Piracy Deterrence and Violence Displacement in Somalia

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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 piracy deterrence are reduced opportunity costs of violence on land. This paper examines how deterring pirates 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 18-30% 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, Institutions, Conflict, Displacement, Development

JEL Classification: K42, H41, O10

[1]We thank seminar participants at WVU Brown Bag 2020 and the Computational Justice Lab 2020.

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

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

1 Introduction

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

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

This paper evaluates how international efforts to deter piracy off the coast of Somalia affects land conflict in Somalia. While it is clear that deterrence of piracy benefits shipping companies and the globalization of markets, security assistance may have positive or negative unintended consequences for vulnerable Somalians. Economic theories of deterrence (Polinsky and Shavell, 1979) suggest that reducing the benefits of piracy will cause these violent actors to displace their violence, potentially on land. Contrasting theoretical predictions, empirical work has found that piracy is used to fund land-based conflict (Daxecker and Prins, 2017). This paper sheds new light on whether land conflict and piracy are substitutes or complements. Understanding how piracy deterrence affects land conflict is of first order concern with respect to the strength of Somalian institutions (Ahmed, 2020) and development (Acemoglu et al., 2005b). Furthermore, poor institutions beget piracy making it crucial to choose appropriate research designs that can separate the endogeneity of piracy from causal effects of piracy.[2]

Our approach exploits quasi-random variation in piracy deterrence due to ocean wind speed, collected from remote sensors on the Jason-2 satellite, using two stage least squares. The negative association between Somali piracy and ocean wind speed is clearly documented (Cook and Garrett, 2013; Besley et al., 2015). Furthermore, ocean wind speed helps circumvent two primary concerns in assessing the effects of deterring piracy. First, there is a strongly held belief that causality runs from land conflict to piracy. Second, naval warships are non-randomly assigned. Indeed, they are assigned to piracy-prone areas that are also located where development assistance is targeted and conflict is more likely. The endogenous assignment of warships makes a direct analysis of piracy deterrence from warships unlikely to yield informative causal estimates. While naval warships and ocean wind speeds are not identical mechanisms for deterring piracy activities, both raise the costs of piracy, resulting in deterrence.[3]

We find that an additional pirate attacks reduces total politically-motivated, armed land conflict by 5.94 events, or about 27%. This result stands in contrast to the naïve OLS results, in which pirate attacks increase land conflict events under some combinations of fixed effects. 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.

The instrument, ocean wind speed, passes the required diagnostics to be relevant and excludable. The first stage F-statistic for instrument strength never falls below the suggested Stock-Yogo

[2]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).

[3]There are no incapacitation effects of wind. However, there are also very little incapacitation effects due to 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 that incapacitation effects of warships are negligible. Often, navies respond solely with maritime aircraft such as helicopters, making capture impossible.

rule of thumb for minimal bias, which supports it being highly relevant for predicting piracy. To ensure appropriate inference in the presence of a potentially weak instrument (Lee et al., 2020), Anderson-Rubin (AR) confidence sets (Anderson et al., 1949) are reported. These are efficient for potentially weak instruments (Andrews and Stock, 2018) which means statistical significance is not due to a weak instrument. The results are typically more statistically significant with weak-instrument robust inference provided by AR confidence sets. Furthermore, results suggest that ocean wind speed is adequately excludable, because peaceful protests are not correlated with ocean wind speed and the results are not sensitive to mild violations of exclusion (Conley et al., 2012).

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, deterring 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 estimates for African individuals (León and Miguel, 2017).

Our results, that piracy and land-based conflict are substitutes, stand in contrast to Daxecker and Prins (2017). The primary difference between our work is that we go beyond simply including fixed effects as an identification strategy for estimating the causal effects of piracy, which is especially important given that reverse causality is 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. Moreover, our results are consistent with economic theory (Becker, 1968; Polinsky and Shavell, 1979), other criminal geographic displacement results in economics (Dell, 2015), and are based on a quasi-natural experiment (Angrist and Pischke, 2010; Dell et al., 2014).

It is not surprising that aid has been provided to address populations engaging in activities detrimental to global commerce. Foreign aid falls into three categories: humanitarian, development (economic, social, or political), and security assistance (Ingram, 2019). Research has found that foreign aid produces positive results. This work notes that assistance programs promote national economic progress and stability (Ingram, 2019) and increases growth (Clemens et al., 2011; Civelli et al., 2018). Other work finds that food (Nunn and Qian, 2014) and foreign aid shocks (Nielsen et al., 2011; Crost et al., 2014) cause conflict, development assistance causes Dutch Disease (Rajan and Subramanian, 2011), and political assistance worsens governance (Bräutigam and Knack, 2004).[4] We add to the research on foreign aid, finding that it has another negative outcome in the form of increased conflict and weakened institutions.

Security assistance, the most fitting categorization for international warship patrols, reduces economic growth (Bove and Elia, 2018). Other findings suggest security assistance is an important complement to development assistance (Berman et al., 2011). In addition to not promoting economic progress, security assistance could have unintended consequences. Security crack downs in regions impacting global commerce could geographically displace violent individuals (Dell, 2015). We add to the debate on security assistance, in particular, by showing another area in which security crackdowns lead to geographic displacement of violent individuals. 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

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

authoritarian, often exacerbating clan rivalries.[5] 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).[6] 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.[7]

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).[8] 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.[9] 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).

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

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

[7] 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.

[8] 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.

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

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.

2.2 Piracy

Previous research has attempted to understand the organization of piracy enterprises (Leeson, 2007a). It is unclear how these efforts contribute to reducing piracy or aiding those adversely affected. It is understood that Somalian pirate crews typically consist of three main actors: the muscle (which are often strongmen from Siad Barre's government), the financiers (warlords), and local fishermen who have knowledge of the waterways (Hunter, 2008). A fourth actor is typically some type of local government official, such as a local governor or law enforcement (Daxecker and Prins, 2016).[10,11] Our results are inconsistent with the alternative explanation that fishermen, who are unaffiliated with pirate actors, are a significant, mediating channel between ocean wind speed and land conflict which would be inconsistent with the exclusion restriction discussed in Section 4.3.1.

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

[10]For information about how local officials are paid off, see The Economist (2013).

[11]*Transparency International* has ranked Somalia as the world's most corrupt country since 2007.

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

Our analysis uses three main data sets: pirate attacks, land conflict events, and ocean wind speed. Each is described below along with descriptive statistics. Then, monthly variation is shown.

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.

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.

[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).

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 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 Land-Ocean Region Pairing

Figure 1d displays how ocean areas are paired with land areas. Assigning land areas to separate water regions is preferred to using a single cross-sectional unit (i.e. all of Somalia) because the

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

[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.

data are spatially dispersed.[20] 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; however, the results are robust to alternative mappings.[21] The panel data is formed over these regions with one observation for each week from week 28 of 2008 to week 40 of 2016.

3.2.1 Benefits of Preferred Pairings

There are two more advantages of aggregating data into relatively large spatial units. First, region fixed effects control for different legal origins.[22] 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 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.[23]

3.3 Summary Statistics

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

[20]For example, piracy in the northeast of the Indian ocean is unlikely to be related to land conflict in the most southwestern land area of Somalia.

[21]The alternative mappings of ocean area to land regions are shown in Figure A.6.

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

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

[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.

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.

Panels B and C 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. 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.

Monthly Ocean Wind Speed, Pirate Attacks, and Conflict 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. As ocean wind speeds slow between monsoon seasons, pirate attacks increase and there are fewer land conflict events.[25]

4 Model and Empirical Method

The analysis aims to identify how deterring piracy affects safety of communities on land. Specifically, we aim to understand how deterring piracy via international aid and displacement of violent actors on shore impacts land violence. The data measures ocean wind speed and aggregated piracy and conflict events within a region-year-week. A naïve model is:

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

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

In Equation 1, β_1 is unlikely to represent the causal effect of an additional pirate attack on land conflict for at least two reasons: omitted variables correlated with the outcome and explanatory variable and endogenously assigned piracy. A common hypothesis is that land conflict causes

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

conditions to be ripe for pirates to thrive (Murphy, 2009), making pirate attacks endogenously assigned with respect to land conflict due to simultaneity. Due to non-random assignment, estimates of β_1 cannot be interpreted causally without (conditional) independence.

It is unlikely that independent assignment of piracy can be achieved by conditioning on covariates. For example, one unobservable in u_{ryw} is legal institutions. Legal institutions are correlated with both piracy and land conflict. Region fixed effects only control for time-invariant characteristics of 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.[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. It is difficult, if not impossible, to obtain data at a weekly frequency for these important factors so they cannot reasonably be included in Equation 1, which makes β_1 uninformative (in terms of magnitude, sign, and statistical significance). To obtain causal estimates of the effect of pirate activity on land conflict, a source for isolating "as-if" random variation in pirate attacks is required to circumvent the issues of omitted variables and endogenous assignment of pirate attacks.

4.1 Theoretical Predictions

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.[27] Skiffs are incapable of

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

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

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.

4.1.1 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).

$Other\ Activities$ 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.[28] Table A.1 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:

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

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

For simplicity, we assume money from pirate activities and money from other activities are perfect substitutes:[29]

$$U = m_P + m_O.$$

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,[30]

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

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.

[29]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.

[30]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.

