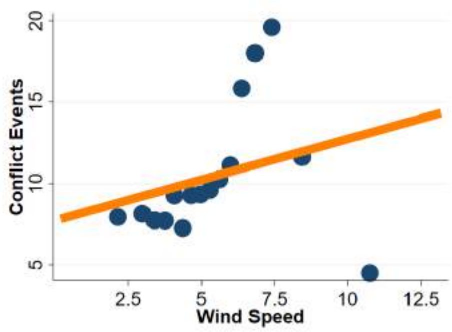
(a): Ocean Wind on Pirate Attacks



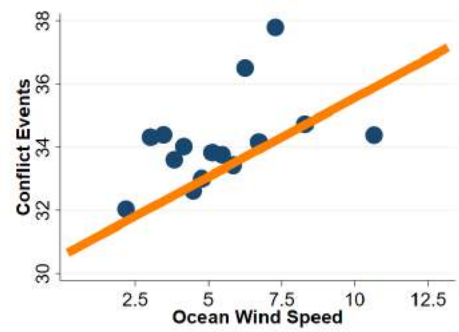
(b): Ocean Wind on Pirate Attacks, Fixed Effects



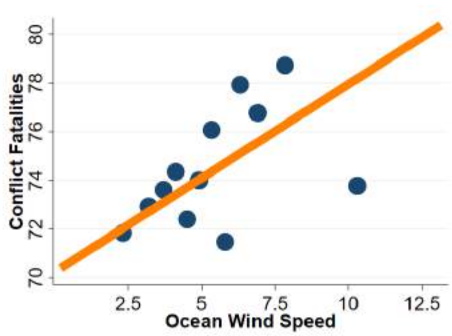
(c): Ocean Wind on Total Land Conflict



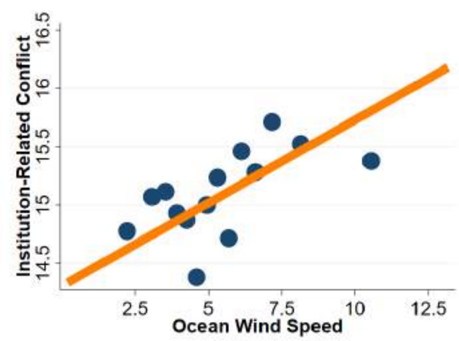
(d): Ocean Wind on Land Conflict, Fixed Effects



(e): Ocean Wind on Conflict Fatalities, Fixed Effects



(f): Ocean Wind on Institutional Conflict, FEs



Note: Y-axis scales differ. All figures show dependent variables conditional on ocean wind speed. Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Equal number of observations in each bin. In (b), (d), (e), and (f), the preferred fixed effects, region X year X month are included. In (a) and (c), no fixed effects are used. In (a) and (b), the dependent variable is pirate attacks. In (c) and (d), the dependent variable is total land conflict. In (e) the dependent variable is land conflict fatalities and in (f) the dependent variable is institutional conflict. Institution-related conflict includes the sub-events: 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 used to identify institutional conflict are: checkpoint, toll, tax, ngo, official, roadblock.

4.2.1 Exclusion Restriction

Adding new assumptions, including most notably the exclusion restriction, enables the two stage estimates to be interpreted as a treatment effect. The exclusion restriction requires that ocean wind speed is not correlated with the error term in the second stage,

$$corr(Ocean\ Wind_{ryw}, u_{ryw}) = 0. \tag{4}$$

In other words, ocean wind speed affects land conflict only through its effect on piracy. This is a strong assumption; however, it can be weakened.

The exclusion restriction can be weakened to conditional exclusion by including the variables in u_{ryw} that one believes that ocean wind speed is correlated with so that the remaining variation in u_{ryw} is uncorrelated with ocean wind speed. Time and region fixed effects play an important role in weakening Equation 4 to

$$corr(Ocean\ Wind_{ryw}, u_{ryw} \mid \mathbf{R}, \mathbf{Y}, \mathbf{M}) = 0.\text{[33]} \tag{4B}$$

In Equation 4B, if ocean wind speed is correlated with the error term, because both vary with region ($\mathbf{R}$), year ($\mathbf{Y}$), and/or month ($\mathbf{M}$) then this specific channel for exclusion to be violated is eliminated. Since monsoons are active in some months and not others, our results are not from comparing non-monsoon to monsoon season months. With a sufficiently saturated specification, there is no concern that ocean wind speed is correlated with u_{ryw} through seasonal factors (e.g. agriculture yields), since it is unlikely that seasonal factors vary significantly within a short time frame in the same place (e.g. region-year-month).[34,35]

Somalia is not a data-rich environment, especially given the need for spatially disaggregated data at a weekly frequency; however, a weaker conditional exclusion restriction is achieved using

[33] In most specifications, region fixed effects are interacted with month and year fixed effects, so $\mathbf{R}$ x $\mathbf{Y}$ x $\mathbf{M}$ is consistent with more of the estimated models in this paper.

[34] Land wind speed is correlated with agriculture production (Zhang et al., 2017), but specifications did not include an interaction between the cross-sectional unit and time like our preferred specification. Furthermore, newer evidence finds no relation between land wind speed and total factor productivity in agriculture (Chen and Gong, 2021). If land wind speed does not affect agriculture productivity, then it is unlikely that ocean wind speed does.

[35] There is also a literature on how commodity price shocks, such as those to agricultural commodities, affects conflict (Maystadt and Ecker, 2014; Koren, 2018; McGuirk and Burke, 2020; Brückner and Ciccone, 2010; Crost and Felter, 2020). For a meta-analysis, see Blair et al. (2021).

three additional variables. These variables are chlorophyll concentration, land temperature, and land precipitation.[36] By including these additional covariates, the (strict, conditional) exclusion restriction is the weakest it can possibly be with the available weekly data,

$$corr(Ocean\ Wind_{ryw}, u_{ryw} \mid \mathbf{R}, \mathbf{Y}, \mathbf{M}, \mathbf{X_L}, X_O) = 0. \tag{4C}$$

We also show monthly level regressions that include prices of Somalian foods. The results are similar under all sets of covariates and exclusion restriction assumptions.

Furthermore, we understand that there could be other potential ways for the strict, conditional exclusion restriction to fail. We relax this assumption in Section 5.2.3. Specifically, we use Conley et al. (2012) to allow

$$corr(Ocean\ Wind_{ryw}, u_{ryw} \mid \mathbf{R}, \mathbf{Y}, \mathbf{M}, \mathbf{X_L}, X_O) > 0. \tag{4D}$$

Even under this condition, in which we estimate the strength of this correlation, the results are consistent.

4.2.2 Threats to Identification

There are two threats to identification that are addressed in this section. The first threat is that variation in ocean wind speed is correlated with other weather phenomena or agriculture on land that also affects conflict, even after including fixed effects. To investigate concerns about ocean wind speeds being correlated with weather, Figure A.3 presents regression coefficients (with 95% confidence intervals) from regressions of other weather, chlorophyll, land temperature, and land

[36] Chlorophyll concentration is associated with piracy and could affect fisherman temperament (Axbard, 2016). Chlorophyll is a nutrient in the fish food chain, meaning higher concentrations leads to better fishing conditions. Fishing 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 (McClanahan, 1988; Chatterjee et al., 2019). Land temperature has been correlated with land conflict, although it is not obvious how ocean wind speed is correlated with land temperature, other than through their correlation with a third variable- the season, which can be controlled for with fixed effects. Land precipitation has also been correlated with land conflict, although it is not obvious how ocean wind speed is correlated with land precipitation, other than through their correlation with a third variable, seasonality, which can be controlled for with fixed effects.

precipitation, on ocean wind speed.[37]

Regardless of whether fixed effects are included in the regression, ocean wind speed is uncorrelated with chlorophyll. Land temperature is not statistically significantly associated with ocean wind speed after interacted fixed effects are included (the orange open dot). Rainfall remains negatively associated with ocean wind speed in all specifications.[38] While it is not ideal that ocean wind speed is correlated with land precipitation, when the regression includes rainfall, the coefficients on ocean wind speed gets larger.[39] Naturally, since precipitation is an important input for agricultural production and agriculture, rainfall, and conflict are all related, a concern would be that because ocean wind speed is correlated with precipitation, maybe it is also correlated with agricultural production.

To investigate whether ocean wind speed is correlated with the agriculture cycle, we collect monthly prices on a range of goods from Somalia (Security and Unit-Somalia, 2021). Then, we regress the agriculture price on ocean wind speed. The results of these balance tests are shown in Figure 4. When no time fixed effects are included, increases in ocean wind speed increases the price of agricultural goods. Once time and region fixed effects are included, the correlation between ocean wind speed and agriculture prices is nearly zero for all agricultural goods. This lack of correlation is not merely due to wide confidence intervals, but due to precisely estimated zeroes. While ideally we would have more temporally disaggregated prices to include in the weekly regressions, this is the best data available and supports that results are not driven by a correlation between agriculture and ocean wind speed.[40]

The second threat is that pirates are sophisticated optimizing agents. For instance, perhaps pirates have access to meteorological equipment that enables them to accurately predict future wind and weather patterns such that they can maximize the proceeds of land and sea piracy activities

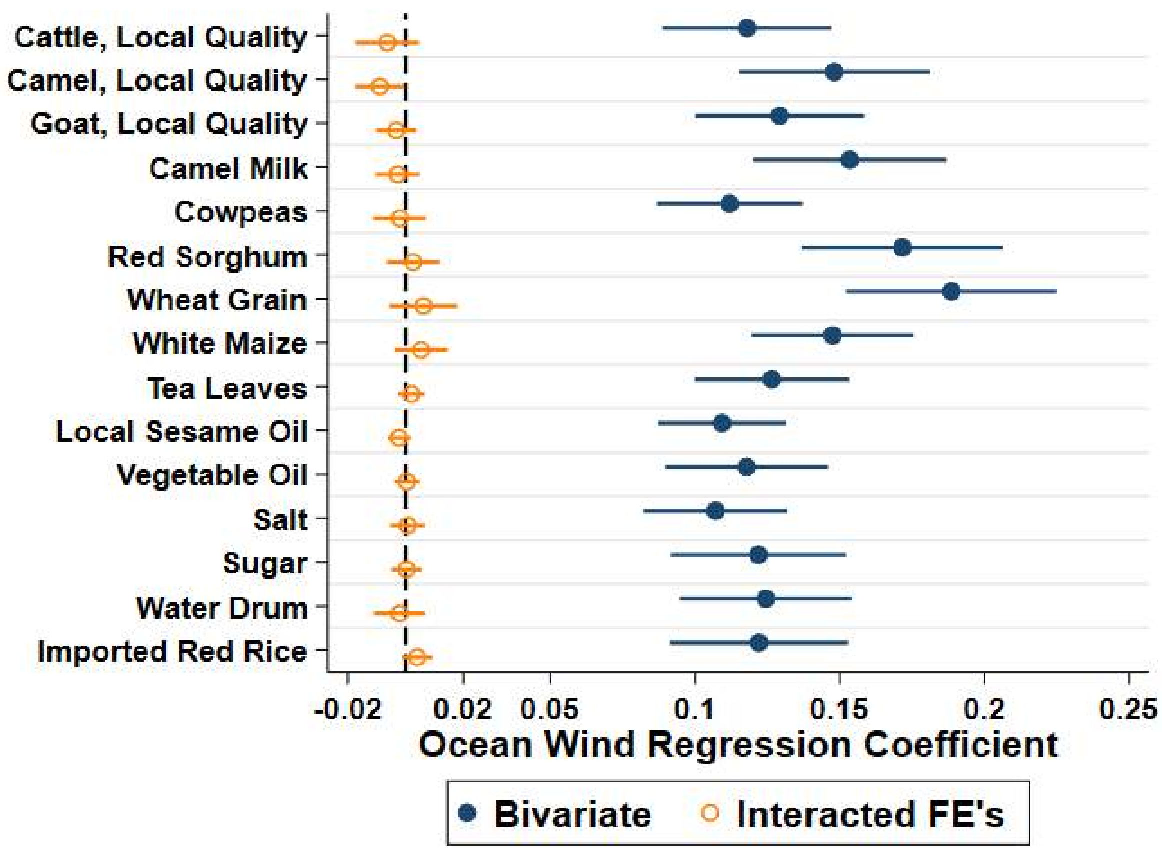
[37]Chlorophyll data is obtained from NASA Ocean Color. CPC Global Temperature data provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their Web site at `https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html`. Land precipitation data comes from NOAA's CMORPH (NOAA, 2021b; Joyce et al., 2004). The spatial grid of land temperature and precipitation are shown in Figure A.6.

[38]The negative correlation is not consistent with monsoon rains from the ocean accumulating on land, but rather is consistent with ocean wind speed pushing land rain clouds away from land, resulting in less rain.

[39]Rainfall is negatively correlated with conflict (Miguel et al., 2004) and rainfall is negatively correlated with ocean wind speed, which causes an upward bias on the ocean wind speed if rain is excluded from the model.

[40]There is also data on other Somalian necessities such as tarps, baskets, blankets, etc. The same figure is replicated in Figure A.4. Similar to agriculture goods, after conditioning on fixed effects, there is no systematic relationship between ocean wind speed and non-agricultural goods in Somalia.

Figure 4: How Ocean Wind is Related to Commodity Prices, Monthly Level



Note: The plots shows regression coefficients on the independent variable of ocean wind speed. The dependent variables are listed on the left, they are logged to facilitate visual interpretation. They are the log of the median price of agriculture within a given region. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from regressions using interacted region and year fixed effects. Agriculture prices are only available at the monthly level, so n=300. The prices are at the "sub-region" (n=18) level, so to aggregate to a single price across multiple subregions within the region (n=3), we take the median in each month.

by ensuring that they are not investing effort in a mismatched scenario (e.g. attempting to board vessels on high wind days). Such sophistication would invalidate our instrument, as on-land conflict activities would be driven directly by predictions about wind and weather patterns, rather than indirectly through piracy behavior at sea.

Figure 5 investigates how ocean wind speed affects a lead and lag of piracy. The first pair of coefficients regresses the previous week's piracy on the current week's ocean wind speed. Once fixed effects are included (the open, orange dot), there is no statistically significant relationship between the current week's ocean wind speed and the previous week's piracy. The second pair of coefficients regresses a lead of piracy on the current week's ocean wind speed. There is no statistically significant relationship once fixed effects are included.

