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Does criminal violence spread? Contagion and counter-contagion mechanisms of piracy☆

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ABSTRACT

Research shows that political and criminal violence cluster spatially but neglects the wide range of mechanisms driving contagion and, more importantly, the role of counter-contagion efforts. After identifying permissive conditions for piracy, I hypothesize that piracy clusters in locations conducive to successful attacks. Pirates engage in risk-reducing behaviour: they return to areas where they have been previously successful but also adapt this learning-based decision to constraints imposed by EU counter-piracy. The analysis relies on uniquely detailed data on piracy and counter-piracy in monthly grid-cells off Somalia (2005–2013). Results show that although successful attacks foster more attacks and contagion, EU counter-piracy reduces contagion. Even within most successful locations, rescue operations reduce incidence of piracy by 89% in the following month. The article contributes to existing contagion/diffusion literature by identifying specific channels of contagion (contiguity and learning) and by factoring in containment policies that can limit and reduce criminal and political violence.

Introduction

Contagiousness is a feature of many social and political phenomena, including conflict, terrorism, protests and crime. Research on violence finds that not only violence clusters in space but it also spreads geographically. Whether this occurs as effect of contiguity, competition, learning, emulation or other diffusion mechanisms is less commonly investigated. Among several typologies of organized crimes, maritime piracy has emerged as a global threat to international security. Piracy incidents are reported all over the world, from South-East Asia and Indian Ocean to Latin America and Caribbean. Yet the distribution of piracy incidents appears to exhibit geographical concentration; indeed, a map of incidents easily identifies hotspots of pirates' activity. Recognizing the presence of crime hotspots, however, *does not* indicate diffusion or contagion per se and cannot explain why spatial clustering emerges. Research has shown that piracy clusters not only in space but also in time (Marchione & Johnson, 2013), thus pointing towards not just clustering but actual contagion processes.[1] However, two question still stands, namely (1) under which conditions piracy diffuses and (2) whether military intervention is apt to contain contagion.

As first contribution, I provide answers to these questions showing that pirates return to location they are familiar with and move around their proximity. This is what I call contagion by reinforcement and contiguity. In addition to this, pirates assess likelihood of success based on previous achievements. This is the third contagion mechanism, which works through learning. A counter-piracy force, however, may limit the geographical diffusion of criminal activities by threatening to or actually imposing costs on criminals. More precisely, deterrence and compellence counter not only piracy occurrence but also its contagion. The inclusion of contagion inhibitors is the second distinctive contribution of the manuscript and improves the comprehensiveness of the contagion mechanisms under investigation. I use unique data on counter-piracy that matches when, where and which incidents resulted in a response from the EU Navy operation (EUNAVFOR) and how pirates subsequently adjusted to this. Focusing on the Somali case, this manuscript argues that pirates' strategic behaviour helps explaining the spatial pattern of attacks and possible contagion. My argument implies that pirates' decision-making is strategic and dependent on their previous history of attacks and assessments of success. Third, the manuscript contributes to the existing literature on spatial contagion by taking advantage of studying contagion and counter-contagion dynamics in an environment with few confounders. On-land phenomena may pose more challenges as they are the result of social interactions and micro dynamics that are more difficult to capture. Thus, it is more

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[1] The distinction between diffusion as conditioned behaviour and contagion as imitative behaviour are from Midlarsky et al. (1980). Since main argument made in the article is that pirates behaviour is indeed purposive rather than random, the term contagion is preferred and used throughout the article.

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straightforward to account for few confounders at sea and explore whether other factors (e.g. learning) have strategic value in decision-making of criminal actors. Therefore, the findings presented here provide further evidence that strategic decisions by violent and criminal actors lead to spread of their activities. This is not the first attempt to detect contagion of piracy (see Marchione & Johnson, 2013), but it is the first one conceptualizing contagion as a *process* and thus proposing explanations for why we see contagion as an *outcome* (Elkins & Simmons, 2005).

The manuscript is organized as follows. First, I summarize the main scholarly contributions on spatial contagion, particularly in the study of violence and crime. In the theoretical section, I argue that attacks by pirates are not completely random and that some locations are potentially preferred not only because of location-specific risk factors (e.g. distance from coast or weather conditions), but also because of pirates' experience of successes and disruptions by EUNAVFOR counter-piracy in that location. To test these hypotheses, I propose a statistical analysis of piracy and counter-piracy efforts in Somalia from 2005 to 2013. Results corroborate contagiousness of piracy as predicted by the reinforcement, contiguity and learning hypotheses on contagion. Additionally, I find that the deployment of the EU mission has overall curbed the incidence of piracy off Somalia in recent years (deterrence) and that pirates avoid areas where EUNAVFOR disrupted their attacks (compellence), though this effect only lasts one month. The conclusion discusses the relevance of piracy for understanding the contagion of violence and (transnational organized) crime and how identifying different mechanisms of contagion or diffusion should lead to different policy interventions.