4.2 Two Stage Least Squares

To leverage variation in the marginal benefit of piracy from ocean wind speed, we employ two-stage least squares (2SLS). 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. Prior literature (Cook and Garrett, 2013; Besley et al., 2015) and Section 4.1 predicts $\phi_1 < 0$.

Both equations include additional covariates. Chlorophyll concentration, X_O, is included because it is important for fish nutrition and has been shown to affect piracy (Flückiger and Ludwig, 2015; Axbard, 2016). Land temperature and land precipitation are included in $\mathbf{X}_L$ to account for their potential correlation with land conflict.

We then examine whether the reduction in the marginal benefit of piracy have adverse effects on Somalian land activities. The second stage regression is:

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

where $\widehat{Pirate\ Attack}_{ryw}$ are fitted values from Equation 2. Section 4.1 predicts $\beta_1 < 0$. Below, the assumptions required to interpret β_1 as a local average treatment effect are discussed.

We consider several types of standard errors. Our preferred estimates use heteroskedasticity robust standard errors.[31] The main result is the same using wild-cluster bootstrapped standard errors.

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

[31] 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.

(as recommended by Dell et al. (2014)), can be is region X year X month.[32]

4.3 Identification Assumptions

Causal identification of heterogeneous local average treatment 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. $\phi_1 \neq 0$). We assess relevance in two ways. First, we show the Stock-Yogo rule of thumb for first-stage Kleibergen-Paap F-statistic (for $\phi_1 = 0$) is exceeded (Stock and Yogo, 2002; Kleibergen and Paap, 2006).[33] Additionally, we construct confidence sets that are efficient for potentially weak instruments in just-identified structural equations using the Anderson-Rubin test (Anderson et al., 1949; Andrews and Stock, 2018; Lee et al., 2020).

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.[34] Under this independence assumption, the reduced form effect of ocean wind speed on land conflict can be interpreted as an intent-to-treat effect.

4.3.1 Exclusion Restriction

Third, 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

[32]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.

[33]The Kleibergen-Paap F-statistic is more appropriate for heteroskedastic errors when the equations are just-identified (Andrews and Stock, 2018).

[34]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.

in weakening Equation 4 to

$$corr(Ocean\ Wind_{ryw}, u_{ryw} \mid \mathbf{R}, \mathbf{Y}, \mathbf{M}) = 0.^{35} \tag{4B}$$

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. 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).[36,37]

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 three additional variables. These variables are chlorophyll concentration, land temperature, and land precipitation.[38] 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.

[35]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.

[36]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.

[37]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).

[38]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.

Assessing Sensitivity to Mild Violations of Exclusion We recognize that there are believable stories by which ocean wind speed could affect land conflict other than through its effect on piracy. These other channels may not be adequately controlled for with the available data, which would violate the (strict, conditional) exclusion restriction. We both investigate the plausibility of the exclusion restriction (van Kippersluis and Rietveld, 2018) in Sections 5.4.1 and 5.4.2 and investigate the sensitivity of the results to mild violations of it (Conley et al., 2012) in Section 5.4.3.

4.3.2 Additional Assumptions Required for Heterogeneous LATE

Under the three previous conditions, β_1 is a causal effect of piracy on land conflict. Two additional assumptions are required for β_1 to represent a heterogeneous local average treatment effect for compliers. The first additional assumption is weak monotonicity, which in our environment means that increases in ocean wind speed do not cause increases in piracy.

The second additional assumption is the stable unit treatment value assumption (SUTVA). Under SUTVA, treatment of one region does not affect the potential outcomes of neighboring regions. It becomes more likely that SUTVA is violated as the spatial area of cross-sectional units decreases (Baum-Snow and Ferreira, 2015), so we aggregate to relatively large spatial units which reduces the likelihood of SUTVA violations (and spatial autocorrelation).

4.4 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 3 presents regression coefficients (with 95% confidence intervals) from regressions of other weather, chlorophyll, land temperature, and land precipitation, on ocean wind speed.[39]

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

[39] 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.5.

wind speed after interacted fixed effects are included (the orange open dot). Rainfall remains negatively associated with ocean wind speed in all specifications.[40] 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.[41] 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.[42]

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 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

[40] 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.

[41] 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.

[42] There is also data on other Somalian necessities such as tarps, baskets, blankets, etc. The same figure is replicated in Figure A.2. Similar to agriculture goods, after conditioning on fixed effects, there is no systematic relationship between ocean wind speed and non-agricultural goods in Somalia.

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

We start by establishing the unreliability of OLS results and verifying 2SLS predictions. Next, exclusion is supported and results are shown to be insensitive to various robustness checks. The section concludes by considering the consequences of piracy eradication on Somalian safety.

5.1 Reduced Form and First Stage Binned Scatter Plots

Figure 6 plots piracy attacks, land conflict, conflict fatalities, and conflict events, conditional on ocean wind speed separately. In all figures, region X year X month fixed effects are included.[43] No functional form is assumed and the number of bins minimizes a bias-variance trade-off (Cattaneo et al., 2019).

Figure 6a shows an approximately linear, negative association between ocean wind speed and piracy. There are no obvious inflection points and each dot is near the linear fit, suggesting a linear first stage fits the data well and the weak monotonicity assumption is reasonable. Figure 6b examines the reduced form estimation of ocean wind speed on land conflict. There is a positive association between ocean wind speed and land conflict. Taken together, these results suggest

[43] Figure A.3 shows the same binned scatter plots without fixed effects and the resulting conclusions are the same.

the IV estimates will be negative.[44] Figure 6c and Figure 6d show similar, positive associations between ocean wind speed, land conflict fatalities, and institution-related land conflict.

5.2 OLS

Table 2 presents estimates of the naïve relationship between piracy and land conflict. The coefficient on pirate attacks always has a statistically significant impact on land conflict, but the sign switches from negative to positive (Daxecker and Prins (2017) reports only positive effects) and remains statistically significant when time fixed effects are added in columns 2 and 3 for all panels. The missing wind observations (Panel B uses observations without missing wind) or estimation method (Panel C uses Poisson models) are not the cause of the sign switching.

A likely explanation for the sign switching is that fixed effects are not an adequate identification strategy to overcome the reverse causality from land conflict to piracy. This would explain why our results switch signs under alternative fixed effects in these naïve models. There are also 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.

5.3 2SLS

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

[44] The primary regression results impose linear functional forms in the first and second stages (Lochner and Moretti, 2015). To examine the relationship between ocean wind speed, piracy, and land conflict without imposing linearity, Figure A.4 presents the distributions of piracy and land conflict, conditional on wind speed quartiles. Figure A.4 shows the effect of wind speed on piracy and land conflict is not solely due to linear functional form assumptions.

[45] The Kleibergen-Paap F statistic is 111.8, indicating that ocean wind speed is a strong predictor of piracy.

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. .[46]

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 conflicts. 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 care about ocean wind speeds.[47]

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 (Lee et al., 2020). 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 (Lee et al., 2020), so the AR confidence sets are also shown (Andrews and Stock, 2018; Lee et al., 2020). 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

[46] Other fixed effects combinations are shown in Table A.4. The results are similar.

[47] 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 5.4.

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.[48] 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 impact on the reduced form effect of ocean wind speed on land conflict, lowering the point estimate by 0.02. 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.[49] 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.[50]

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.[51] The coefficients in columns 1 and 2 lose statistical significance at conventional levels, but the p-value on pirate attacks is still statistically significant

[48]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.

[49]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.

[50]This is not to say that land temperature or precipitation have no effect on conflict. Table A.5 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.

[51]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, 2019; Wang, 2021).

at the 99% confidence level.

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.[52,53]

Alternative Mappings 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 aggregating our data to all of Somalia, using fully spatially disaggregated units, and other mappings. The results for all of Somalia are shown in Table A.8. Most specifications retain statistical significance and a reasonable magnitude with only 509 observations. The only specifications that do not are when region, year, and month fixed effects are added, but the AR confidence set still does not include zero. This is strong support that the results are not driven by spatial autocorrelation or due to pirates moving around. Table A.9 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.[54]

5.4 Exclusion Restriction Validity

The assumption that is the most tenable, as in most instrumental variable estimates, is the exclusion restriction. 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.[55] This section investigates exclusion in three ways: on conflict that is likely/unlikely to be attributed to violent actors such as pirates, on conflict in geographic areas

[52]The coefficient for the monthly sample, without controls, is shown in Table A.3. 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.

[53]We also show that the strongest effect of piracy is on land conflict that occurs closer to the coast in Table A.7.

[54]Table A.10 shows alternate estimates for 3 other spatial aggregations and the results are the similar in statistical significance and magnitude. Figure A.6 shows these alternate mappings. There are estimates from 3 spatial units (Figure A.6b), 4 spatial units (Figure A.6c), and 5 spatial units (Figure A.6d)

[55]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. 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.

without piracy (similar to Nunn and Wantchekon (2011)), and allowing mild violations of the exclusion restriction using the plausibly exogenous methods in Conley et al. (2012).

5.4.1 Evaluating the Exclusion Restriction in Somalia with Conflict Subsets

We start by subsetting conflicts to event types and actors 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. Table 4 presents these results. In Panel A, conflict events that involve militaries, rebels, civilians, or sole actors are dropped prior to aggregating conflict. 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.[56] 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.[57,58]

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] See rows 3 and 4 of Table A.1, which shows how these weapons are used both on land and at sea for hijacking and violence.