Finally, the third pair of coefficients investigates the same week's wind on the same week's pirate attacks (i.e. the proposed first stage). Even after fixed effects are included there is a large negative association between ocean wind speed and pirate attacks. The point estimate for the fixed effects regression is about twice as large as the next largest fixed effects coefficient. In conclusion, controlling for interacted fixed effects addresses potential threats to identification, but does not preclude an adequately strong first stage.

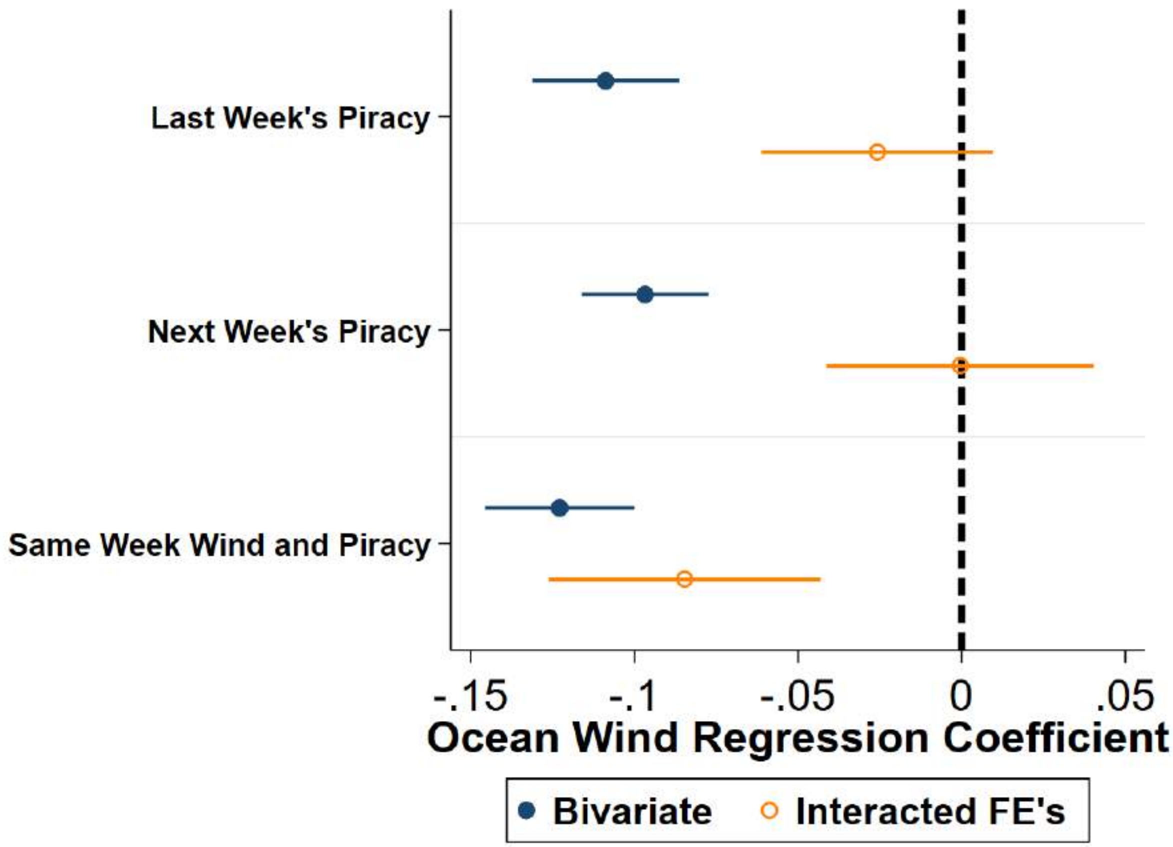
5 Results

Following Equations 2 and 3, Table 3 presents 2SLS results. Panel A uses no additional variables or fixed effects, besides ocean wind speed, pirate attacks, and land conflict. All 3 estimates shown in Panel A are statistically significant above 99% confidence.The first stage, Kleibergen-Paap F statistic is 111.8, indicating that ocean wind speed is a strong predictor of piracy. Also, column 3 shows the AR 95% confidence set, which is efficient for potentially weak instruments. The AR 95% confidence set is similar to the 95% confidence interval that can be constructed from the standard error (reported underneath the pirate attack coefficient) and does not include zero.

Panel B uses region-year-month interacted fixed effects since these remove correlations between land temperature (Figure A.3), prices of agriculture goods (Figure 4) and ocean wind speed.[41] Furthermore, it removes temporal mismatch (Figure 5) and allows the effects to be identified from

[41] Other fixed effects combinations are shown in Table A.5. The results are similar.

Figure 5: Examining Whether Pirates Shift Operations Across Time in Anticipation of High Ocean Wind Speeds



Note: The plots shows regression coefficients from regressions of piracy attacks on ocean wind. Different rows represent different lags. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from regressions using interacted region, year, and month fixed effects. Row 1 uses piracy lagged by 1 week and that week's wind. Row 2 uses a 1 week lead of piracy and that week's wind. Row 3 uses no lags or leads on piracy or wind. n = 1,516 in all regressions.

Table 3: 2SLS Estimates of Piracy on Land Conflict

	(1)	(2)	(3)
Dep Var.	Reduced Form Conflict Events	First Stage Pirate Attacks	Second Stage Conflict Events
Panel A: Single Independent Variable			
Median Wind Speed	0.50***	-0.12***	
	(0.16)	(0.01)	
Pirate Attacks			-4.08***
			(1.25)
Observations	1519	1519	1519
Kleibergen-Paap F			111.8
A-R 95% Confidence Set			[-6.59, -1.75]
RegionXYearXMonth FEs			No
Panel B: Preferred Fixed Effects (PFE)			
Median Wind Speed	0.50***	-0.08***	
	(0.17)	(0.02)	
Pirate Attacks			-5.90**
			(2.35)
Observations	1519	1519	1519
Kleibergen-Paap F			16.00
A-R 95% Confidence Set			[-12.87, -2.27]
RegionXYearXMonth FEs			Yes
Panel C: PFE with Covariates			
Median Wind Speed	0.48***	-0.08***	
	(0.19)	(0.02)	
	[0.35]	[0.15]	
Precip. Mean	-0.17	-0.01	-0.22
	(0.23)	(0.01)	(0.22)
Temp. Max. Mean	-0.31	-0.01	-0.38
	(0.21)	(0.02)	(0.25)
Chlorophyll Concentration	0.01	0.07	0.46
	(0.03)	(0.05)	(0.35)
Pirate Attacks			-6.40**
			(2.74)
			[0.00]
Observations	1425	1425	1425
Kleibergen-Paap F			15.58
A-R 95% Confidence Set			[-14.54, -1.94]
RegionXYearXMonth FEs			Yes
Panel D: With Price Covariates			
Median Wind Speed	2.30***	-0.58***	
	(0.84)	(0.10)	
Pirate Attacks			-3.94***
			(1.39)
Observations	290	290	290
Kleibergen-Paap F			35.35
A-R 95% Confidence Set			[-7.17, -1.46]
RegionXYearXMonth FEs			No
RegionXYear FEs			Yes

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. In Panel A, no fixed effects are used. In Panel B, region X month X 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. Panel C includes additional covariates related to weather. Panel C shows wild cluster bootstrap p-values in brackets with Webb weights, a non-studentized test statistic (Young, 2022), and the test is Anderson-Rubin (AR) (Anderson et al., 1949). Panel D includes price covariates (available monthly). The price covariates are for: cattle, daily labor rate, local sesame oil, sugar, wheat flour, camel, charcoal, cowpeas, diesel, firewood, fresh camel milk, goat, grinding cost, imported red rice, kerosene, petrol, red sorghum, salt, sheep, soap, tea leaves, vegetable oil, water drum, wheat grain, and white maize. All panels show the corresponding AR 95% confidence sets for the IV estimate (Anderson et al., 1949), which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

weather shocks (Dell et al., 2014). Finally, using region X year X month interacted fixed effects makes a weaker assumption, Equation 4B, than Panel A requires to be causally identified.

Column 1, the reduced form effect of ocean wind speed on piracy, retains the same magnitude and statistical significance, meaning a 1 m/s increase in ocean wind speed increases land conflict by 0.5 events. While ocean wind speed is no longer correlated with land temperature or prices, there is still enough covariation within a given region-year-month to obtain a statistically significant relationship between ocean wind speed and land conflict events. Furthermore, under the independence assumption only, this is an intent-to-treat effect of ocean wind speed on land conflict. Other than through the effect on piracy, there is no obvious reason why violent actors on land should be affected by ocean wind speeds.[42]

In column 2, the first stage effect of ocean wind speed on piracy, produces estimates that are 33% smaller than Panel A (0.12 to 0.08), but retains statistical significance above 99% confidence due to the relatively precise estimation (SE = 0.02). A 1 m/s increase in ocean wind speed reduces piracy by 0.08 attacks and the Kleibergen-Paap F-statistic is 16 (see column 3). This F-statistic means that the second stage coefficient is minimally biased (Stock and Yogo, 2002), but may be too small to make appropriate inferences using standard Wald confidence intervals (Lee et al., 2022). Ocean wind speed covaries enough with piracy within a specific region-year-month to pass diagnostic tests for appropriately strong instruments.

Column 3 presents the second stage coefficient of the effect of piracy on land conflict. The negative and minimially-biased point estimate indicates that an additional pirate attack reduces land conflict by 5.9 events. The confidence intervals from the heteroskedasticity-robust standard errors indicate that the estimate is statistically significant above 95% confidence. One issue is that these standard errors may be too small for the strength of the instrument, so the AR confidence sets are also shown (Andrews and Stock, 2018; Lee et al., 2022). The AR confidence set and associated p-value is presented below and indicates that zero is not in the AR confidence set with 99% confidence (p-value = 0.00139), ruling out the possibility that our results being driven by a "weak instrument".

Unlike when fixed effects are added to the OLS results in Table 2, the IV results shown in

[42] We return to the question of whether the data supports ocean wind speed affecting land conflict other than through its effect on piracy in Section 5.2.

Panels A and B of Table 3 do not switch signs. Prior literature (Daxecker and Prins, 2017) has relied on fixed effects for identification, but that does not produce consistent signs for different sets of fixed effects.[43] Our identification strategy of using random variation provided by ocean wind speed does not have this drawback. The consistently negative sign implies that piracy and conflict are substitutes, which has vastly different policy implications than if they are complements.

Panel C uses the same interacted fixed effects as Panel B and adds land weather covariates (temperature and precipitation) and chlorophyll concentration, which weakens the conditional exclusion restriction further to Equation 4C. Column 1 shows that including additional covariates has virtually no impact on the reduced form estimates of ocean wind speed on land conflict, lowering the point estimate by 0.02 and remaining statistically significant. Column 2 shows that including weather variables has a negligible impact on the effect of ocean wind speed on piracy, and the weather variables do not have a statistically significant effect on pirate attacks.[44] The Kleibergen-Paap F-statistic indicates that the strength of the instrument is the same. Finally, column 3 shows that weather variables have no significant effect on conflict. Adding land weather variables and chlorophyll concentration increases the magnitude of the estimated effect of pirate attacks on land conflict from 5.9 (Panel B) to 6.4. Furthermore, within a given region-year-month, chlorophyll, land temperature, and land precipitation do not have a statistically significant effect on land conflict in either the reduced form or second stage.[45]

The standard errors in all the panels are heteroskedasticity robust, but there is reason to believe that the errors may be correlated within regions. To investigate this possibility, the brackets show the p-value using the wild cluster bootstrap.[46] The coefficients in columns 1 and 2 lose statistical significance at conventional levels, but the p-value on instrumented pirate attacks is still statistically

[43] Another possible reason that the implications differ from Daxecker and Prins (2017) is due to Somalia which has relevant differences than the other countries in the sample used by Daxecker and Prins (2017) which are also Asian and other African countries.

[44] The context for this study is slightly different from Axbard (2016) because we are examining deeper ocean, which lowers the amount of cholorophyll detectable. This could be a potential reason that there is no relationship between chlorophyll and piracy in these results.

[45] This is not to say that land temperature or precipitation have no effect on conflict. Table A.7 shows that when no fixed effects are included, land temperature and precipitation have statistically significant associations with land conflict. These associations actually cause the coefficient of interest, pirate attacks, to be larger. However, with our preferred fixed effects specification, there is no statistically significant effect of chlorophyll, land temperature, and land precipitation on conflict in this context.

[46] The Anderson-Rubin test is used. Webb weights are used because the number of replications exceeds the number of clusters. The distribution of coefficients is bootstrapped, not the test statistics, because it is more reliable for instrumental variables estimation (Young, 2022; Wang, 2021).

significant at the 99% confidence level.

Nonetheless, one could remain concerned that there are not enough controls for other factors such as agricultural prices. Panel D uses a sample at the region-month level that allows the inclusion of agricultural and other product prices. All coefficients remain statistically significant. Also, the IV coefficient is of similar magnitude, suggesting that ocean wind speed is not affecting land conflict through agricultural or other product prices.[47]

5.1 Robustness

Next we turn to assessing additional concerns. One could be concerned that pirates move across the boundaries of the sub-national regions. Indeed our whole research question is based on the mobility of criminal actors, so we are aware of this. Our test to account for this possibility relies on aggregating up to all of Somalia, so that violent actors are not moving across regions by definition. If our results are robust to this test, then the subnational results are not due to violent actors moving across subnational boundaries. Region fixed effects are no longer possible at this aggregation, so we substitute year X quarter fixed effects. As shown in Panel A of Table 4, aggregating up to all of Somalia produces similar results. As shown in Table A.6, these similar results persist regardless of the granularity of time fixed effects.[48]

It could be that pirate attacks and ocean wind speed are not assigned to the associated land conflict. We investigate whether the results depend on this assignation by using fully spatially disaggregated units and other mappings. Table A.10 shows that when the units are fully disaggregated (i.e. 11 spatial units) so that conflict is associated with piracy and wind speed right off the coast, the results remain statistically significant and at comparable magnitudes.[49,50]

Next, one might desire a model that is fully saturated with time fixed effects to account most strictly for potential third factors. The most saturated specification includes a week of year fixed

[47]The coefficient for the monthly sample, without controls, is shown in Table A.4. The coefficient is smaller in magnitude relative to the specification without controls, suggesting that the estimates without agricultural prices in the weekly samples are biased towards zero.