Spatial diffusion and contagion of violence and crime

Early political science studies on diffusion paid particular attention to the spread of violence. Starr and Most (1985) indicate reinforcement and diffusion as possible processes through which war spreads across countries. Intuitively, they argue that countries are at greater risk of war if they have experienced war in the past or are proximate to other countries at war. Braithwaite and Li (2007) also finds that countries located in terrorist hotspots are more likely to experience terrorist attacks in the immediate future.

The connections among countries may be defined by different criteria, one of which is geographic proximity. Contiguity provides the opportunity for inter-state interactions, which facilitate the diffusion of violence across countries (Braithwaite, 2006; Lake & Rothchild, 1998). While proximity plays a role in the diffusion of phenomena or adoption of policies, it is not the only channel (Braithwaite, 2010; Buhaug & Gleditsch, 2008; Zhukov, 2012). Alliances, shared membership in IGO, intergovernmental ties, migration flows and even civilization lines are alternative channels through which phenomena, as infections, spread faster than proximity would predict (Bove & Böhmelt, 2016; Most & Starr, 1989; Neumayer & Plümper, 2010; Zhukov & Stewart, 2013). For example, Midlarsky, Crenshaw, and Yoshida (1980) argue that the risk terrorism contagion depends on the diplomatic status of the country where terrorism occurs since status indicates a degree of "imitability". Indeed, non-state actors e.g. terrorists and criminals, *observe* how other groups and the results of such actions; according to what they see, they decide whether to adopt the tactic or not (Elkins & Simmons, 2005). Observing who adopts a strategy and its outcome implies a learning process. Learning, in opposition to mimicry, emulation and imitation, involves a rationalist adoption of a practice based on its observed consequences and consistency with one's own objectives.[2] Also, likelihood of adopting a tactic such as suicide terrorism largely depends on the capability of a group to do so (Horowitz, 2010). Notably, however, while for military strategies like suicide bombings capability is a significant constraints, pirates do not incur in major costs when deciding to move to locations where attacks are more successful.

Insurgents and terrorists are not the only non-state actors whose activities diffuse via contagion and learning. Crime is as infectious as violence and terrorism (Cohen & Tita, 1999; Ye & Wu, 2011). Criminology has developed its own theoretical framework to explain the spatial distribution of crimes which distinguishes two mechanisms, namely flag and boost effects (Pease, 1998). Some victims "advertise their vulnerability" (Johnson & Bowers, 2004, p. 12), for example, a house with poor lighting is a potential target for any burglar. This heterogeneity in risk is at the core of the flag effect. The second mechanism driving crime diffusion is the boost effect, namely the tendency of offenders to learn from their previous crimes and use this information to choose future targets. Burglars are likely to return to previously robbed houses because they have knowledge of the environment and consequently may feel confident to operate more efficiently.

Political Science and Criminology have used different terms and methods to explore similar mechanisms behind patterns of diffusion. As argued below, compared to Criminology, the so-called Galton's Problem of distinguishing risk heterogeneity from spatial interdependence (Galton, 1889) is more explicitly addressed in the violence and terrorism literature, both theoretically and methodologically. Conversely, research on crime contagion identifies hotspots without distinguishing whether these result from spatial distribution of crime-prone features (i.e. common exposure[3]) or actual contagion of crime. As Buhaug and Gleditsch (2008) pointed out, hotspots of conflicts may also be the result of countries' individual characteristics that cluster in space, rather than a neighbourhood effect. This clustering could emerge not as consequence of interdependence among units but more as consequence of Tobler's first law of geography according to which closer things are more similar than distant things (Tobler, 1970).

This distinction between spatial *interdependence* and spatial *heterogeneity* or common exposure (Franzese & Hayes, 2008) is crucial as it has theoretical and methodological implications. First of all, arguing that the geographical clustering of conflict is only the result of the distribution of countries' features supports the conclusion that, for example, terrorism in neighbouring countries is not a threat for other states. Second, if there is an actual neighbourhood effect (diffusion or contagion), non-independence of observations is a problem for statistical inference. This manuscript acknowledges these issues and connects the Criminology and Political Science literature using piracy as instance of transnational violent crime to pin down contagion and counter-contagion mechanisms underlying the geography of piracy.

Risk factors of maritime Piracy in Somalia

Identifying factors that affect the occurrence of piracy is important for separating contagion (spatial interdependence) from common exposure (clustering of risk factors). The literature on the occurrence of piracy adopts an aggregated perspective and identifies three classes of risk factors.