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

[58] 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.

5.4.2 The Effect of Ocean Wind Speed on Conflict, in Countries Without Pirates

An increasingly popular way to evaluate the reasonability of exclusion is to examine the reduced form effect of the instrument on the outcome when the treatment is not present.[59] If exclusion is reasonable, then the effect of the instrument, in these zero first stage contexts, on the outcome should be close to zero (Angrist et al., 2010; van Kippersluis and Rietveld, 2018). This diagnostic is used by Nunn and Wantchekon (2011) to examine if distance to the coast has an effect on trust when slavery is not determined by distance. To do this, Nunn and Wantchekon (2011) examine Asian countries where slaves were not kidnapped and find that distance to the coast has no effect on trust, without the mediation of the slave trade.

We mimic this approach by estimating the effect of ocean wind speed on land conflict in geographic areas where there is no piracy. We select three countries each with their own strengths and weaknesses.[60] First, we use Tanzania, because it is close to Somalia; however, there is relatively little conflict in Tanzania. The results are presented in Panel A of Table 5. The effect of ocean wind speed on land conflict is only marginally statistically significant in the final column, with a very small effect size.

Second, we examine Libya because there is no piracy and a significant amount of stateless conflict, similar to Somalia. But there was an internationally backed regime change in the middle of the sample period. Panel B of Table 5 presents the Libyan results and again finds that ocean wind speed reduces land conflict, except the coefficient is about 5 times larger than Panel A, column 3. This means that ocean wind speed is more negatively associated conflict in Libya. Third, we use South Africa, because there is a lot of land conflict and no regime change.The result is that ocean wind speed reduces land conflict by 0.057 events, which is statistically significant at 99 percent confidence.

Finally, Panel D uses all 3 countries and finds an aggregate negative effect that a 1 m/s increase in ocean wind speed *reduces* conflict by 0.06 events. First, ocean wind speed reduces land conflict in these placebo countries, while ocean wind speed *increases* land conflict in Somalia. Second, the magnitude (-0.06) is roughly 10% of the size of Somalia's reduced form coefficient (0.5), suggesting the exclusion restriction is only violated, at most, mildly.

[59] van Kippersluis and Rietveld (2018) calls this the zero first stage test.

[60] The mappings of country regions to ocean areas are presented in Figure A.7.

5.4.3 Sensitivity of Results to Minor Violations of Exclusion

While the estimates in Table 5 suggest that the size of the exclusion restriction violation is small, it is not consistent with the strict exclusion restriction holding. To assess whether the estimated results in Table 3 are sensitive to this violation, we employ the plausibly exogenous methods developed in Conley et al. (2012). This method is also used in Dincecco and Prado (2012) and Nunn and Wantchekon (2011) to examine how mild violations of exclusion affect the main results. Intuitively, these methods allow the instrument, ocean wind speed, to directly affect the second stage outcome of interest, land conflict (Equation 3) and re-estimate the effects on the (instrumented) endogenous variable, pirate attacks. Importantly, the method requires specifying a prior (or distribution of priors) for how severely violated the 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 Panel D, column 3 of Table 5.

Table 6 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 size 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 issue is that the -0.06 prior is estimated with error and ideally the parameter estimates would reflect this uncertainty. To do this we use the local to zero (LTZ) methods developed by Conley et al. (2012). With this method, we can 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). In

[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 $((.125)(S_0^2 + S_{-0}^2)^{.5})^2$, 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).

conclusion, allowing for mild violations of exclusion, 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.

Finally, it is worth noting that almost all of the estimates (including those that incorporate time and region fixed effects) are negative in Table 5. For all negative values, the standard errors get farther away from including zero in the 95% confidence set. Using the LTZ method with zero variance, the estimated gamma would have to be about 0.161 for the 95% confidence set to include zero, which is 1.5 times larger than any of the estimates of the exclusion violation shown in Table 5. This provides empirical support that the results are not sensitive to plausible violations of the exclusion restriction.[62]

5.5 Alternative Specifications

It is also important to ensure that the results are not sensitive to alternative specifications. Table 7 shows the main alternative specifications. In Panel A, all 3 regressions also include a week of year (1-52) vector of fixed effects that allows the estimates to hold the week of year constant, which might be correlated with any of the main variables.[63] 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.

Panel B shows the results when the ocean wind speed is aggregated to the mean in a region-week. 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.

[62]The values of the parameters describing the distribution of γ that would force zero to be in the 95% confidence interval of the estimate of piracy on conflict are shown in Table A.11.

[63]Since they are not interacted with the region X year X month they are not the unit of analysis. Also, week of year does not vary within a region-year-month. 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.

5.5.1 Conflict Transformations

Panels C and D of Table 7 consider transformations of land conflict to investigate whether the skewed distribution of conflict is responsible for the results. First, Panel C uses the log transformation, finding an additional pirate attack reduces land conflict by about 83 percent and is statistically significant at the 5% level. However, the log of conflict is not defined if conflict takes on a value of zero, resulting in 266 (17.5% of the "full sample") observations where conflict is undefined in Panel D.

Dropping zero-valued observations is not desirable and may be why the estimate of piracy attacks on conflict in Panel C is large in magnitude compared to prior results. To retain zero-valued dependent variable observations, Panel D transforms conflict using the inverse hyperbolic sine (IHS) transformation. The IHS transformation is defined at zero. The second stage coefficient can be interpreted as a 1 unit increase in piracy leading to a $(\beta_1 * 100)\%$ change in conflict. β_1 is transformed to be relevant at the means of piracy and conflict (Bellemare and Wichman, 2020). After transforming the estimated effect, an additional pirate attack leads to a 27.3 percent reduction in land conflict at the mean (10.42).[64] Outliers or other distributional issues in conflict do not appear to be driving the estimated effects since Panels C and D are also statistically significant with reasonable magnitudes. 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).[65] The results presented in Table A.13 are similar in terms of statistical significance and magnitude.[66]

5.6 Consequences of Stopping Piracy

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.

[64] Although not shown, this semi-elasticity is statistically significant at 95% confidence, with the lower bound being 0.04.

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

[66] 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.13 presents Poisson coefficients, they are interpreted: $(e^{\beta_1} - 1) * 100 \approx x\%$.

Miscellaneous Institutional Impacts Panel A of Table 8 investigates the impact of pirate attacks on conflict events related to the quality of institutions.[67] 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.[68]

Fatalities In Panel B of Table 8 the dependent variable is the number of land casualties 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 C uses this estimate (and estimates from Besley et al. (2015)) as an input to calculate the implied value of a statistical Somalian life.

5.6.1 Violence Against Civilians

The effect of additional pirate attacks on fatalities and violence against civilians is estimated to see if the documented violence displacement has additional negative consequences. Panel C of Table 8 presents estimates of the effect of an additional pirate attack on ACLED-defined violence against civilians events. These events include: sexual violence, attacks, and abduction/forced disappearances. Column 3 shows that there is a 0.97 event reduction in conflict events, which is statistically significant at the 10% level, classified as violence against 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.

[67]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.

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

Fatalities and violence against civilians begs the question, how many additional fatalities are civilians? The conflict data is imperfect for the question, because fatalities are not disaggregated by actor. To answer this question, fatalities during events classified as violence against civilians is examined. Panel 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 deter 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 deterring 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 deterrence, 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, saving money for shipping companies via piracy deterrence leads to additional Somalian fatalities and implies the value of a Somalian life is $607,836.