[48]Adding month fixed effects (Panel D) does not change point estimates much, but does cause larger standard errors in the first stage. Regardless, the AR confidence set which produces robust inference for weak instruments finds the same lower bound of the confidence set.

[49]Table A.11 shows alternate estimates for 3 other spatial aggregations and the results are the similar in statistical significance and magnitude. Figure A.7 shows these alternate mappings. There are estimates from 3 spatial units (Figure A.7b), 4 spatial units (Figure A.7c), and 5 spatial units (Figure A.7d)

[50]We also show that the strongest effect of piracy is on land conflict that occurs closer to the coast in Table A.9.

Table 4: 2SLS Robustness

	(1) Reduced Form	(2) First Stage	(3) Second Stage
Dependent Variable:	Conflict	Pirate Attacks	Conflict
Panel A: Aggregate Somalia			
Median Wind Speed	1.52***	-0.16***	
	(0.43)	(0.05)	
Pirate Attacks			-9.26**
			(4.32)
Observations	509	509	509
Kleibergen-Paap F			9.098
A-R 95% Conf. Set			[..., -3.62]
Panel B: Also Include Week of Year FE			
Median Wind Speed	0.31*	-0.09***	
	(0.17)	(0.02)	
Pirate Attacks			-3.25*
			(1.72)
Observations	1519	1519	1519
Kleibergen-Paap F			17.17
A-R 95% Conf. Set			[-7.67, -0.19]
Panel C: Mean Wind Speed			
Mean Wind Speed	0.39**	-0.08***	
	(0.17)	(0.03)	
Pirate Attacks			-4.93*
			(2.55)
Observations	1519	1519	1519
Kleibergen-Paap F			9.830
A-R 95% Conf. Set			[-14.72, -0.99]
Panel D: Inverse Hyperbolic Sine Conflict			
Median Wind Speed	0.05***	-0.08***	
	(0.02)	(0.02)	
Pirate Attacks			-0.60**
			(0.26)
Observations	1519	1519	1519
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-1.33, -0.18]
Semi-Elasticity	0.275***		-0.273**
	(0.105)		(0.117)
Panel E: Drop Wind Speed > 10 m/s			
Median Wind Speed	0.51***	-0.10***	
	(0.20)	(0.02)	
Pirate Attacks			-5.25**
			(2.23)
Observations	1446	1446	1446
Kleibergen-Paap F			16.31
A-R 95% Conf. Set			[-11.69, -1.63]

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 year X quarter fixed effects. Panels B-E include region X month X year interacted fixed effects. Panel A does not disaggregate into 3 regions, instead using all of Somalia. In Panel B, week of the year (1-52) fixed effects are included. In Panel C, the ocean wind speed measure is the mean of all wind in a certain ocean region in a given week. In Panel D, the dependent variable is an inverse hyperbolic sine transformation applied to land conflict. The coefficients require re-transforming to be interpreted as a semi-elasticity, which is presented (Bellemare and Wichman, 2020). In Panel E, all "monsoon" observations are dropped in which monsoon is defined as ocean wind speed greater than 10 m/s. All panels show the corresponding AR 95% confidence sets for the IV estimate (Anderson et al., 1949), which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

effect, although interacting these with the region-year-month fixed effects are impossible due to that being a literal observation and exhausting all degrees of freedom. In Panel B of Table 4, all 3 regressions also include week of year (1-52) fixed effects.[51] In column 1, the reduced form estimate gets smaller, but remains statistically significant at 90% confidence. The first stage estimate gets slightly larger and the F-statistic also slightly increases. In column 3, the second stage coefficient remains statistically significant at 90% confidence with the robust standard errors Wald test and above 95% confidence with the AR test.

Next, aggregating all ocean wind speed readings in a given region could be done different ways. We chose median originally to reduce the impact of potential outliers, but using the mean might provide greater variation. As shown in Panel C which uses average wind speed instead, the reduced form coefficient is slightly smaller and the first stage is estimated with slightly more error, which is unsurprising given the influence of outliers. Nevertheless, the second stage coefficient is still statistically significant (at 10% with Wald test and at 5% with the AR test) and of a similar magnitude.

Next, this is a design-based approach in which the results should be unaffected by transformations of the dependent variable, but there are several outliers in conflict which could be concerning.[52] If the results are affected, this would give cause for suspicion, so we apply the log and inverse hyperbolic sine transformations to conflict and re-run the regressions. As shown in Table A.13, the log regression results in statistically significant results; however, it does drop about 266 observations (17.5% of the sample) due to them being zero-valued. In order to rectify this, Panel D of Table 4 uses the inverse hyperbolic sine which is defined at zero and does not require dropping 0 valued observations (Bellemare and Wichman, 2020). The results remain statistically significant and the estimated semi-elasticity is an additional pirate attack reduces land conflict by 27.3% which is in line with the results in levels. The number of conflict events is a count variable, so we also use generalized method of moments (GMM), which allows the second stage to be modeled as a count variable (Mullahy, 1997; Angrist, 2001).[53] The results presented in Table A.14 are

[51] Since they are not interacted with the region-year-month they are not the unit of analysis. Including a week of year fixed effect allows the average correlation between a week of the year, piracy, and conflict to not bias the estimates. This confusion around including a week of year fixed effects is another reason we prefer to not include them in the preferred specifications.

[52] Difference-in-differences is typically sensitive to outcome transformations due to the linearity implied in typical parallel trends assumptions, see Fredriksson and Oliveira (2019) and Roth and Sant'Anna (2020).

[53] For a similar empirical application, see Dube and Vargas (2013).

similar in terms of statistical significance and magnitude.[54]

So far the regression models impose linearity which may be an unrealistic assumption. To examine the relationship between ocean wind speed, piracy, and land conflict without imposing linearity, Figure A.5 presents the distributions of piracy and land conflict, conditional on wind speed quartiles. Figure A.5 shows consistent and detectable differences in conflict and piracy cumulative distributions by ocean wind speed quartile that persist over most of the distributions.

5.2 Exclusion Restriction

Giving the estimates presented above a causal interpretation has depended so far on the strict, conditional exclusion restriction holding. One story that would violate the exclusion restriction in this context is if fishermen's income from fishing decreases with increases in ocean wind speed, inducing fishermen to commit violent acts on land. 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.[55] So far, we have shown that controlling for chlorophyll, which is associated with fisher income (Axbard, 2016), does not alter the results. This section further investigates exclusion in four ways: removing observations where ocean wind is most likely to affect land conditions (monsoons), considering various types of conflict that is likely/unlikely to be attributed to violent actors such as pirates, investigating conflict in geographic areas without piracy, and relaxing the strict exclusion restriction using the plausibly exogenous methods in Conley et al. (2012).

5.2.1 Evaluating the Exclusion Restriction in Somalia with Subsamples

First, the type of ocean wind speed that is most likely to violate exclusion by affecting land conditions is monsoon weather. Our approach already partially accounts for this since monsoons are during certain months and we use region-year-month fixed effects, but one might be concerned that

[54] The first stage assumes a linear model with integer data. The second stage assumes the dependent variable is a count variable and uses a log link function. The errors are multiplicative, which provides an intuitive connection to the log-link function to maximum likelihood estimation. Since Table A.14 presents Poisson coefficients, they are interpreted: $(e^{\beta_1} - 1) * 100 \approx x\%$.

[55] In other words, it would need to be the case that wind speeds affecting fishing would violate the exclusion restriction such that fishermen come home after experiencing windy conditions and participate in armed conflict. Nevertheless, it is impossible to rule out this possibility a priori.

this is not enough. To directly address this, we drop all observations in which the ocean wind speed is faster than 10 m/s and re-estimate the equations.[56] As shown in Panel E of Table 4, the estimates from the no monsoon subsample are virtually identical to our earlier estimates. This supports that exclusion is not violated by monsoons once our interacted fixed effects are added.

Next, we consider different types of conflict that are more or less likely to be undertaken by fishermen. If exclusion is a reasonable assumption, then ocean wind speed should have no effect on events that could likely be attributed to fishermen and should have the largest effect on events that are unlikely to be attributed to fishermen. First, we remove any events that involve militaries, rebels, civilians, or sole actors. As shown by Panel A of Table 5, the reduced form and second stage point estimates are nearly identical to the estimates in Table 3, suggesting that most or all of the effect of wind speed on conflict can be attributed to violent, non-state actors.

In Panel B, conflict events that are not violent and unlikely to be associated with pirates are dropped prior to aggregating conflict. The reduced form and second stage estimates are again very close to those presented in Table 3, suggesting that ocean wind speed's effect on conflict operates primarily through violent events that are unlikely to involve fishermen. In Panel C only conflict events that use pirate weapons are used as the dependent variable.[57] In columns 1 and 3 about 40% of the reduced form effect of ocean wind speed on land conflict can be attributed to the effect of ocean wind speed on land conflict in which we could identify a pirate weapon.[58]

Finally, pirates are violent actors, so it is unlikely they take part in peaceful protests. Panel D, column 1 shows that there is not a statistically significant effect of ocean wind speed on peaceful protest events, which supports the notion that ocean wind speed operates exclusively through the piracy channel and not through "unlucky" fishermen. In summary, ocean wind speed affects violent conflict perpetrated by violent actors with deadly weapons and not on peaceful protests, providing support that the exclusion restriction is reasonable.

[56]For perspective, this is a good cutoff, because it roughly aligns with the 95th percentile and is about 2 standard deviations from the mean. We show the distribution of ocean wind speeds in Figure A.8.

[57]See rows 3 and 4 of Table A.2, which shows how these weapons are used both on land and at sea for hijacking and violence.

[58]There is likely under-reporting of weapons used in conflict events, which would make these estimates a lower bound. 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.

Table 5: 2SLS Estimates of Pirate Attacks on Conflict Subsets for Investigating Exclusion

Dep. Variable	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Conflict Amongst Violent Actors			
Median Wind Speed	0.43***	-0.08***	
	(0.16)	(0.02)	
Pirate Attacks			-5.09**
			(2.12)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-11.20, -1.65]
Obs. Where Y = 0			333
Panel B: Violent Conflict Sub-events			
Median Wind Speed	0.38***	-0.08***	
	(0.14)	(0.02)	
Pirate Attacks			-4.51**
			(1.86)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-9.87, -1.49]
Obs. Where Y = 0			355
Panel C: Conflict 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
A-R 95% Conf. Set			[-4.50, -.87]
Obs. Where Y = 0			768
Panel D: Peaceful Protests			
Median Wind Speed	0.02	-0.08***	
	(0.02)	(0.02)	
Pirate Attacks			-0.26
			(0.19)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-0.73, 0.09]
Obs. Where Y = 0			1073

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. Panel A uses conflict amongst actors that are less likely to be fishermen or not pirates by dropping: a sole military actor, military on military, sole rebel action, rebel vs rebel, sole protestor, sole protestors vs civilians, or other sole actions. Panel B considers a subset of conflict events based on sub-event type that are violent and not perpertuated by state actors. 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. Panel C only considers conflict events where a pirate weapon was used such as a gun, rocket-propelled grenade, or grenade. Panel D uses peaceful protests from the same dataset that provides the violent conflict events. See Table A.15 for more information on the hierarchy of events. All panels show the corresponding AR 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

5.2.2 Ocean Wind Speed and Conflict, in Countries Without Pirates

A skeptical reader may still believe that the strict conditional exclusion restriction (Equation 4C) is unreasonable. A corollary of this restriction is that ocean wind speed will have no association with land conflict, in the absence of piracy. Since there is always some amount of piracy in Somalia during our sample period, our test of this corollary will make use of ocean wind and conflict in other countries which are as similar as possible to Somalia, other than having no piracy. If there is no association between ocean wind and piracy in other countries, in which piracy is much rarer or non-existent, then the exclusion restriction will be supported suggesting the two stage estimates are identified. A theoretical basis for this test can be found in van Kippersluis and Rietveld (2018), in which it has been named the "zero first-stage test". Applications to other questions can be found in various contexts (Angrist et al., 2010) and the closest is Nunn and Wantchekon (2011) in which distance to shore (instrument) does not affect trust (outcome) in countries that were not part of the African slave trade (endogenous treatment) which supports distance to coast being an appropriately excludable instrument for studying mistrust.

We select three countries, Tanzania, Libya, and South Africa, each with significant coastline and other similarities to Somalia.[59] First, we use Tanzania, because it is geographically close to Somalia. Second, we examine Libya because there is no piracy and a significant amount of conflict that occurs in a weakly institutionalized country, similar to Somalia. Third, we use South Africa, because there is also much land conflict. Figure A.10 shows the yearly incidence of piracy by each country. Tanzania experiences some piracy, though these may just be due to the algorithm that assigns possibly Somalian origin pirate attacks to the nearest country; both South Africa and Libya experience nearly no piracy at all over the entire period of study.

Table A.16 shows the results from each country under different combinations and interactions of fixed effects. All estimates are either slightly negative or zero. The largest negative estimate (Libya) is an increase of ocean wind speed of 1 m/s being associated with 0.091 less land conflict events. The smallest estimate, which is closest to those from Somalia, is in Tanzania where land conflict is a relatively rare event and piracy is sometimes active like Somalia. Estimating a more precise zero effect would have been the most supportive of exclusion. We do not know the mechanism behind why there are some significant, though small relative to Somalia, negative

[59]The mappings of country regions to ocean areas are presented in Figure A.9.

associations which is tangential to the research question we seek to answer. We can say that the statistical significance of such associations depends on which fixed effects are included, but this is not the case for Somalia.

We combine all 3 countries and re-run the regressions. Table 6 shows that the statistical significance varies by which fixed effects are included, primarily due to the size of the point estimate and not due to the way the fixed effects affect the estimates' precision. The point estimate of the association between ocean wind speed and land conflict varies from -0.023 to -0.06, depending on which fixed effects are included. These small, negative estimates stand in stark contrast to the strong, positive relationship between ocean wind speed and land conflict in Somalia. Our Somalian estimates are that a 1 m/s increase in ocean wind speed increases land conflict by 0.5 events which is approximately 10 times larger and oppositely signed than in these other countries in which piracy is barely existent at all. This means that the net effect of all other factors that one could propose as theoretically violating exclusion is barely detectable and negligible compared to our main proposed channel through which ocean wind affects land conflict, displacing violent pirate activity.