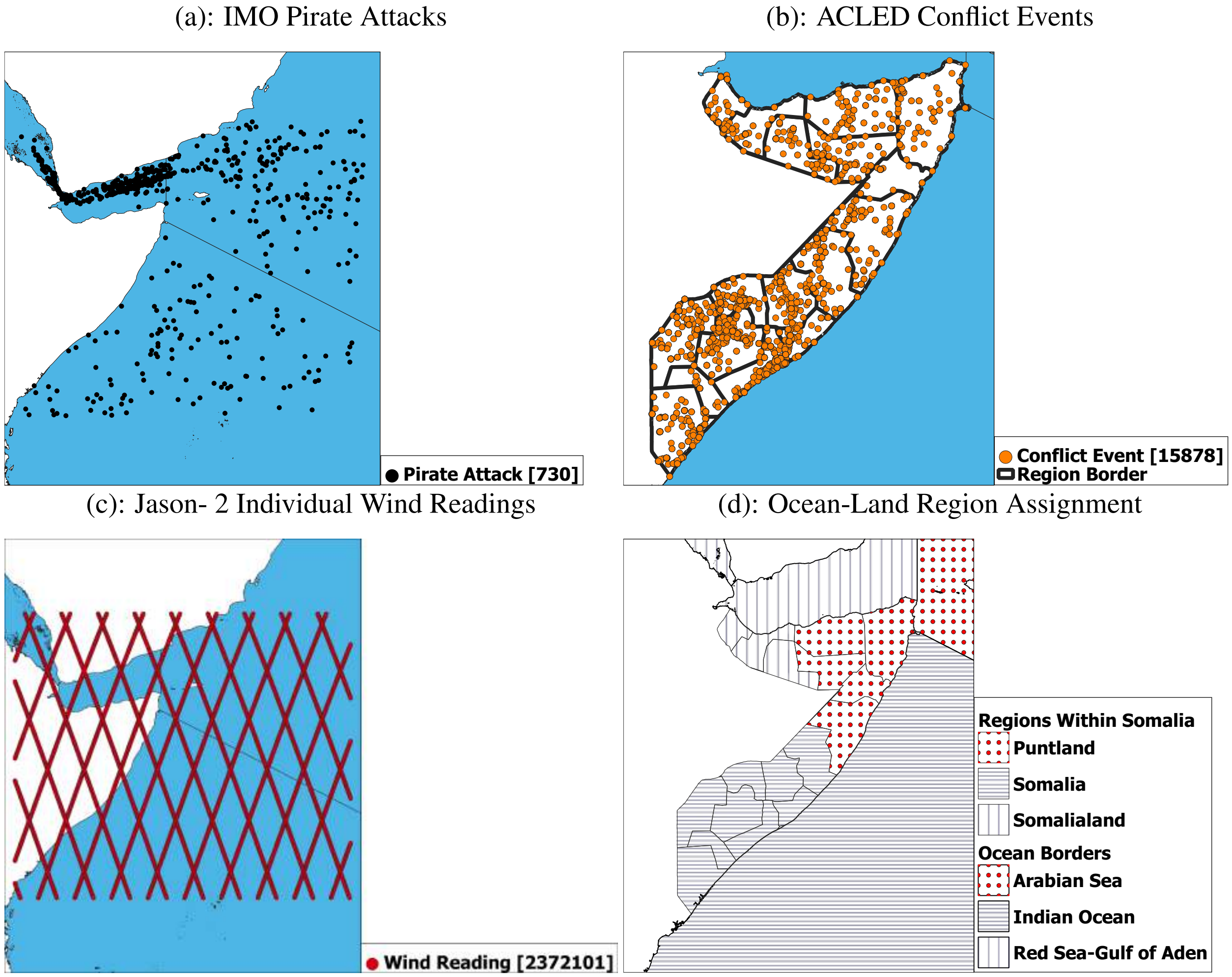
Typically, the main limitations of instrumental variable estimates pertain to their applicability for a sub-population of compliers or the validity of the exclusion restriction assumption. With regards to the exclusion restriction in this paper, we have shown that the results hold for mild violations 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 deterrence 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 deter piracy has financial costs for the provider, this research reveals an additional cost of this policy for Somalians. Providing security assistance to deter piracy has the unintended consequence of increasing conflict and conflict fatalities on land in Somalia. Thus, while the primary benefactor from using warships for piracy deterrence 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.

There are several potential directions for future research. First, it would be straightforward to examine if pirates have an impact in other geographic areas besides Somalia. Second, there may be better measures of institutional functionality that would be interesting as a different dependent variable, measuring similar outcomes. Finally, displaced violent individuals may also have other measurable effects, for instance leading to low birthweight babies in utero during unattractive times to be a pirate or new business formation that future research could examine.

Figure 1: Spatial Distribution of Primary Variables and Region Definitions



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.6 and the corresponding regressions in Tables A.8, A.9, and A.10.

Table 1: Descriptive Statistics

Panel A: Aggregate

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

Panel B: Wind Speed $>$ Mean

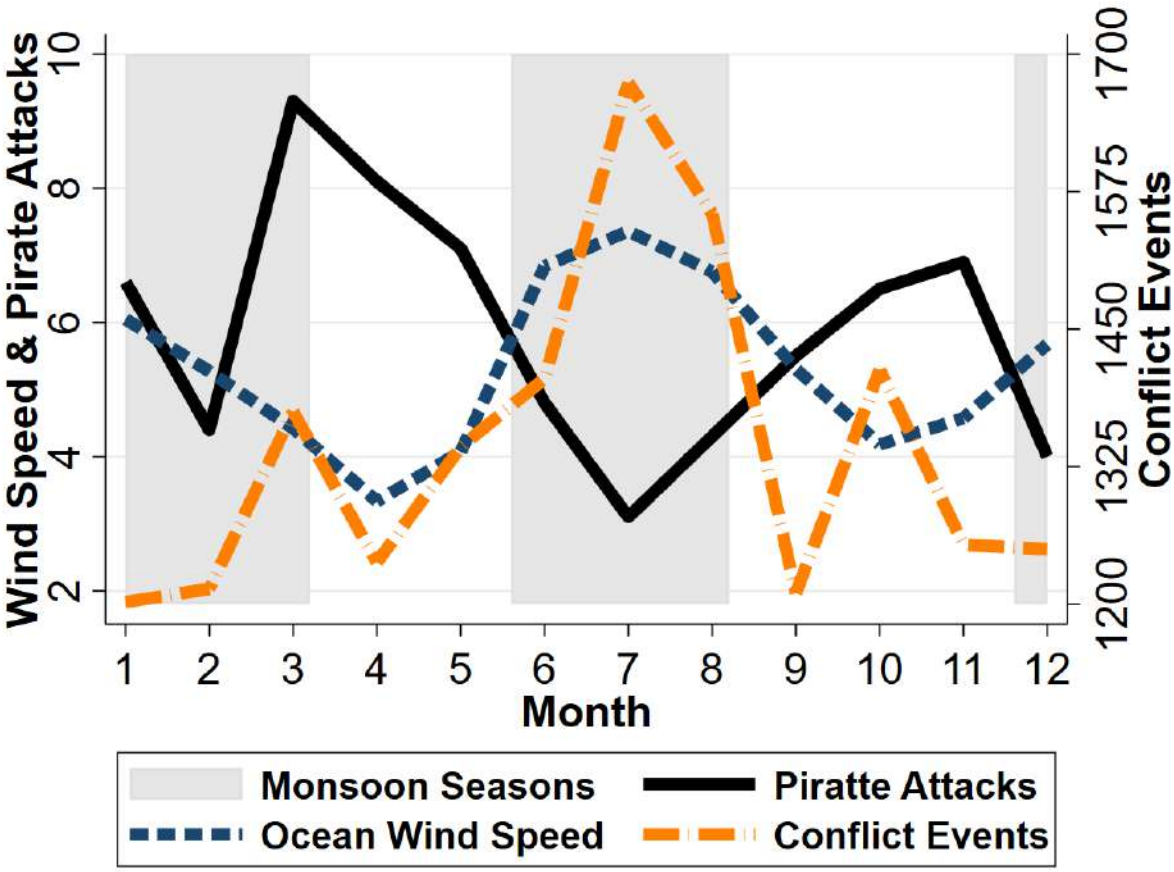
	Mean	Median	SD	Min	Max	Count
Pirate Attacks	0.16	0.00	0.55	0.0	6.0	691
Total Conflict Events	12.85	5.00	16.14	0.0	80.0	691
Median Wind Speed	7.34	6.84	1.69	5.4	13.4	662
Chlorophyll	0.27	0.25	0.18	0.1	3.4	667
Land Conflict Fatalities	21.80	4.00	36.52	0.0	309.0	691
Land Conflict, No Unlikely Events	11.09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

Panel C: Wind Speed $<$ Mean

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

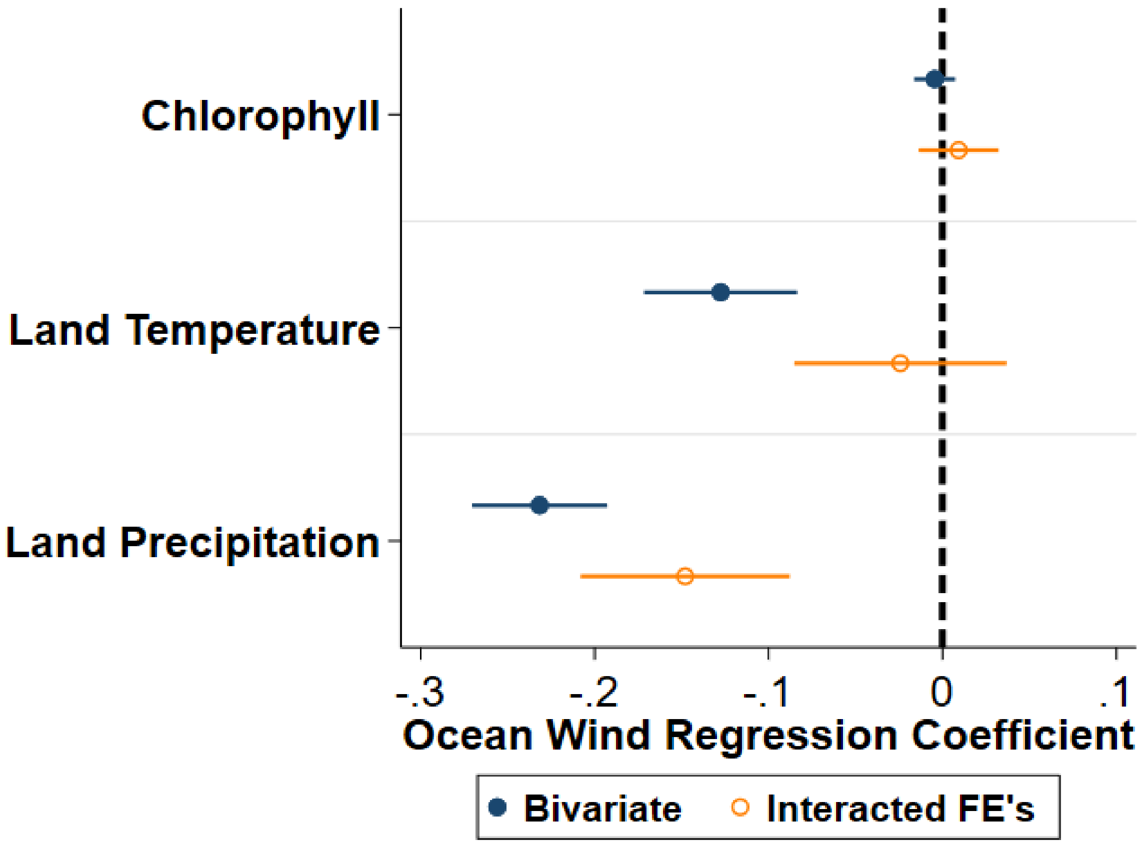
Notes: Panel A reports summary statistics for all crimes in entire sample. Panel B subsamples to only weeks where the wind speed was greater than the aggregate median wind speed. Panel C subsamples to only weeks where the wind speed is less than the median.

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



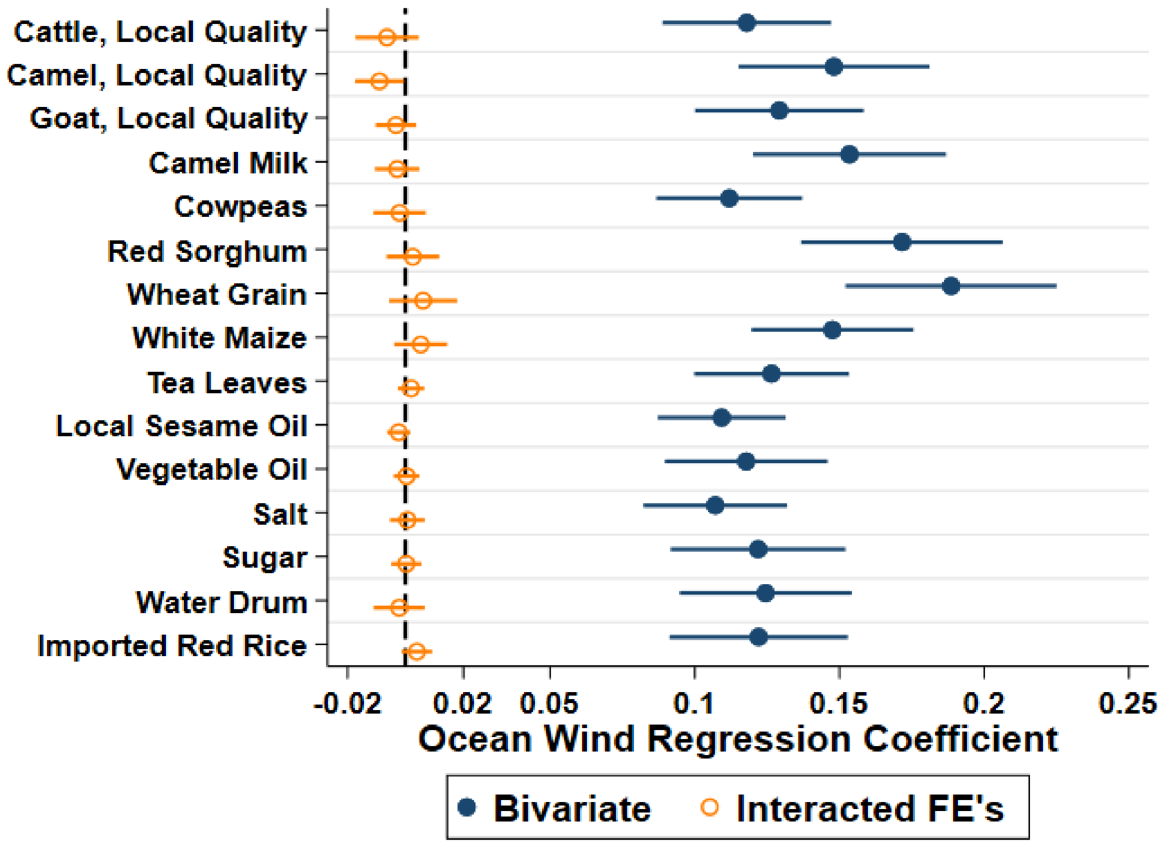
Note: N= 1519. Time frame is 2008-2016. Conflict events and pirate attacks are totals within months. Conflict events are a long dash with a small dot between dashes. Pirate attacks are a solid line. Wind speeds' median is used. Ocean wind speed is the dashed line. Monsoon season defined according to Shortland and Vothknecht (2011). Pirate attacks are in 10s. The equivalent weekly-level is shown in Figure A.1.

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



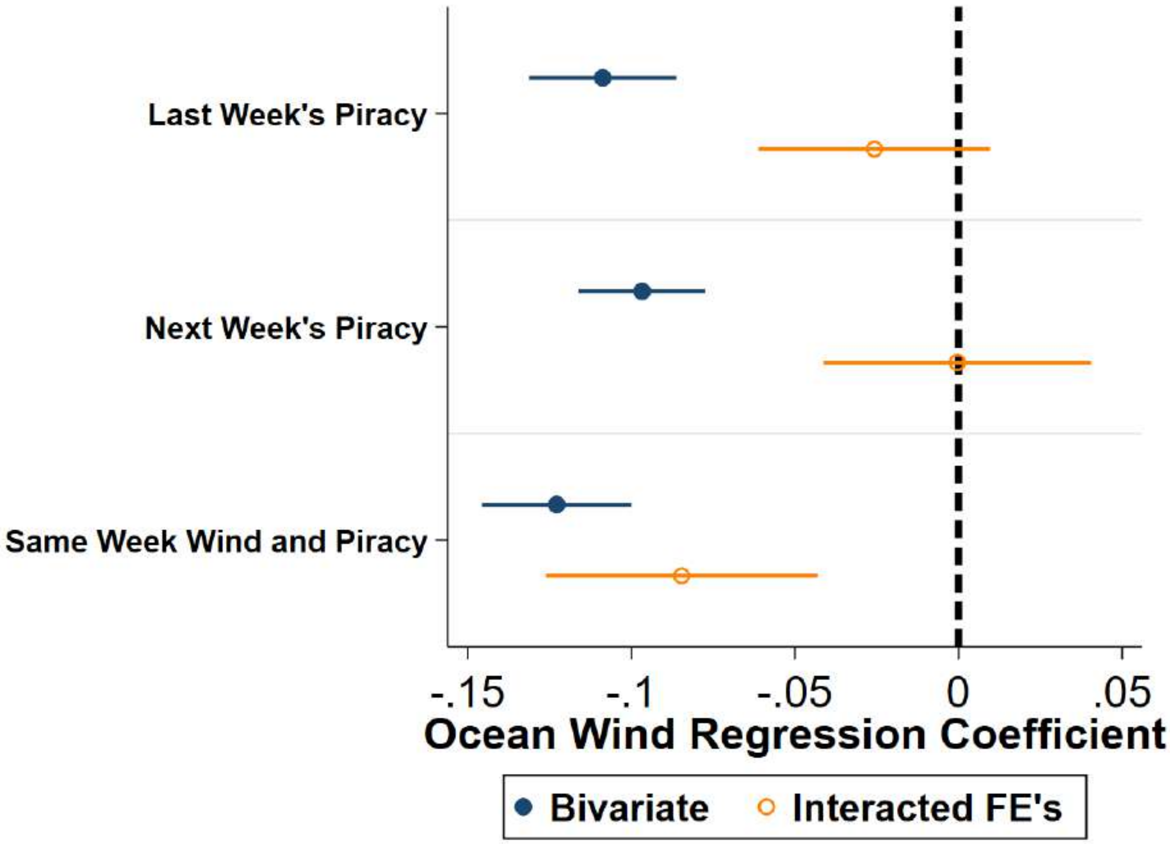
Note: The plot shows regression coefficients on the independent variable of ocean wind speed. The dependent variables are listed on the left. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from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

Figure 4: How Ocean Wind is Related to Agriculture 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.

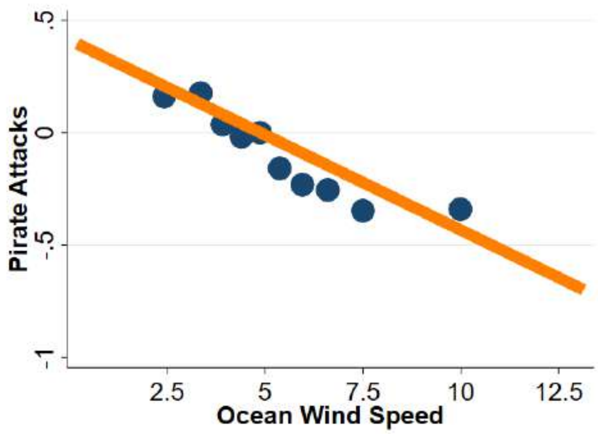
Figure 5: Examining Whether Pirates Shift Operations Across Time in Anticipation of High Ocean Wind Speeds



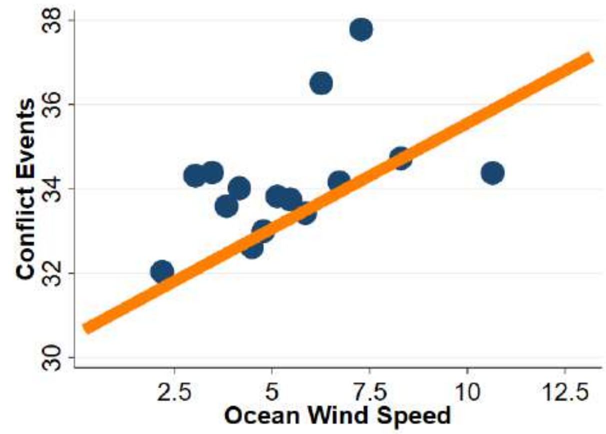
Note: The plots shows regression coefficients from regressions of piracy attacks on ocean wind. Different rows represent different lags. Whiskers represent 95% confidence intervals. Standard errors are heteroskedasticity robust. Blue dots are from bivariate regreesions. Orange, open dots are from regressions 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.