Table 6: 3 Placebo Countries With No Piracy

	(1)	(2)	(3)
Median Wind Speed	-0.036*	-0.023	-0.060***
	(0.019)	(0.018)	(0.018)
Observations	5454	5454	5454
Region FE		X	
Year FE		X	
Month FE		X	
RegionXYearXMonth FE			X

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Heteroskedasticity robust standard errors in parentheses. The table displays OLS regressions of ocean wind speed on total land conflict events in countries with no piracy. Panel A uses 3 regions of data from Tanzania, Panel B uses 3 regions of data from Libya, Panel C uses 6 regions of data from South Africa, Panel D uses data from all 3 countries.

5.2.3 Relaxing Strict Conditional Exclusion

While the estimates in Table 6 suggest that the size of the exclusion restriction violation is small, it may not be consistent with the strict exclusion restriction holding. To assess whether the estimates are sensitive to this violation, we employ the plausibly exogenous methods developed in Conley et al. (2012).[60] Intuitively, these methods allow the instrument, ocean wind speed, to directly affect the second stage outcome of interest, land conflict, and re-estimates the (instrumented) endogenous variable, pirate attacks. The method requires specifying a prior (or distribution of priors) for how severely violated the strict exclusion restriction is, which means specifying a parameter value for the coefficient on the instrument in the second stage equation. As advised in van Kippersluis and Rietveld (2018), we use the parameter estimate (-0.06) from the placebo countries in Table 6.

Table 7 presents the estimates from using these methods. In Panel A, we use the union of confidence intervals approach and no uncertainty in the prior for the magnitude of the parameter representing the severity of the exclusion restriction violation. The point estimate gets larger compared to Panel B, column 3 of Table 3 and the 95% confidence interval still does not include zero.

One drawback with this approach is that the -0.06 prior is estimated with error and ideally the parameter estimates would reflect this uncertainty. To address this shortcoming, we use the local to zero (LTZ) Bayesian implementation developed by Conley et al. (2012). With this method, we specify a distribution for the severity of the violation of exclusion.[61]

Panel B presents the LTZ results with uncertainty and a normally distributed prior. The pirate attacks point estimate, 4.56, is slightly smaller than those presented in Table 3. Also the confidence interval is tighter, with a lower bound that is slightly farther from zero and an upper bound that is approximately 4 conflict events smaller. The confidence interval is tighter once uncertainty is incorporated due to the asymptotic properties of the LTZ method (Conley et al., 2012).

It is worth noting that all of the estimates are negative in Table 6 and for all negative values, the standard errors get farther away from including zero in the 95% confidence set. Table A.17 shows how much larger the mean and variance of the exclusion violation would have to be for 0 to be included in the 95% confidence set. The mean would have to be 0.161 which is 2.68 times larger than 0.06 and of the opposite sign. In conclusion, allowing for mild violations of exclusion,

[60]This method is found throughout the literature (Dincecco and Prado, 2012; Nunn and Wantchekon, 2011; Angrist et al., 2010; McArthur and McCord, 2017).

[61]We use the normal distribution, in which the mean is -0.06. For the variance of the distribution of priors, as advocated for by van Kippersluis and Rietveld (2018), we use the rule of thumb developed by Imbens and Rubin (2015) in which the normalized difference in a covariate between treatment and control groups in a regression setting should not exceed one-quarter (0.25). We set the variance to equal $((.125)(S_0^2 + S^2_{-0})^{.5})^2$, so that the normalized difference in direct effects between the zero first stage group and the full sample does not exceed one-quarter in 95% of cases (van Kippersluis and Rietveld, 2018).

Table 7: Estimates Allowing for Mild Violations of Exclusion

Panel A: No Uncertainty in the Prior			
	Pt. Estimate	Confidence Interval, 95%	
	Beta	Lower Bound	Upper Bound
Pirate Attacks	-6.61	-11.34	-1.88
Method			UCI
γ Upper Bound			-0.06
γ Lower Bound			-0.06

Panel B: Recommended Uncertainty in Prior			
	Pt. Estimate	Confidence Interval, 95%	
	Beta	Lower Bound	Upper Bound
Pirate Attacks	-4.56	-7.03	-2.10
Method			LTZ
γ Distribution			Normal
γ μ			-0.06
γ Ω			0.0004

Note: The table displays the second stage coefficient from 2SLS regressions. Ocean wind speed is used to instrument for pirate attacks in the first stage, then predicted pirate attacks is used to predict land conflict. The coefficient on predicted piracy is shown. In both panels, the estimates allow for mild violations of the strict exclusion restriction by incorporating a parameter, γ, that allows ocean wind to directly affect land conflict, not through piracy. Conley et al. (2012) shows that consistent estimates of the endogenous explanatory variable, piracy in this case, can be obtained in this manner in several ways. In Panel A, γ is fixed to -0.06, because that is the estimate in Panel D, column 3 of Table 6. The panel uses the union of confidence interval (UCI) method from Conley et al. (2012). In Panel B the local to zero (LTZ) method is used and a normal distribution assumed for γ. The mean of γ is -0.06 and the variance is 0.0004. The variance is 0.0004, because this value causes the normalized difference in direct effects between the zero-first-stage group (placebo countries) and the full sample (Somalia) to not exceed one-quarter in 95% of the cases (Imbens and Rubin, 2015). Intuitively, it takes the standard error from the reduced form estimates in column 1, Panel B of Table 3 and the standard error from Table 6, Panel D, column 3 as inputs. This is the suggested variance by van Kippersluis and Rietveld (2018).

in which we estimate how mild the violations are in countries with no piracy (i.e. have a zero first stage), does not overturn the results. We believe the exclusion restriction rests on strong empirical grounds.

5.3 Additional Consequences

Are there more specific consequences besides general violence? We examine this along two different dimensions. First, we look at how piracy affects institution-related conflict and, second, we look at how piracy affects fatalities and violence towards civilians. As shown in Figures 3e and 3f, ocean wind speed affects land conflict fatalities and institution-related conflict in much the same way as it does total conflict.

Panel A of Table 8 investigates the impact of pirate attacks on conflict events related to the quality of institutions.[62] 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 that weak institutions have caused conflict. Panel C finds that 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 that is bad for institutions.[63]

In Panel B of Table 8 the dependent variable is the number of land fatalities from all conflict events. The effect of piracy on land conflict fatalities is statistically significant at the 5% level. An additional pirate attack reduces land conflict fatalities by 9.11 ($\approx$ 1/3 of a standard deviation). Deterring piracy to facilitate commerce, as noted in Besley et al. (2015), harms Somalians. Section D uses this estimate (and estimates from Besley et al. (2015)) as an input to calculate the implied value of a statistical life for Somalians.

[62]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.

[63]The other institutional impacts we examine, presented in Appendix C, are the effect of piracy on inter-clan conflicts. There are some suggestive results that reducing piracy increases inter-clan conflict.

Table 8: 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: 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
A-R 95% Conf. Set			[-3.88, -0.40]
Obs. Where Y = 0			714
Panel B: All Fatalities			
Median Wind Speed	0.77**	-0.08***	
	(0.38)	(0.02)	
Pirate Attacks			-9.11**
			(4.62)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-22.08, -1.25]
Obs. Where Y = 0			589
Panel C: Violence Against Civilians Events			
Median Wind Speed	0.08*	-0.08***	
	(0.04)	(0.02)	
Pirate Attacks			-0.97*
			(0.54)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-2.44, -0.05]
Obs. Where Y = 0			673
Panel D: Fatalities During Violence Towards Civilians Events			
Median Wind Speed	0.11*	-0.08***	
	(0.06)	(0.02)	
Pirate Attacks			-1.28*
			(0.73)
Kleibergen-Paap F			16.00
A-R 95% Conf. Set			[-3.21, -0.03]
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 region X year X month fixed effects. Panel A uses institution-related conflict as the dependent variable. Panel A uses institution-related sub-events and event descriptions to identify institution-related conflict. Sub-events include: abduction/forced disappearance (transactions costs), 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". Panel B uses fatalities from any conflict event type, taken from the fatalities column in the ACLED data. Panel C uses only conflict events where the type was violence against civilians. Panel D uses the number of fatalities from violence against civilians events. All panels also show the corresponding AR 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

5.3.1 Violence Against Civilians

Fatalities and institution related conflict may only indirectly harm non-violent actors. To overcome this limitation, the effect of additional pirate attacks on violence against civilians is estimated. 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 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 raises 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 D shows an additional pirate attack reduces fatalities during violence against civilian events by 1.28. Thus, we conclude that reducing piracy increases civilian fatalities.

6 Conclusion

Ocean-borne trade is a major driver of economic progress, but pirates impede it. To reduce piracy and enable trade, the international response has been to provide security assistance that can protect international commerce. An unintended consequence of this support is that it reduces the opportunity costs of other nefarious activities for violent actors, such as land-based conflict. Land-based conflict is particularly concerning given the claims that prolonged conflict has severely damaged Somalian institutions (Ahmed, 2020).

We investigate how reducing piracy affects land conflict by using variation in piracy provided by ocean wind speed, which removes concerns of reverse causality from conflict to piracy. The main finding is that piracy reductions, due to ocean wind speed, increases land conflict. All empirical tests support the adequacy of the exclusion restriction and fewer pirate attacks increase the amount of conflict with pirate weapons, fatalities, and violence against civilians. Thus, anti-piracy operations may make shipping safer, but is not benign in that it violent actors still commit violent acts in another area which shifts the costs of violence. In Appendix D, we calculate the approximate costs and benefits of anti-piracy. We find saving money for shipping companies via anti-piracy operations leads to additional Somalian fatalities and implies the value of a Somalian life is $607,836.

Typically, the main limitations of instrumental variable estimates pertain to their applicability for a sub-population of compliers or the validity of the exclusion restriction assumption. With regards to the exclusion restriction in this paper, we have shown that the results hold for mild violations of exclusion. Even allowing ocean wind speed to have a direct effect on land conflict, there is still a statistically significant and economically meaningful effect of pirate attacks on land conflict. Despite generic critiques of weather as an excludable instrument, the adequacy of the exclusion restriction is empirically supported in this application.

With regards to the estimated effects only being valid for a sub-population (i.e. a local average treatment effect), it is unlikely that an average treatment effect of piracy deterrence on conflict can be recovered in an RCT setting, as it would be unethical and impractical to randomly assign naval law enforcement or piracy. Therefore, examining the effect of piracy on land conflict using observational data is the next best option. Observational data has its limitations, though, such as a small number of clusters, which explains why statistical significance is not obtainable under certain assumptions about the standard errors. Limited, imperfect observational data forces the trade-off between the assumptions required for causal inference and statistical assumptions about how the standard errors are best calculated.

While providing warships to reduce piracy has financial costs for the provider, this research reveals an additional cost of this policy for Somalians. Providing security assistance to reduce piracy has the unintended consequence of increasing conflict and conflict fatalities on land in Somalia. Thus, while the primary benefactor from using warships for anti-piracy operations are the shipping companies, this benefit comes at the cost of increased Somalian deaths and conflict, which has been an obstacle in the way of establishing reliable institutions in Somalia.

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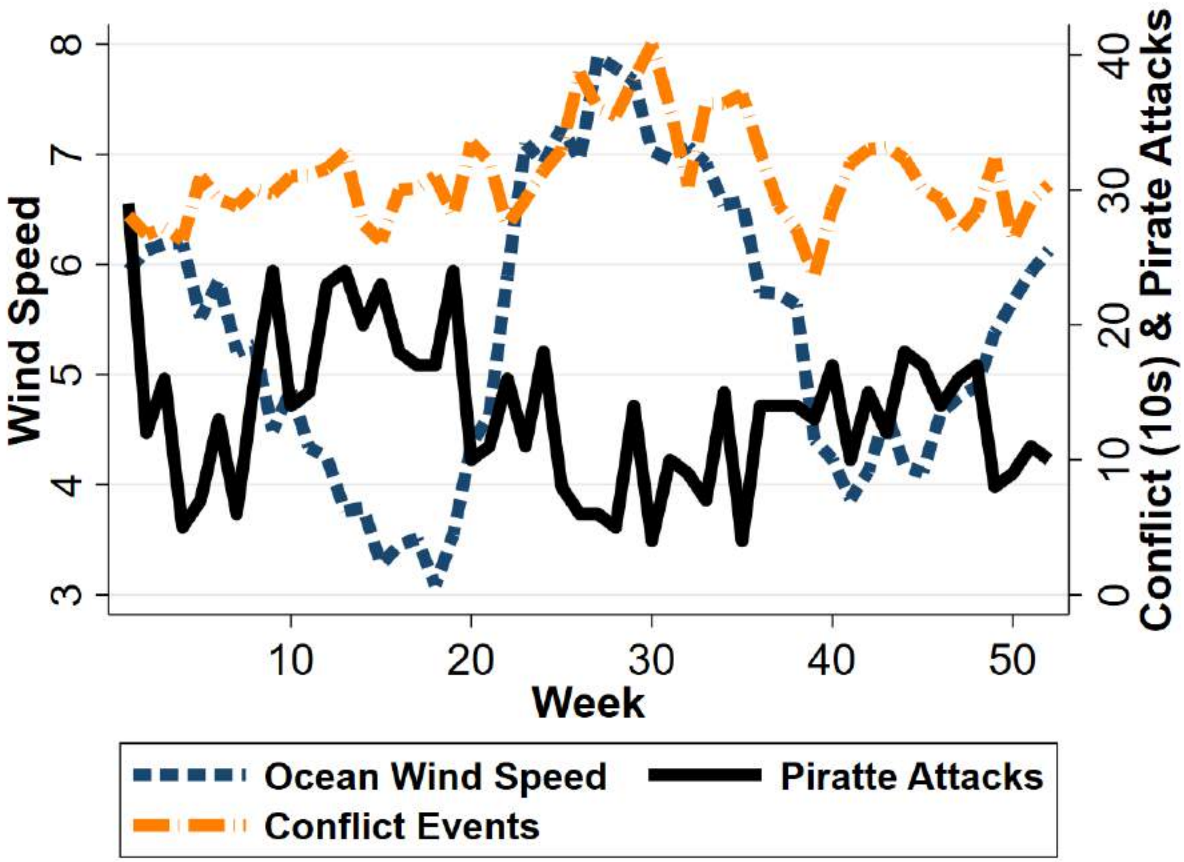
A Additional Tables and Figures

Table A.1: Naive Regressions Accounting for Count Dependent Variable and Missing Wind

Panel A: Aggregate Somalia, Missing Wind	(1)	(2)	(3)
Pirate Attack	-2.91***	0.76***	1.51***
	(0.30)	(0.28)	(0.30)
Observations	509	509	509
Year FEs	-	X	-
Month FEs	-	X	-
MonthXYear FEs	-	-	X
Panel B: Aggregate Somalia, Poisson	(1)	(2)	(3)
Pirate Attack	-0.12***	0.04***	0.08***
	(0.01)	(0.01)	(0.01)
Observations	516	516	516
Year FEs	-	X	-
Month FEs	-	X	-
MonthXYear FEs	-	-	X
Panel C: 3 Region Somalia, No Missing Wind	(1)	(2)	(3)
Pirate Attack	-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 D: 3 Region Somalia, Poisson	(1)	(2)	(3)
Pirate Attack	-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. The table displays regressions of land conflict events on pirate attacks. Panels A and C estimates the regressions by OLS and Panels B and D use Poisson regressions. In Panel A, Somalia is not disaggregated into constituent regions and missing wind observations are dropped. In Panel B, Somalia is not disaggregated. In Panel C, Somalia is disaggregated and missing wind observations are dropped. In Panel D, Somalia is disaggregated.