Figure 6: Binned Scatter Plots of Ocean Wind Speed on Piracy and Land Conflict

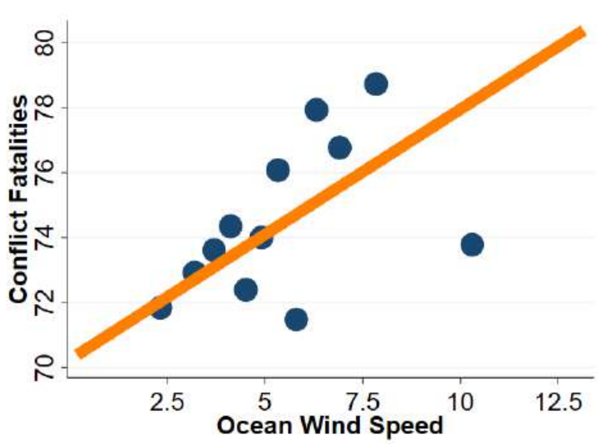
(a): Ocean Wind and Pirate Attacks



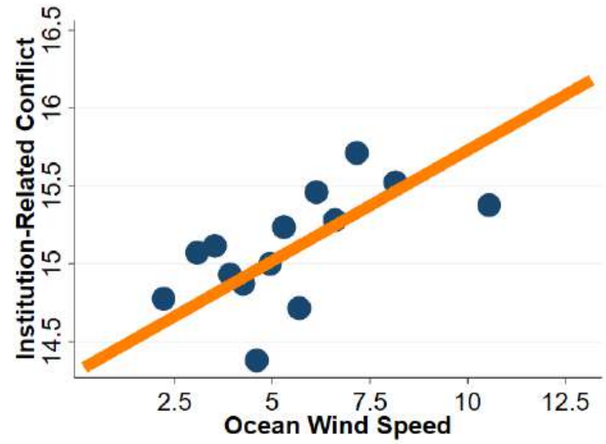
(b): Ocean Wind and Total Land Conflict



(c): Ocean Wind and Land Conflict Fatalities



(d): Ocean Wind and Institution-Related Conflict



Note: (a) shows average piracy, conditional on ocean wind speed. (b) shows average total conflict events conditonal on ocean wind speed. (c) shows average conflict fatalities, conditional on ocean wind speed. (d) shows average institution-related conflict events, 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. The preferred fixed effects, region X year X month are included. Figure A.3 shows the same subfigures without fixed effects from which similar conclusions can be drawn. 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 are: checkpoint, toll, tax, ngo, official, roadblock.

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

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

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

Table 3: 2SLS Estimates of Piracy on Land Conflict

Dep Var.	(1) Reduced Form Conflict Events	(2) First Stage Pirate Attacks	(3) 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			[-6.5927,-1.75523]
A-R P-Value			0.000773
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			[-12.8713, -2.2746]
A-R P-Value			0.00139
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			[-14.5408,-1.94962]
A-R P-Value			0.00371
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			[-7.17737,-1.46841]
A-R P-Value			0.00267
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, 2019), 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. (2020) for just-identified structural equations.

Table 4: 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			[-11.2072,-1.65552]
A-R P-Value			0.00289
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			[-9.87706,-1.49813]
A-R P-Value			0.00228
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			[-4.50419,-.874164]
A-R P-Value			0.000747
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			[-.738125, .091638]
A-R P-Value			0.147
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.14 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. (2020) for just-identified structural equations.

Table 5: 3 Placebo Countries With No Piracy

	(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
Panel D: All 3 Countries			
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.

Table 6: 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 5. 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 5, Panel D, column 3 as inputs. This is the suggested variance by van Kippersluis and Rietveld (2018).

Table 7: 2SLS Alternative Specifications

	(1) Reduced Form Conflict	(2) First Stage Pirate Attacks	(3) Second Stage Conflict
Dependent Variable:			
Panel A: Also Include Week of Year FE			
Median Wind Speed	0.31*	-0.09***	
	(0.17)	(0.02)	
Pirate Attacks			-3.25*
			(1.72)
Kleibergen-Paap F			17.17
Observations	1519	1519	1519
A-R 95% Conf. Set			[-7.67385,-.194788]
A-R P-Value			0.0386
Panel B: Mean Wind Speed			
Mean Wind Speed	0.39**	-0.08***	
	(0.17)	(0.03)	
Pirate Attacks			-4.93*
			(2.55)
Kleibergen-Paap F			9.830
Observations	1519	1519	1519
A-R 95% Conf. Set			[-14.724,-.995026]
A-R P-Value			0.0130
Panel C: Log Conflict			
Median Wind Speed	0.05***	-0.07***	
	(0.02)	(0.02)	
Pirate Attacks			-0.83**
			(0.35)
Kleibergen-Paap F			13.66
Observations	1253	1253	1253
Panel D: Inverse Hyperbolic Sine Conflict			
Median Wind Speed	0.05***	-0.08***	
	(0.02)	(0.02)	
Pirate Attacks			-0.60**
			(0.26)
Kleibergen-Paap F			16.00
Observations	1519	1519	1519
Semi-Elasticity at Mean			-0.273

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

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			[-3.88737, -.40752]
A-R P-Value			0.0122
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			[-22.0893,-1.25388]
A-R P-Value			0.0221
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			[-2.4453,-.055094]
A-R P-Value			0.0417
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			[-3.21972,-.035193]
A-R P-Value			0.0520
Obs. Where Y = 0			837

Notes: N = 1,519. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. The table displays 2SLS regressions. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All models include regionXyearXmonth fixed effects. Panel A uses 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. (2020) for just-identified structural equations.

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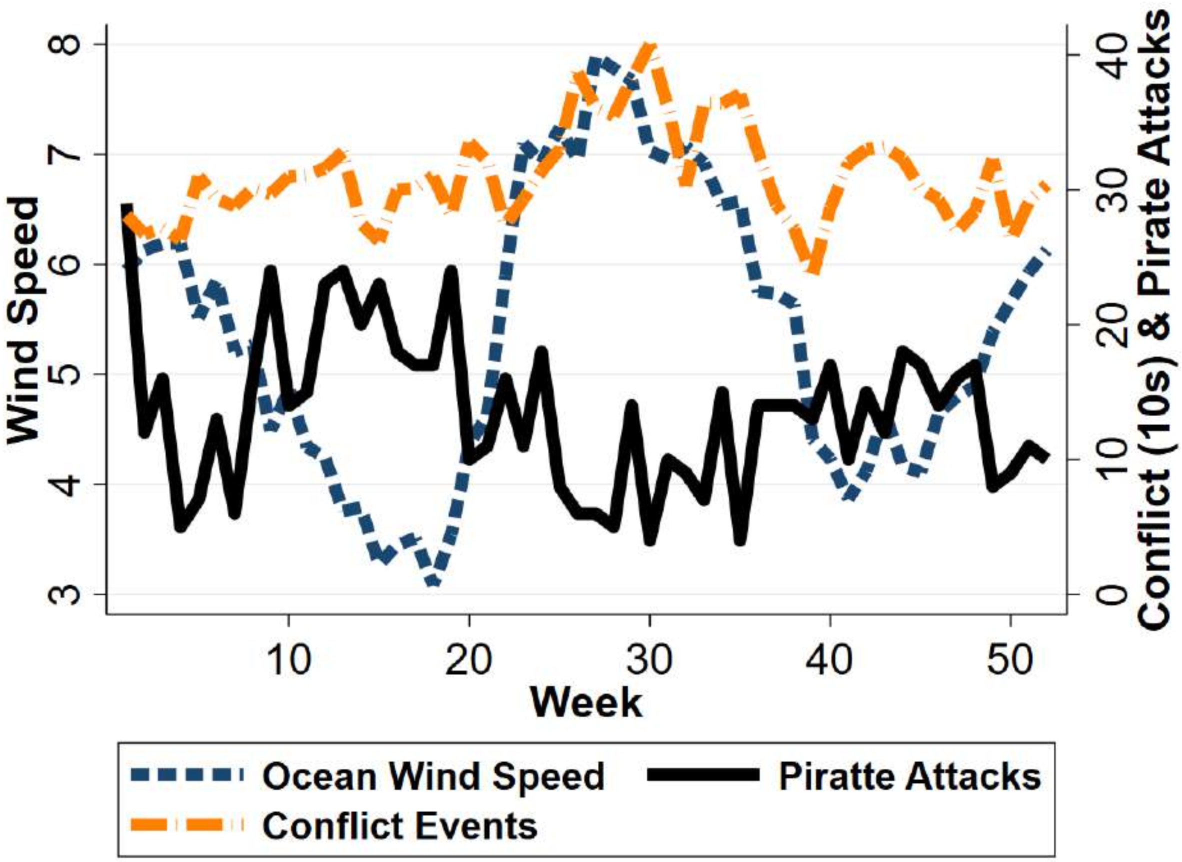
A Additional Tables and Figures

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.1: Descriptions of Events

Row	Event	Description
1	Ocean Hijacking	Non-violent activity: Somali gunmen have hijacked a freighter ship off the coast of El-Maan.
2	Land Hijacking	A truck carrying goods from Bargal to Bosasso and belonging to a member of the Siwaqron 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.