Figure A.1: Weekly Wind Speed, Pirate Attacks, and Land Conflict



Note: N= 1519. Time frame is 2008-2016. Conflict events and pirate attacks are totals within weeks. Conflict events are a long dash with a small dot between dashes. Pirate attacks are a solid line. Ocean wind speeds' median is used. Ocean wind speed is a dashed line. Monsoon season defined according to Shortland and Vothknecht (2011). Conflict is in 10s. The equivalent monthly-level is shown in Figure 2.

Table A.2: 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 sub-clan 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.

Note: Data comes from ACLED event description and IMB piracy event descriptions.

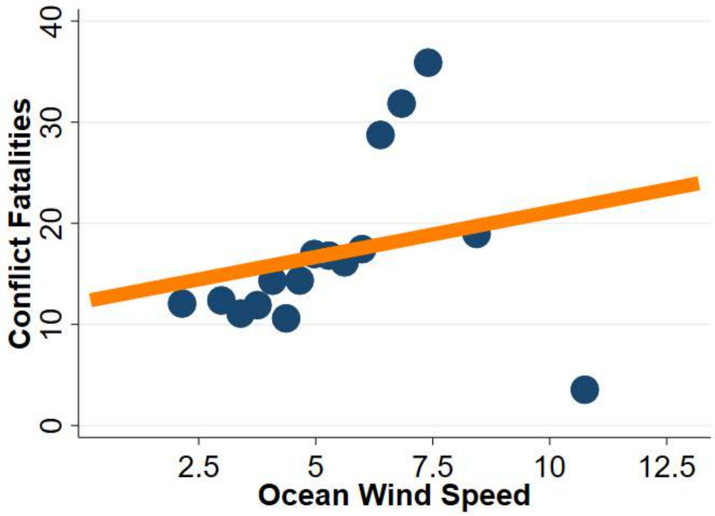
Table A.3: Wind Statistics By Month

	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

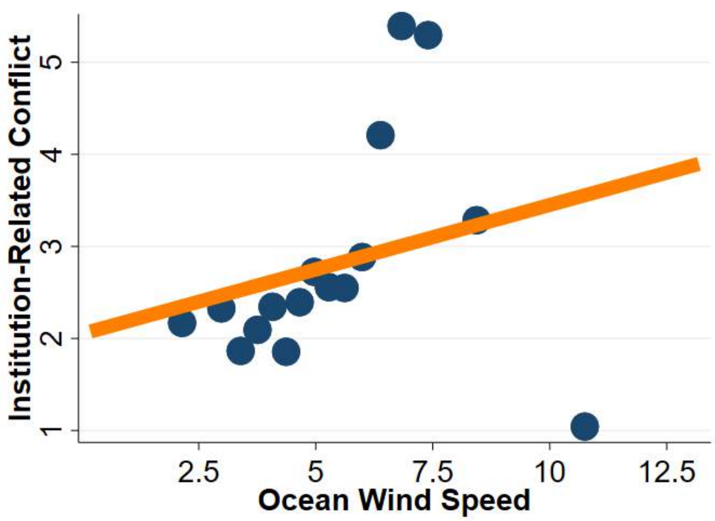
Notes: Table shows descriptive statistics of ocean wind speed for each month over the length of the estimating sample.

Figure A.2: Binned Scatter Plots of Ocean Wind Speed on Conflict Fatalities and Institutional Conflict Without Fixed Effects

(a): Ocean Wind and Conflict Fatalities

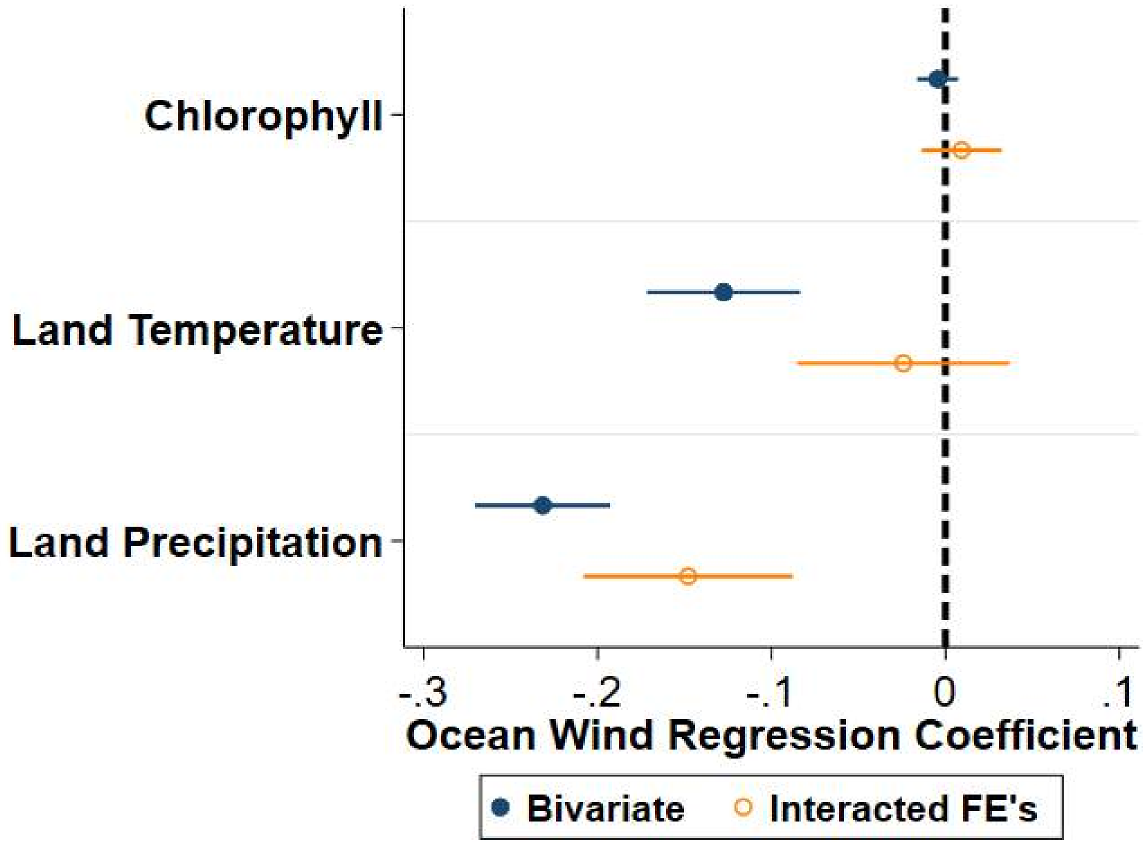


(b): Ocean Wind and Institutional Conflict



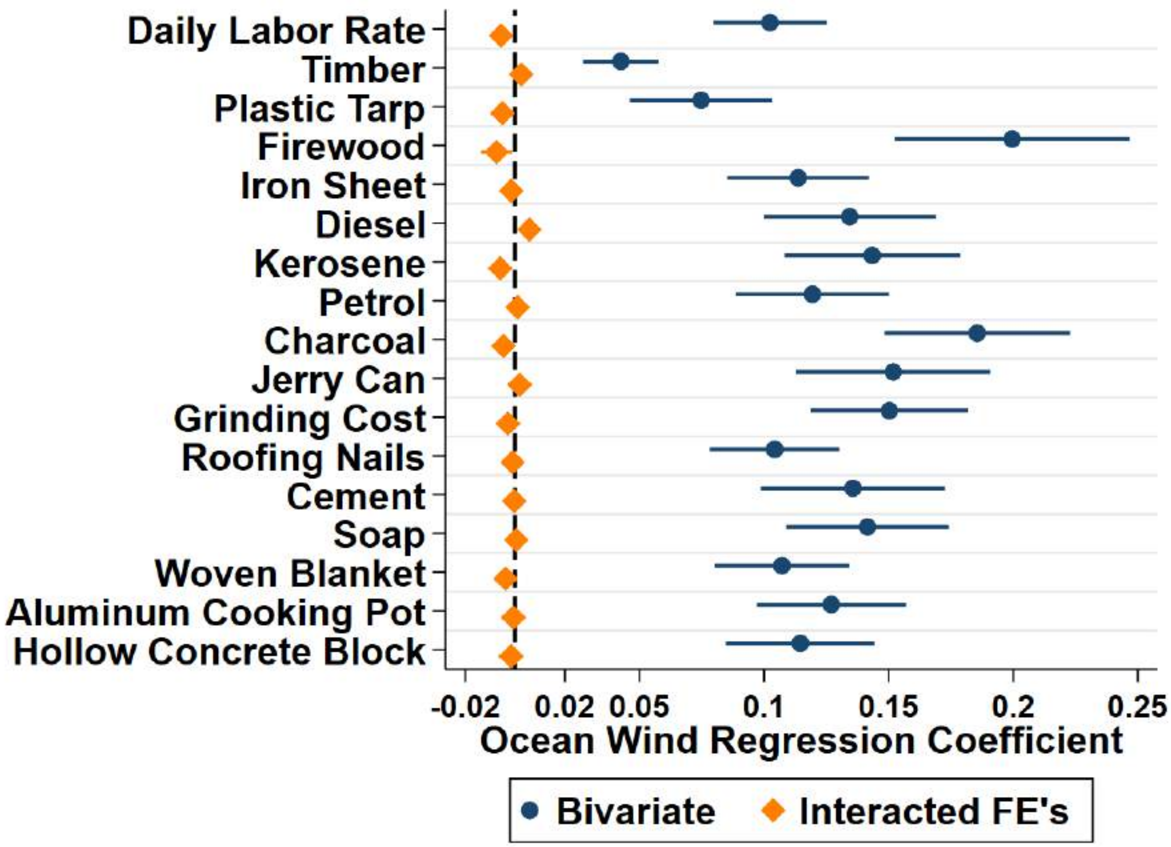
Note: Y-axis scales differ. All figures show dependent variables conditional on ocean wind speed. Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Equal number of observations in each bin. No fixed effects are used in either subfigure. In (a) the dependent variable is land conflict fatalities and in (b) the dependent variable is institutional conflict. Institution-related conflict includes the sub-events: 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 used to identify institutional conflict are: checkpoint, toll, tax, ngo, official, roadblock.

Figure A.3: How Ocean Wind Speed is Related to Other Relevant Weather



Note: The plot shows regression coefficients on the independent variable of ocean wind speed. The dependent variables are listed on the left. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from regressions using interacted region, year, and month fixed effects. n= 1428 for chlorophyll. n=1516 for land temperature. and Panel C.

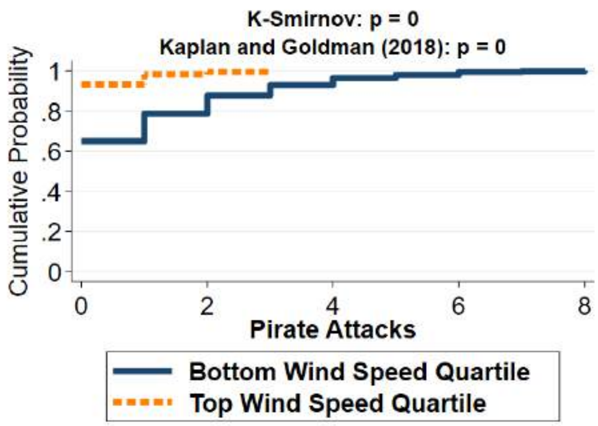
Figure A.4: Non-Agriculture Goods Prices Correlation with Ocean Wind Speed



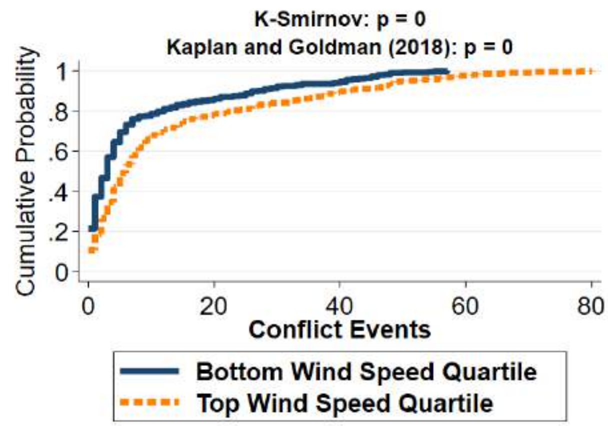
Note: The plots shows regression coefficients on the independent variable of ocean wind speed. The dependent variables are listed on the left, they are logged to facilitate visual interpretation. They are the log of the median price of agriculture within a given region. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from regressions using interacted region and year fixed effects. Agriculture prices are only available at the monthly level, so n=300. The prices are at the "sub-region" (n=18) level, so to aggregate to a single price across multiple subregions within the region (n=3), we take the median in each month.