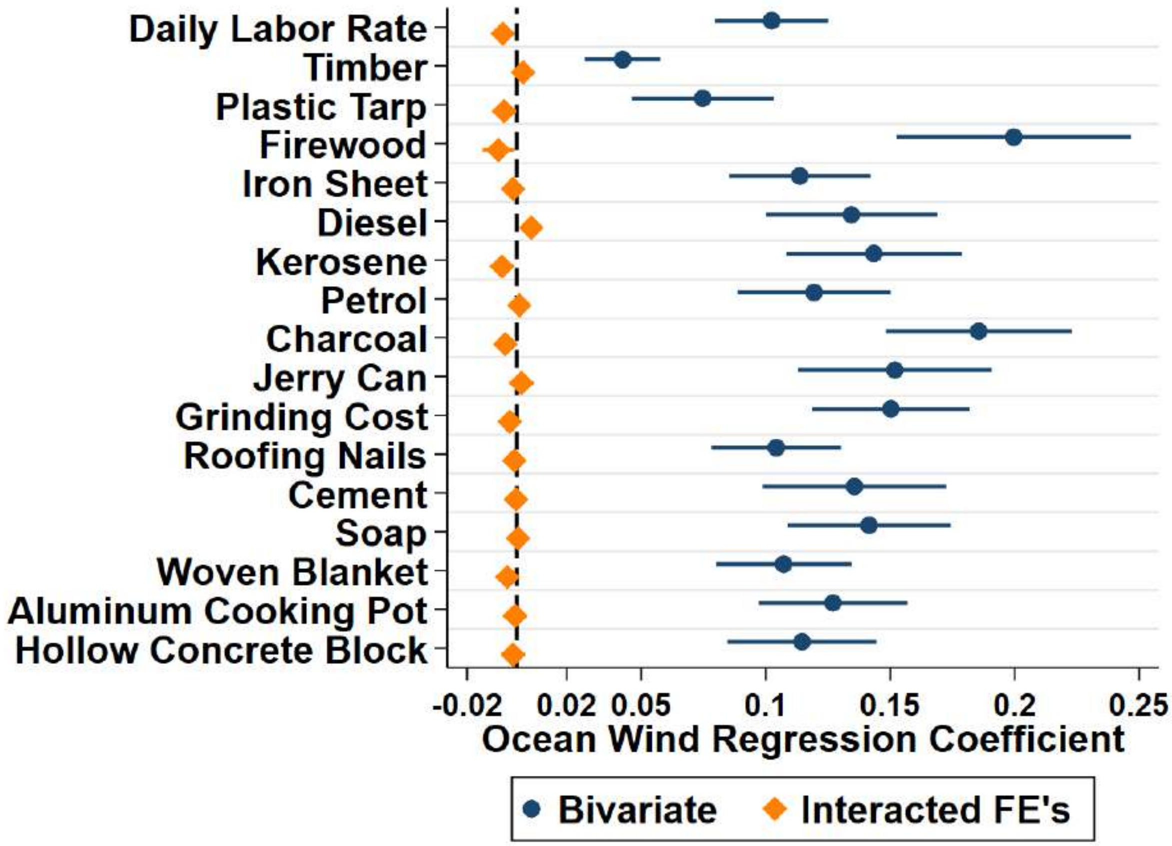
Note: Data comes from ACLED event description and IMB piracy event descriptions.

Table A.2: Wind Statistics By Month

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

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

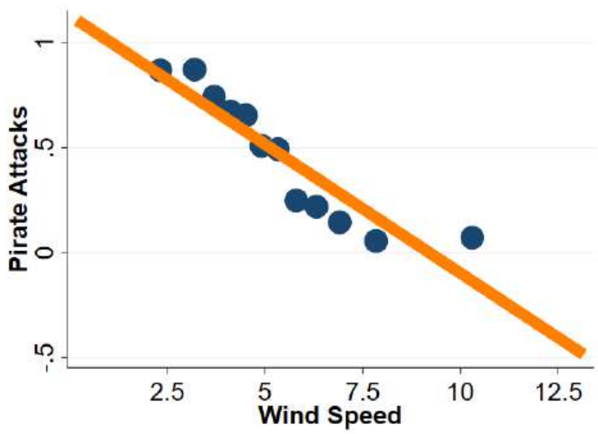
Figure A.2: Non-Agriculture Goods Prices Correlation with Ocean Wind Speed



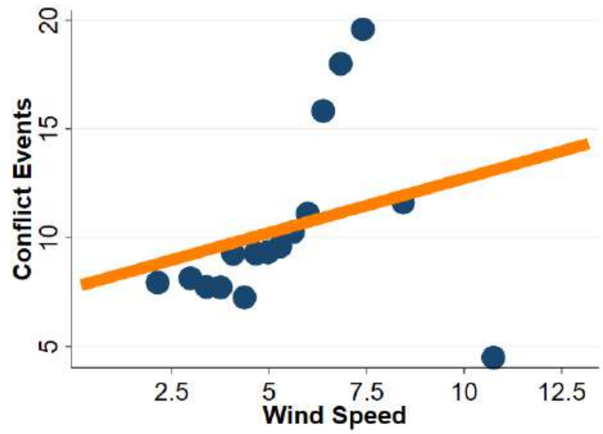
Note: The plots shows regression coefficients on the independent variable of ocean wind speed. The dependent variables are listed on the left, they are logged to facilitate visual interpretation. They are the log of the median price of agriculture within a given region. Whiskers represent 95% confidence 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.3: Binned Scatter Plots of the Effect of Ocean Wind on Piracy, Land Conflict, Land Conflict Fatalities, and Institution-Related Conflict

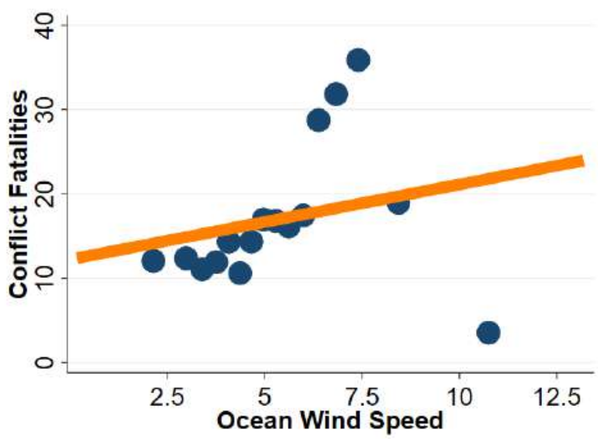
(a): Ocean Wind on Pirate Attacks



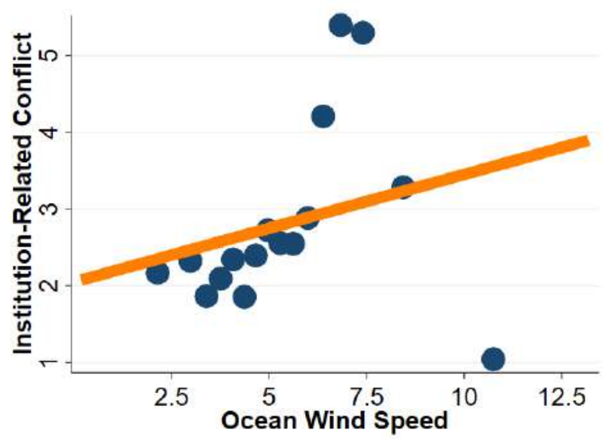
(b): Ocean Wind on Total Land Conflict



(c): Ocean Wind on Land Conflict Fatalities



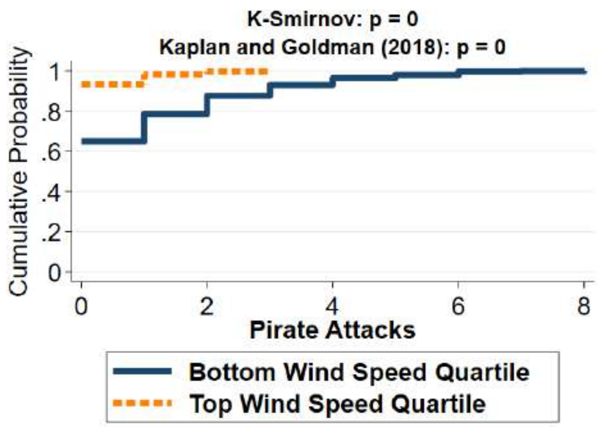
(d): Ocean Wind on Institution-Related Conflict



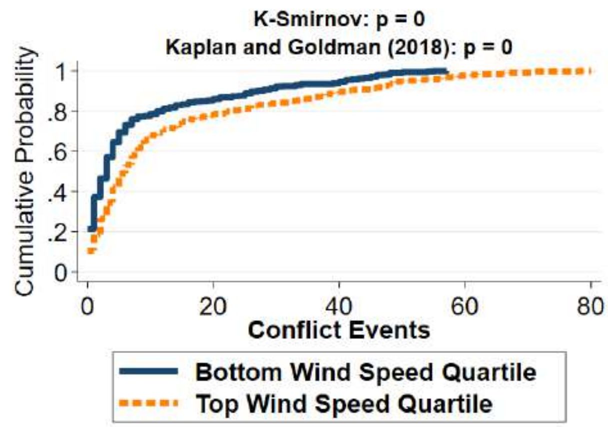
Note: (a) shows average piracy, conditional on ocean wind speed. (b) shows average total conflict events conditonal on ocean wind speed. (c) shows average conflict fatalities, conditional on ocean wind speed. (d) shows average institution-related conflict events, conditional on ocean wind speed. Procedure 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. The preferred fixed effects, region X year X month are included. Figure 6 shows the same subfigures with fixed effects from which similar conclusions can be drawn. 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 are: checkpoint, toll, tax, ngo, official, roadblock.