Figure A.5: Cumulative Distributions of Variables by Top and Bottom Ocean Wind Speed Quartiles

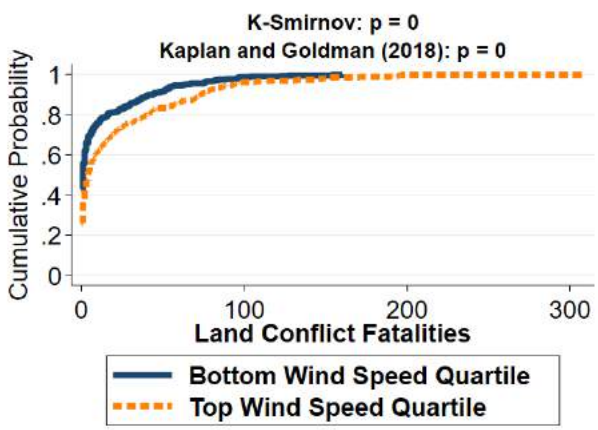
(a): Cumulative Distributions of Pirate Attacks



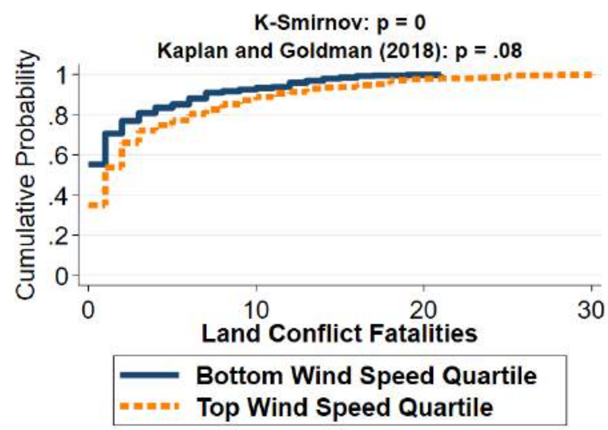
(b): Cumulative Distributions of Conflict Events



(c): Cumulative Distributions of Land Conflict Fatalities



(d): Cumulative Distributions of Institution-Related Land Conflict



Note: Distributions of pirate attacks and land conflict events by ocean wind speed. In (a)-(d) the Kolmgorov-Smirnoff (K-S) tests reject equality of distributions with a p-value < 0.000. In (a)-(c), the Goldman and Kaplan (2018) tests reject (global) equality of distributions with a p-value < 0.000. In (d) the Goldman and Kaplan (2018) tests reject (global) equality of distribution with a p-value $< .08$.

Table A.4: Monthly 2SLS Estimates of Piracy on Land Conflict With No Covariates

	(1)	(2)	(3)
	Reduced Form	First Stage	Second Stage
Dep Var.	Conflict Events	Pirate Attacks	Conflict Events
Panel A: Monthly, No Covariates			
Median Wind Speed	1.26**	-0.53***	
	(0.61)	(0.08)	
Pirate Attacks			-2.40**
			(1.14)
Observations	300	300	300
Kleibergen-Paap F			40.06
A-R 95% Confidence Set			[-4.98204,-.270158]
A-R P-Value			0.0307
RegionXYearXMonth FEs			No
RegionXYear FEs			Yes

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. All panels show the corresponding AR 95% confidence sets for the IV estimate (Anderson et al., 1949), which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

Table A.5: 2SLS Estimates of Piracy on Land Conflict, Alternative Specifications

	(1)	(2)	(3)
Dep Var.	Reduced Form Conflict Events	First Stage Pirate Attacks	Second Stage Conflict Events
Panel A: 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
A-R 95% Conf. Set			[-6.05048,-.602444]
A-R P-Value			0.0135
Panel B: Region X Year, 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
A-R 95% Conf. Set			[-5.24556,-.753816]
A-R P-Value			0.00634

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. In Panel A, region, year, and month fixed effects are included. In Panel B, region X 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. All panels show the corresponding AR 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

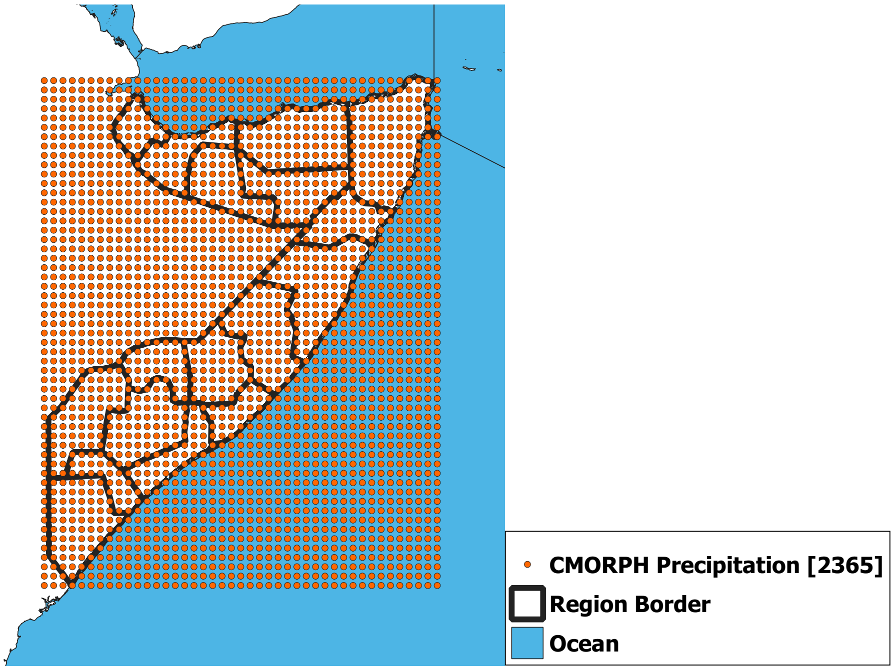
Table A.6: 2SLS Estimates, 1 Geographic Unit

Dep Var: Panel A: Single Independent Variable	(1) Reduced Form Conflict Events	(2) First Stage Pirate Attacks	(3) Second Stage Conflict Events
Median Wind Speed	1.64*** (0.52)	-0.25*** (0.05)	
Pirate Attacks			-6.51*** (2.28)
Observations	509	509	509
Kleibergen-Paap F			23.24
A-R 95% Conf. Set			[-12.3615,-2.45113]
A-R P-Value			0.00225
Panel B: Year FE's			
Median Wind Speed	1.10*** (0.38)	-0.21*** (0.05)	
Pirate Attacks			-5.16** (2.32)
Observations	509	509	509
Kleibergen-Paap F			21.73
A-R 95% Conf. Set			[-11.8469,-1.58032]
A-R P-Value			0.00490
Panel C: Year FE's, Quarter FE's			
Median Wind Speed	1.58*** (0.43)	-0.17*** (0.05)	
Pirate Attacks			-9.17** (4.16)
Observations	509	509	509
Kleibergen-Paap F			10.16
A-R 95% Conf. Set			[... ,-3.41411]
A-R P-Value			0.000449
Panel D: Year, Month FE's			
Median Wind Speed	1.88** (0.74)	-0.12 (0.08)	
Pirate Attacks			-15.94 (13.79)
Observations	509	509	509
Kleibergen-Paap F			1.966
A-R 95% Conf. Set			[... ,-3.38283]
A-R P-Value			0.0102

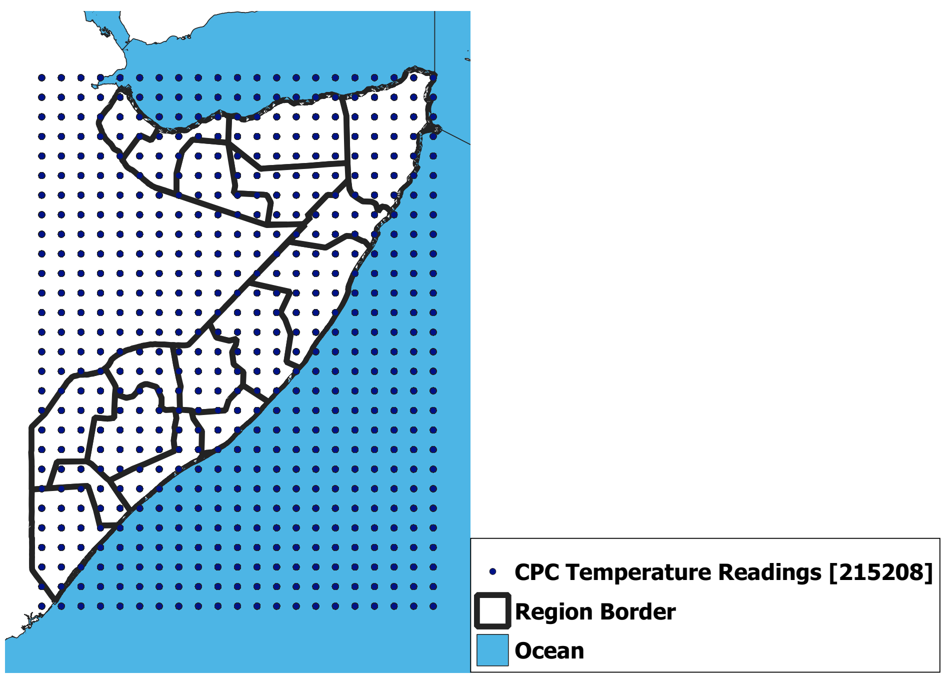
Note: * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. The table displays 2SLS regressions of pirate attacks on land conflict events, using ocean wind speed as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. The primary difference is that the unit of analysis is a week in Somalia without any spatial disaggregation. In Panel A, no fixed effects are included. In Panel B, year fixed effects are included. In Panel C, year and quarter (1-4) fixed effects are included. In Panel D, year and month fixed effects are included. All panels show the corresponding AR 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) and Lee et al. (2022) for just-identified structural equations.

Figure A.6: Spatial Resolution of Meteorological Variables

(a): CMORPH Precipitation



(b): CPC Temperature



Note: Figures show the spatial resolution of precipitation (a) (NOAA, 2021b) and temperature (NOAA, 2021a) readings (b). Points outside of Somalia (e.g. in Ethiopia, Eritrea, or a body of water) are dropped from the analysis. Precipitation is 1 day and temperature is 1 year of points in the same spot, which explains the large difference in the count in the legends. Temperature is a total of 588 observations per day and precipitation is 2,365. For precipitation, about 2/3 of the points are not in Somalia, so are not used.

Table A.7: 2SLS Estimates, Meterological Covariates Included, No Other Fixed Effects

Dep. Var. Panel A: Both, No FE's	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Median Wind Speed	1.10***	-0.14***	
	(0.16)	(0.01)	
Precip. Mean	1.63***	-0.04***	1.35***
	(0.21)	(0.01)	(0.20)
Temp. Max. Mean	1.74***	-0.06***	1.27***
	(0.13)	(0.01)	(0.17)
Pirate Attacks			-8.11***
			(1.24)
Kleibergen-Paap F			118.9
A-R 95% Conf. Set			[-10.817,-5.89138]
A-R P-Value			9.76e-15

Note: n=1,516. * 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. The corresponding AR 95% confidence sets are shown for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

Table A.8: 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 3. 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 drops pirate-marine incidents which are coded in the ACLED data from the conflict dependent variable. Panel B reassigns disputed sub-regions.

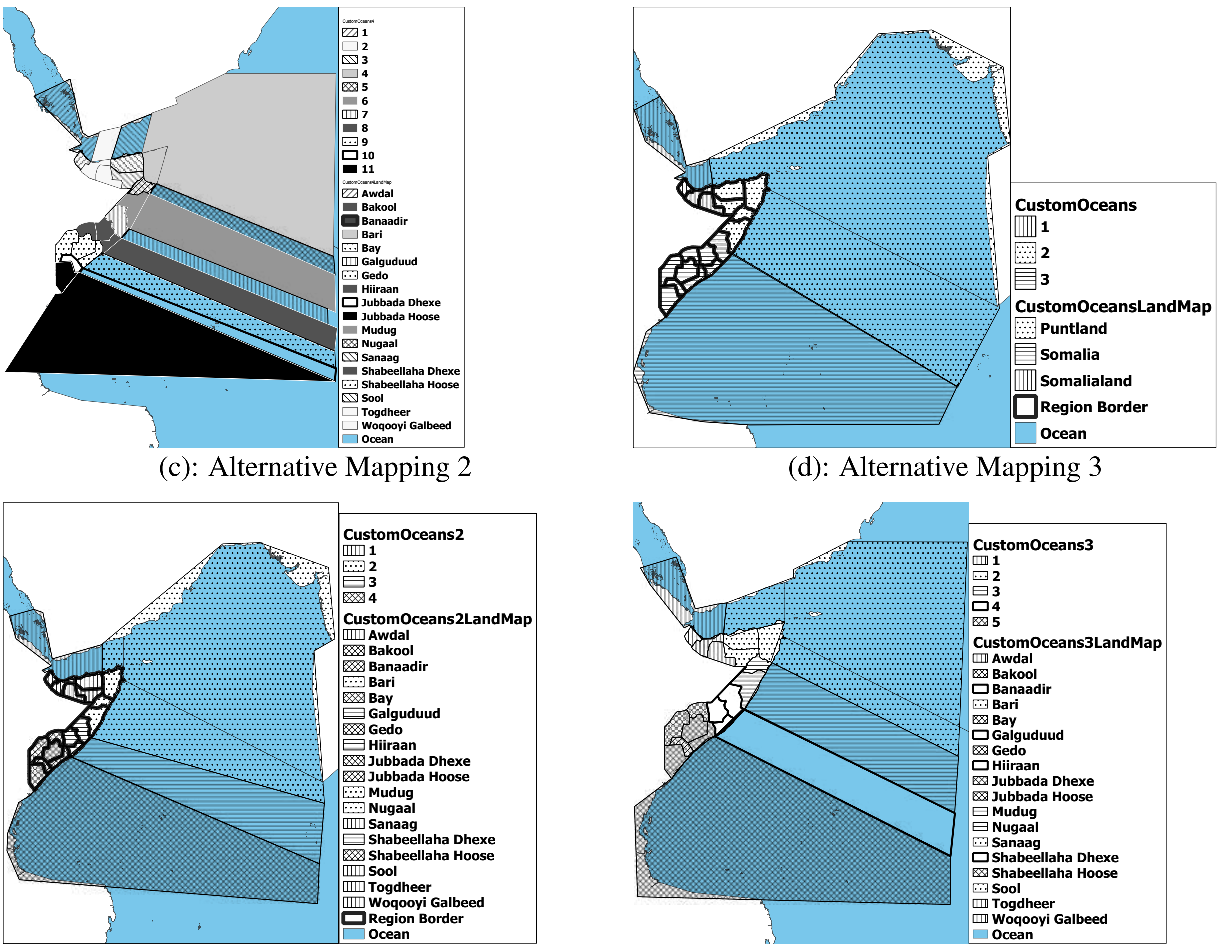
Table A.9: Excluding Land Conflict Events Closer To Coast

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

Figure A.7: All Alternative Mappings Considered

(a): Full Spatial Disaggregation (b): Alternative Mapping 1



(c): Alternative Mapping 2 (d): Alternative Mapping 3

Note: These are all the alternative land-ocean region pairings that are considered in regression analyses in Tables A.10 and A.11. Regressions for (a), which has 11 spatial units (basically the number of Somalian regions on the coast), are shown in Table A.10. A regression for (b), which has 3 spatial units like the preferred aggregation but are different because the ocean and regions "line up", is shown in Table A.11, Panel A. A regression for (c), which has 4 spatial units even though it comes at the cost of no longer being able to interpret the unit fixed effects as controlling for legal origins (Glaeser et al., 2004; Draper, 2009) as discussed in Section 3.2, is shown in Table A.11, Panel B. (d) which has 5 spatial units even though it comes at the cost of no longer being able to interpret the unit fixed effects as controlling for legal origins (Glaeser et al., 2004; Draper, 2009) as discussed in Section 3.2, is shown in Table A.11, Panel C.

Table A.10: 2SLS Estimates for Full Spatial Disaggregation

	(1)	(2)	(3)
	Reduced Form	First Stage	Second Stage
Dep Var.	Conflict Events	Pirate Attacks	Conflict Events
Panel A: Single Independent Variable			
Median Wind Speed	0.09***	-0.02***	
	(0.03)	(0.00)	
	[0.22]	[0.00]	
Pirate Attacks			-4.00***
			(1.55)
			[0.22]
Kleibergen-Paap F			27.99
A-R 95% Conf. Set			[-7.62537,-1.24295]
A-R P-Value			0.00594
Panel B: Region, Year, and Month FE's			
Median Wind Speed	0.06***	-0.02***	
	(0.02)	(0.01)	
	[0.03]	[0.07]	
Pirate Attacks			-2.79**
			(1.15)
			[0.01]
Kleibergen-Paap F			17.01
A-R 95% Conf. Set			[-6.00926,-.923787]
A-R P-Value			0.00336
Panel C: RegionXYearXMonth FE's			
Median Wind Speed	0.07***	-0.02***	
	(0.03)	(0.01)	
	[0.06]	[0.06]	
Pirate Attacks			-4.23**
			(1.99)
			[0.00]
Kleibergen-Paap F			7.496
A-R 95% Conf. Set			[... , -1.3105]
A-R P-Value			0.00282

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. The primary difference from Table 3 is that the unit of analysis is there are 11 regions as defined by Figure A.7a. In Panel A, no other variables or fixed effects are included, just ocean wind, pirate attacks, and land conflict. In Panel B, the fixed effects are region, year, and month uninteracted. In Panel C, the preferred region X year X month fixed effects are included. The corresponding AR 95% confidence sets are shown for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations. The wild cluster bootstrapped p-values are shown in brackets. Webb weights are used, because those are the same weights used in Table 3 even though there are more combinations of weight draws than replications with 11 clusters in this table. The Webb distribution is symmetric, like the Rademacher distribution, and both have performed better in Monte Carlo simulations in the sense of yielding tests of more accurate size. The distribution of coefficients are bootstrapped, rather than the z statistics, because Young (2022) presents evidence that bootstrapping the coefficient is more reliable in IV estimates. Furthermore, Wang (2021) presents theory and simulation evidence that the non-studentized test is favored when the instrument is weak (but strong in at least one cluster).

Table A.11: 2SLS Estimates, Alternative Mappings

Dep. Var.	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Panel A: Alternative Mapping 1			
Median Wind Speed	0.40**	-0.06***	
	(0.16)	(0.02)	
Pirate Attacks			-7.02*
			(3.71)
Observations	1502	1502	1502
Kleibergen-Paap F			6.570
A-R 95% Conf. Set			[-25.28562,-1.593995]
A-R P-Value			0.00922
Panel B: Alternative Mapping 2			
Median Wind Speed	0.32***	-0.06***	
	(0.12)	(0.02)	
Pirate Attacks			-5.28**
			(2.26)
Observations	2016	2016	2016
Kleibergen-Paap F			13.26
A-R 95% Conf. Set			[-12.28231,-1.616211]
A-R P-Value			0.00366
Panel C: Alternative Mapping 3			
Median Wind Speed	0.18**	-0.04***	
	(0.07)	(0.01)	
Pirate Attacks			-4.31**
			(2.15)
Observations	2510	2510	2510
Kleibergen-Paap F			10.77
A-R 95% Conf. Set			[-11.39679,-.8145409]
A-R P-Value			0.0146

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. All regressions include regionXyearXmonth interacted fixed effects. The primary difference from Table 3 is that there are different land-ocean region pairings as defined by Figure A.7. In Panel A, there are 3 spatial units (Figure A.7b). In Panel B, there are 4 spatial units (Figure A.7c). In Panel C, there are 5 spatial units (Figure A.7d). The corresponding AR 95% confidence sets are shown for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews and Stock (2018) and Lee et al. (2022) for just-identified structural equations.

Table A.12: 2SLS Wind Dummy Specifications

	(1) Reduced Form	(2) First Stage	(3) Second Stage
Dependent Variable:	Conflict	Pirate Attacks	Conflict
Panel A: 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 B: 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

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 dummies, for high or low 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, wind speed is transformed to a binary variable = 1 if wind ≥ 6. In Panel B, wind speed is transformed to a binary variable = 1 if wind ≤ 5.

Table A.13: 2SLS Log Conflict

Dependent Variable: Panel A: Log Conflict	(1) Reduced Form Ln(Conflict)	(2) First Stage Pirate Attacks	(3) Second Stage Ln(Conflict)
Median Wind Speed	0.05*** (0.02)	-0.07*** (0.02)	
Pirate Attacks			-0.83** (0.35)
Kleibergen-Paap F			13.66
Observations	1253	1253	1253

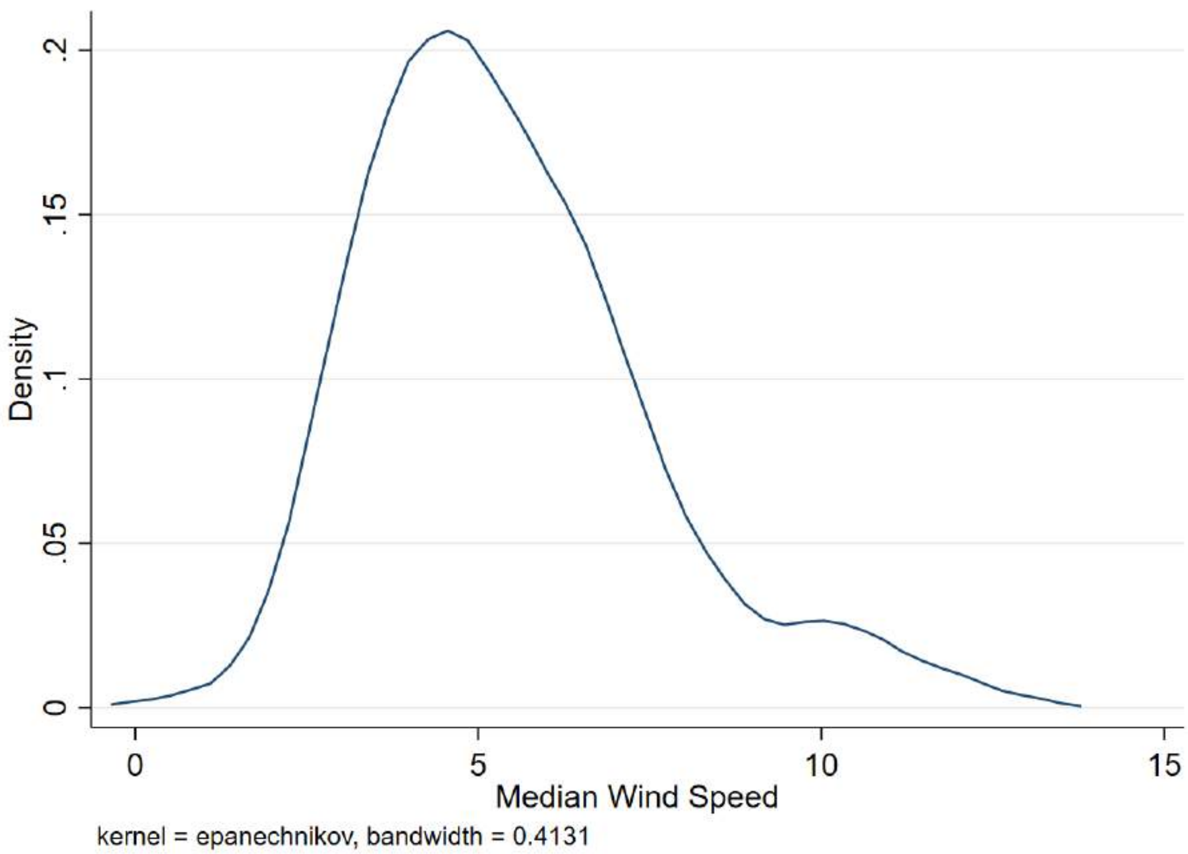
Note: * p<0.1, ** p<0.05, *** p<0.01. Heteroskedasticity robust standard errors in parentheses. The table displays 2SLS regressions of pirate attacks on land conflict events, using (sometimes transformed) ocean wind speed as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes year X quarter fixed effects and region fixed effects. Panels B-E include region X month X year interacted fixed effects. Panel A does not disaggregate into 3 regions, instead using all of Somalia. In Panel B, week of the year (1-52) fixed effects are included. In Panel C, the ocean wind speed measure is the mean of all wind in a certain ocean region in a given week. 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 (Bellemare and Wichman, 2020).

Table A.14: 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. General method of moments used, with a log link function. Second stage modeled as a Poisson count model. Multiplicative errors assumed. This is the approach advocated for by Mullahy (1997) and Angrist (2001). A similar empirical example can be seen in Dube and Vargas (2013).

Figure A.8: Distribution of Wind Speed



Note: Figure shows the distribution of ocean wind speeds.

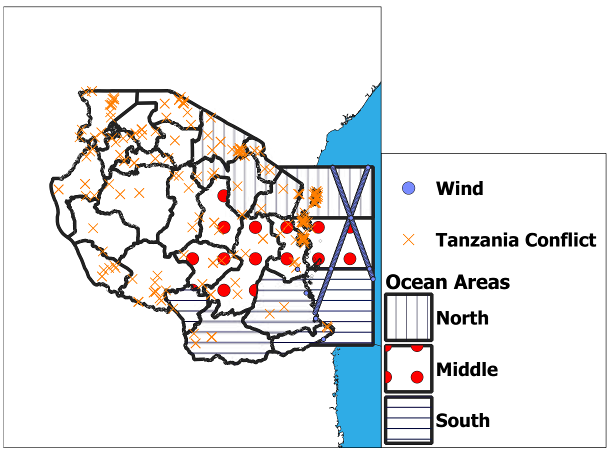
Table A.15: ACLED Event Hierarchy

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

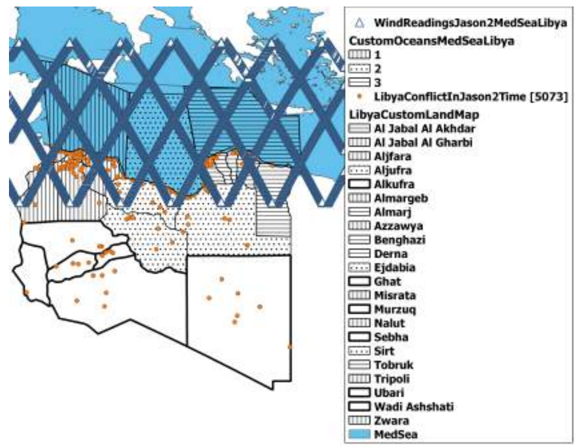
Note: Events hieracrchy comes from ACLED codebook.

Figure A.9: Placebo Countries

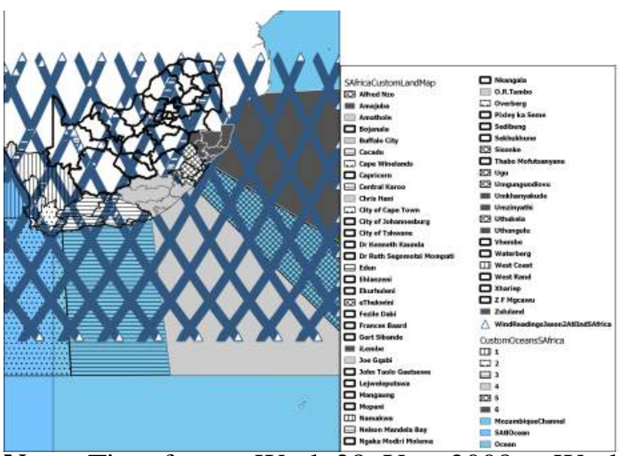
(a): Tanzania



(b): Libya

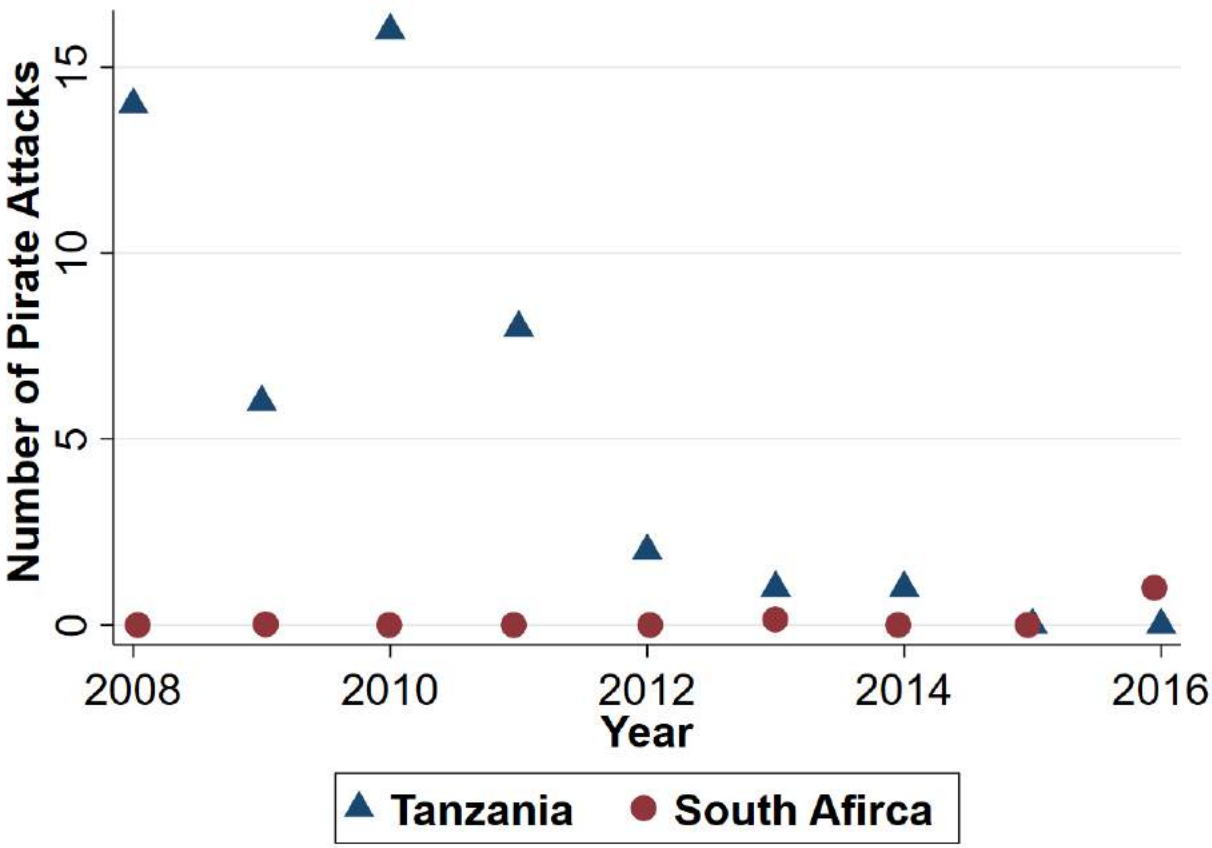


(c): South Africa



Note: Time frame: Week 28, Year 2008 to Week 40 Year 2016.