Figure A.4: Cumulative Distributions of Variables by Top and Bottom Ocean Wind Speed Quartiles

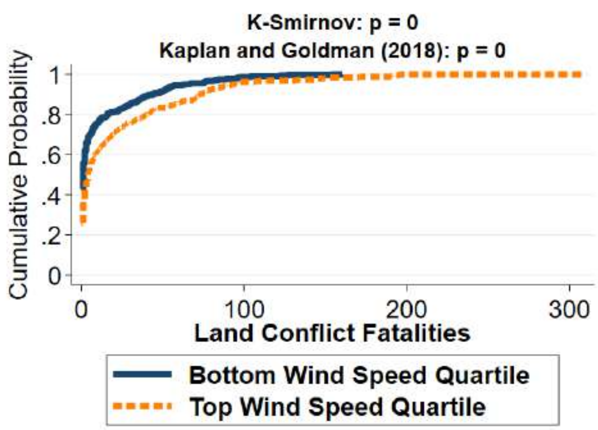
(a): Cumulative Distributions of Pirate Attacks



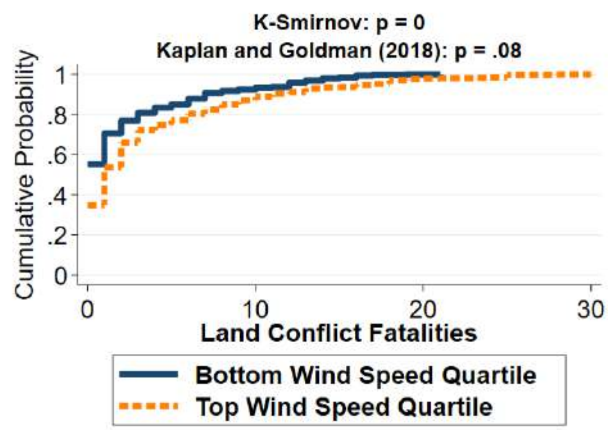
(b): Cumulative Distributions of Conflict Events



(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.3: 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. (2020) for just-identified structural equations.

Table A.4: 2SLS Estimates of Piracy on Land Conflict, Alternative Specifications

Dep Var.	(1) Reduced Form Conflict Events	(2) First Stage Pirate Attacks	(3) Second Stage Conflict Events
Panel A: Region, Year, Month, FE's			
Median Wind Speed	0.28** (0.11)	-0.09*** (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. (2020) for just-identified structural equations.

Table A.5: 2SLS Estimates, Meterological Covariates Included, No Other Fixed Effects

	(1)	(2)	(3)
	Reduced Form	First Stage	Second Stage
Dep. Var.	Conflict	Pirate Attacks	Conflict
Panel A: Both, No FE's			
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. (2020) for just-identified structural equations.

Table A.6: 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.7: Excluding Land Conflict Events Closer To Coast

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

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

Table A.8: 2SLS Estimates, 1 Geographic Unit- All of Somalia

Dep Var:	(1) Reduced Form Conflict Events	(2) First Stage Pirate Attacks	(3) Second Stage Conflict Events
Panel A: Single Independent Variable			
Median Wind Speed	1.64***	-0.25***	
	(0.52)	(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***	-0.21***	
	(0.38)	(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***	-0.17***	
	(0.43)	(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: YearXQuarter FE's			
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			[... ,-3.62377]
A-R P-Value			0.000585
Panel E: Year, Month FE's			
Median Wind Speed	1.88**	-0.12	
	(0.74)	(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 X quarter fixed effects are included. In Panel E, 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 and Stock (2018) and Lee et al. (2020) for just-identified structural equations.

Table A.9: 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.6a. 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. (2020) 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 (2019) 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.10: 2SLS Estimates, Alternative Mappings

	(1)	(2)	(3)
	Reduced Form	First Stage	Second Stage
Dep. Var.	Conflict	Pirate Attacks	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.6. In Panel A, there are 3 spatial units (Figure A.6b). In Panel B, there are 4 spatial units (Figure A.6c). In Panel C, there are 5 spatial units (Figure A.6d). 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. (2020) for just-identified structural equations.

3

Table A.11: 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.

Table A.12: 2SLS Wind Dummy Specifications

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

Table A.14: 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.

B Clan Related Conflict

Panels A-D of Table B.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 B.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 B.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 B.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 B.1 investigates conclusions of Panels A-D of Table B.1 by showing reduced form binned scatter plots with and without fixed effects.[69] Figure B.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 B.1c, monsoon winds are a bad leverage point again causing the slope to flatten.[70] Figure B.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 B.1d. Despite the inclusion of fixed effects causing points to be more dispersed (greater error), clan-related conflict still increases with wind speed.

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

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

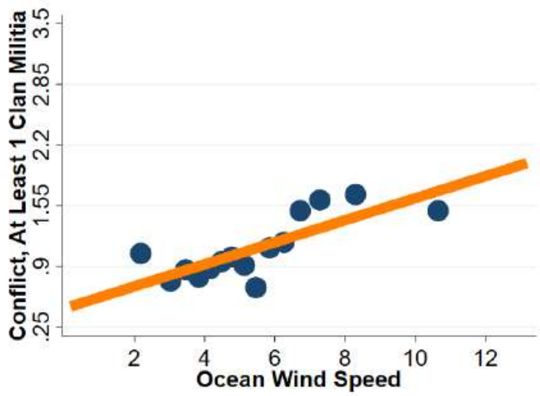
Table B.1: 2SLS Estimates of Pirate Attacks on Institution-Related Conflict

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

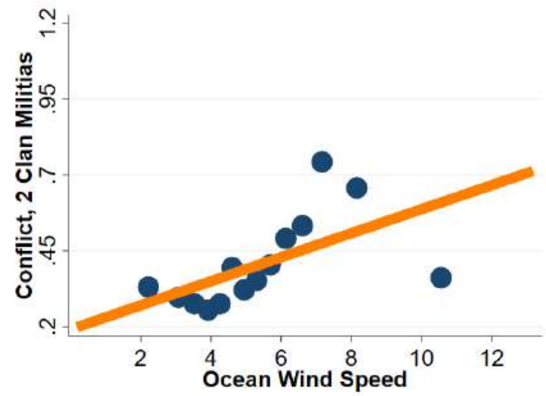
Notes: N = 1,519. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Robust standard errors in parentheses. The table displays 2SLS regressions. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. All models include regionXyearXmonth fixed effects. In Panel A and B the dependent 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 B.1: Reduced Form Effect of Wind Speed on Clan-Related Conflict

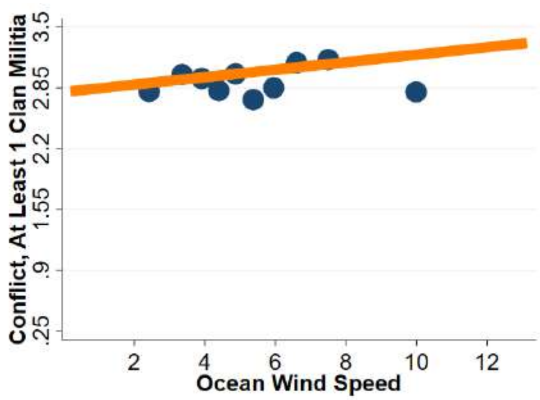
(a): At Least 1 Communal Militia, No Fixed Effects



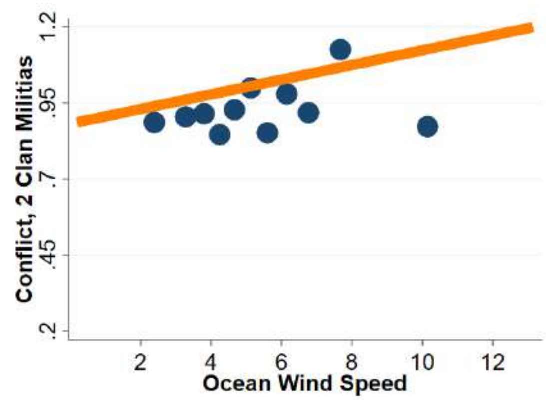
(b): Only 2 Communal Militias, No Fixed Effects



(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.

C 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:

$$C_{Gulf\ of\ Aden,\ Lower\ Rate\ Increase} = 0.476 * 0.0005 * 30.3 * 646,064,000.^{71} \tag{5}$$

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

[71] 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.

C.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.