Figure A.10: Pirate Attacks By Countries Other than Somalia



Note: Attacks assigned to country that is closest by distance. There are no pirate attacks that are closest to Libya.

Table A.16: Country Level Estimates of Land Conflict on Ocean Wind Speed

	(1)	(2)	(3)
Panel A: Tanzania			
Median Wind Speed	-0.010	-0.004	-0.018*
	(0.009)	(0.008)	(0.010)
Observations	982	982	982
Region FE		X	
Year FE		X	
Month FE		X	
RegionXYearXMonth FE			X
Panel B: Libya			
Median Wind Speed	-0.002	-0.053	-0.091*
	(0.056)	(0.052)	(0.049)
Observations	1468	1468	1468
Region FE		X	
Year FE		X	
Month FE		X	
RegionXYearXMonth FE			X
Panel C: South Africa			
Median Wind Speed	0.109***	-0.027	-0.057***
	(0.018)	(0.017)	(0.018)
Observations	3004	3004	3004
Region FE		X	
Year FE		X	
Month FE		X	
RegionXYearXMonth FE			X

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Heteroskedasticity robust standard errors in parentheses. The table displays OLS regressions of ocean wind speed on total land conflict events in countries with no piracy. Panel A uses 3 regions of data from Tanzania, Panel B uses 3 regions of data from Libya, Panel C uses 6 regions of data from South Africa.

Table A.17: The Size of Parameters About Prior For Severity of Exclusion Violation So Confidence Interval Includes Zero

Panel A: Changing Mean of γ			
	Pt. Estimate	Confidence Interval, 95%	
	Beta	Lower Bound	Upper Bound
Pirate Attacks	-2.77	-5.53	0.00
Method			LTZ
γ Distribution			Normal
γ μ			.16068
γ Ω			0

Panel B: Changing Variance of γ			
	Pt. Estimate	Confidence Interval, 95%	
	Beta	Lower Bound	Upper Bound
Pirate Attacks	-4.56	-9.13	0.00
Method			LTZ
γ Distribution			Normal
γ μ			-0.06
γ Ω			.05175

Note: The table displays the second stage coefficient from 2SLS regressions. Ocean wind speed is used to instrument for pirate attacks in the first stage, then predicted pirate attacks is used to predict land conflict. The coefficient on predicted piracy is shown. In both panels, the estimates allow for mild violations of the strict exclusion restriction by incorporating a parameter, γ, that allows ocean wind to directly affect land conflict, not through piracy. Conley et al. (2012) shows that consistent estimates of the endogenous explanatory variable, piracy in this case, can be obtained in this manner in several ways. In Panel A, the local to zero (LTZ) method is used with a normal distribution around the prior for the severity of the exclusion violation. γ is fixed to 0.16068, because that is the parameter value required (for the mean of γ, assuming 0 variance) for the 95% confidence interval for the piracy coefficient to include 0. In Panel B the local to zero method is used and a normal distribution assumed for γ. The mean of γ is -0.06 and the variance is 0.05175. The variance is set to this value, because this is approximately how large the variance must be for the 95% confidence interval for the piracy coefficient to include 0.

B Ocean Wind Speed, Piracy Business, and Rational Pirates

To identify the causal effect of piracy deterrence, the research design leverages quasi-random deterrence due to ocean wind speed. Wind is connected to two basic economic frameworks to derive testable predictions. Both models illustrate how high ocean wind speeds make piracy less attractive at the margin.

Supply of Piracy 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 (a small wooden "skiff") commonly used in Somalian piracy.[64] 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. 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.

B.1 Rational Pirates

This extends the theory of rational criminals (Becker, 1968) to pirates. 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 that have relatively higher returns. High ocean wind speed reduces the attractiveness of piracy, like naval warships, displacing violent individuals onto land (Axe, 2009).

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

$Other\ Activities$ 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, although Somalian nationals pursuing piracy implies the return is higher at sea compared to land activities. Someone willing to shoot, abduct, and loot at sea is likely to be willing to engage in violent behavior on land.[65] Table A.2 shows examples from the data demonstrating how pirates hijack on land (row 1) and at sea (row 2) 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 land conflict through piracy. 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:[66]

$$U = m_P + m_O.$$

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:

$$T = t_p + t_o.$$

The expected wage rate, $E[W_P]$, depends on the probability of boarding, $\rho \in$ (0,1), the loot on board, L, and the expected ransom money from holding hostages, R,[67]

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

[66] 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.

[67] 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.

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

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 $\overline{E[W_P]}$,

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

This occurs because the probability of boarding in calm conditions, ρ_c, is greater than the probability of boarding in windy conditions, ρ_h Existing studies suggest ρ = 0 if wind speed exceeds 9 m/s (Cook and 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 toward other activities as the marginal benefits of piracy are reduced by high wind speed.

In essence, higher wind speeds and naval warships are substitute forms of deterrence for piracy. Both high wind speeds and naval patrols make piracy less attractive at the margin. While one might be concerned that navies can have an incapacitation effect, such an effect is negligible because international maritime law makes it difficult to prosecute pirates and it is costly for nations.

C Clan Related Conflict

Panels A-D of Table C.1 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 C.1 uses wind speed > 6 as the instrument. In Panel B, the reduced form effect in column 1 is larger and statistically significant above 95% confidence. Correspondingly, the second stage effect is statistically significant above 95% and a larger magnitude.

Panel C of Table C.1 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 C.1 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 C.1 investigates conclusions of Panels A-D of Table C.1 by showing reduced form binned scatter plots with and without fixed effects.[68] Figure C.1a 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 reducing conflict. When fixed effects are added in Figure C.1c, monsoon winds are a bad leverage point again causing the slope to flatten.[69] Figure C.1b 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 C.1d. Despite the inclusion of fixed effects causing points to be more dispersed (greater error), clan-related conflict still increases with wind speed.

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

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

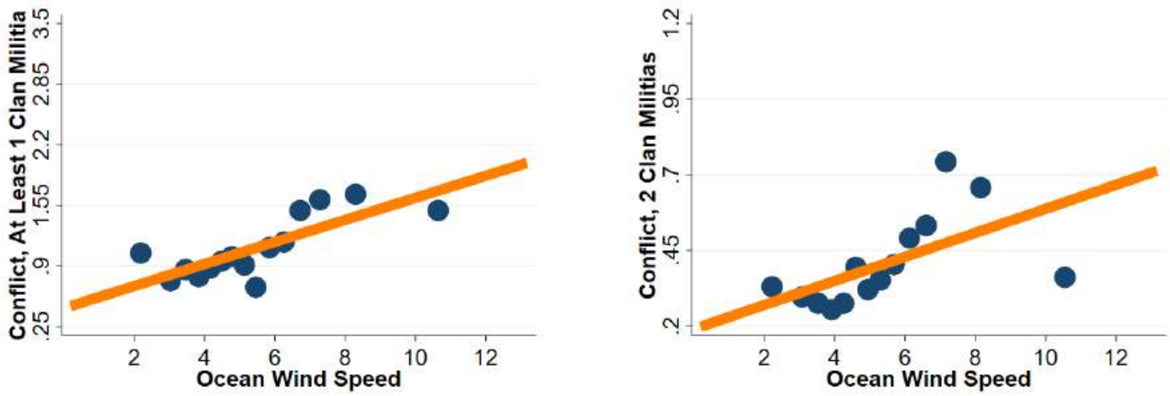
Table C.1: 2SLS Estimates of Pirate Attacks on Institution-Related Conflict

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

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. In Panel A and B the dependent variable is conflict events that are coded as conflict with at least 1 communal militia (the most likely actor to represent a clan-related actor). In Panel C and D the dependent variable is conflict events between 2 communal militias (the most likely actors to represent clan disputes). Panels A and C use a linear measure of ocean wind speed. Panels B and D use a dummy variable for whether wind is above 6 as the instrument.

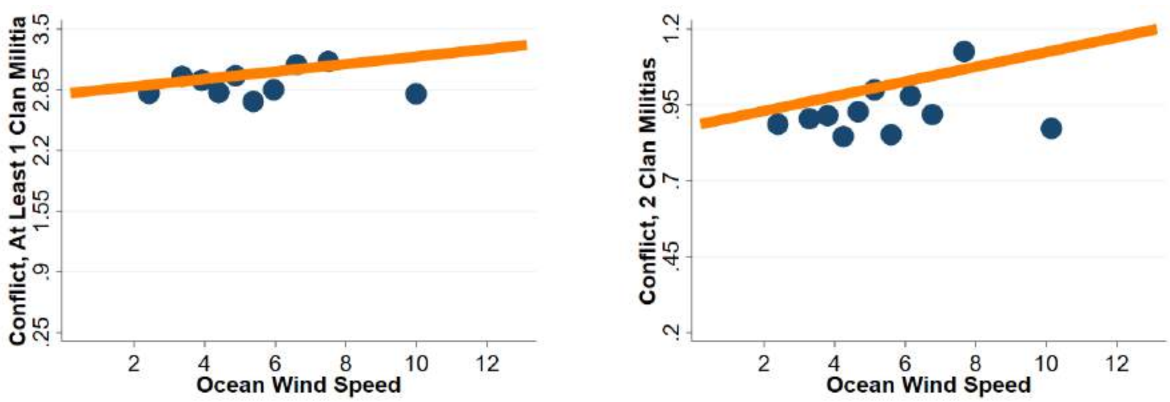
Figure C.1: Reduced Form Effect of Wind Speed on Clan-Related Conflict

(a): At Least 1 Communal Militia, No Fixed Effects (b): Only 2 Communal Militias, No Fixed Effects



(c): At Least 1 Communal Militia, Region-by-Year-by-Month Fixed Effects

(d): Only 2 Communal Militias, Region-by-Year-by-Month Fixed Effects



Note: Procedure selects number of bins to optimize a bias-variance tradeoff in the asymptotic integrated mean square error (IMSE) (Cattaneo et al., 2019). Equal number of observations in each bin. For (a) and (c) the y-axis shows the average number of conflict that includes at least 1 communal militia (the most likely actor for clans) as an actor, conditional on ocean wind speed. For (b) and (d) the y-axis shows the average number of conflict that includes at 2 communal militias (representing clan disputes) as an actor, conditional on ocean wind speed. Panels A and B are "cannonical" binned scatter plots (Cattaneo et al., 2019) and Panels C and D include regionXyearXmonth interacted fixed effects.

D 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 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:

$$C_{Gulf\ of\ Aden,\ Lower\ Rate\ Increase} = 0.476 * 0.0005 * 30.3 * 646,064,000.^{70} \tag{5}$$

Thus, preventing 1 pirate attack benefits shipping companies by saving them \$5,537,390. This

[70] 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.

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 (Viscusi and Aldy, 2003; Gonzalez, 2020). 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 (e.g. to taxpayers supporting naval warships) (Oceans Beyond Piracy, 2010) , leaving out this relevant negative safety externality.

D.1 Assuming Higher Piracy Costs to Shipping

Equation 5 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 (Viscusi and Aldy, 2003; Gonzalez, 2020), this is still only approximately 14.59% of the value of a US life.

Table D.1: Implied Value of Somalian Life

Panel A: Coefficient Estimates	
Fatalities due to Stopping 1 Pirate Attack	9.11
Panel B: Shipping Rate Increase (Besley et al, 2015)	
Higher Bound	8.2
Lower Bound	12.3
Panel C: Attacks by Period	
Pre-Period (September 2005- April 2008)	44
Post-Period (May 2008-December 2010)	181
Increase in Attacks	137
Panel D: Percent Rate Increase due to 1 Attacks	
Higher Bound	0.0599
Lower Bound	0.0898
Panel E: Additional Cost Inputs (Besley et. al, 2015)	
Total Cargo (DWT)	$ 646,064,000.00
Transit and Loading Time (days)	30.3
Charter Rate (Gulf of Aden, DWT/Day)	0.4726
Panel F: Cost of 1 Pirate Attack	
Gulf of Aden, Low Rate	$ 5,537,390.78
Gulf of Aden and Indian Ocean, High Rate	$ 13,291,703.92
Panel G: Implied Value of Somalian Life	
Lowest Cost of Piracy	$ 607,836.53
Highest Cost of Piracy	$ 1,459,023.48

Note: Table summarizes the inputs for calculating the value of a statistical life implied by the trade benefits and life costs from stopping piracy.