First, states' institutional capacity affects the intensity of piracy activities within states' territorial waters. Scholars have argued for a non-linear relationship, with weak states being more likely to be affected by endemic piracy than failed states (Groot et al., 2011; Hastings, 2009). More sophisticated typologies of piracy require some degree of governance and are threatened by instability caused by violent conflicts and anarchy (Shortland & Percy, 2013). Daxecker and Prins (2013)

[2] For a discussion of differences, see Maggetti & Gilardi, 2015.

[3] In the manuscript, the term common exposure is borrowed from Franzese and Hayes to indicate "similar exogenous internal/domestic or external/foreign stimulus" (2008:4). In the same vein, common exposure is implied in Buhaug and Gleditsch (2008:215) when the authors mention "similar distribution of relevant country characteristics" associated with the emergence of the phenomenon of interest.

qualified this finding specifying that the non-linearity holds only for extreme, rare cases of state fragility.

Second, economic conditions affect the cost-opportunity for individuals deciding to join the piracy business. These economic conditions include both the availability of opportunities in the fishery sector and, more generally, macro fluctuation of capital-intensive and labour-intensive commodities (Daxecker & Prins, 2013; Jablonski & Oliver, 2012). Finally and intuitively, geographical and meteorological circumstances affect the risk of piracy. The seasonality of adverse weather conditions suggests that also piracy has seasonal variation particularly in Somalia, where summer and winter monsoons make waters extremely rough and dangerous (Hansen, 2009; Percy & Shortland, 2013). Among geographical factors, proximity to the coast (access to safe havens) and chokepoints are additional favourable conditions (Chalk & Hansen, 2012).

Differently from existing work, this manuscript makes an additional step and focuses on factors affecting pirates' decision-making instead of aggregate patterns of piracy. While I recognize and account for the importance of aggregate-level factors, I aim at exploring more localized manifestations of the phenomenon and the precise location of each single attack. Using sea locations as observation unit also allows to isolate more convincingly the role of experience and learning from land-based features associated with piracy. While conflict violence can explain why pirates select certain areas as safe havens, the effect of conflict on crimes perpetrated at sea should be less and less important as pirates move away from shores.

Alongside these aggregate factors, the first decision for pirates involves selecting the location where they want to search for targets. This decision is based on a set of characteristics broadly defined as contextual. Contextual features describe the risk of operating in a location. For pirates, location matters more than targets' features since targets are not fixed. While burglars can select a house and repeatedly victimize it, pirates rarely attack the same ship. This does not imply that pirates do not select targets at all, but before assessing how easy it would be to board the ship that is sailing in front of them (e.g. does it have ladders?), pirates have to decide which areas to scout (Hansen, 2009). Pirates hold beliefs on the feasibility of attacks in several locations, and these beliefs are partly based on their previous experience. Assessment on vessels' level of security is contingent on whether one is ever spotted. It is not surprising, then, that pirates often operate in the same areas, as Fig. 1 shows for the Somali case. Most incidents attributed to Somali pirates occur in specific areas rather than being scattered throughout the Western Indian Ocean. Fig. 1 also illustrates that the Gulf of Aden is not the only dangerous area for vessels. Of course the chokepoint at Bab-el Mandeb forces ships to travel along a limited area, thus making pirates more likely to hit nearby locations and, consequently, hotspots more likely to emerge (Chalk, 2009; Coggins, 2012; Shortland, 2015). However, not only the density of attacks extends well beyond the Gulf's entrance, but also areas in the larger Somali Basin experience intense piracy activity. This pushes for further investigation since clustering is not simply explained by favourable geography and may be the result of strategic choices made by pirates.

To summarize, quality of governance, economic opportunities, geography and weather reveal something about the aggregate risk of piracy but fail to explore the contagion of piracy. Some areas are more vulnerable than others, but high risk does not imply interdependence of events occurring in nearby units. The explanations in the literature are best conceived as permissive conditions that precede incidents, but there are also *consequences* of incidents that affect future (and nearby) events (Morenoff, Sampson, Raudenbush, 2001: 523). These consequences embed event-dependency and are the focus of the mechanisms driving the contagion of piracy.

Piracy is not so different from car theft or burglary: it is also an acquisitive crime, but with transnational and organized characteristics (UNODC, 2010). Whether it involves robbing, hijacking or kidnapping, pirates engage in an illicit behaviour aimed at acquiring money or valuables from a victim (Rosenfeld and Messner, 2013). As with other classes of crime, spatial analyses of piracy find clear evidence of regularities in the location of incidents (Marchione & Johnson, 2013).

Why should we expect piracy to be contagious? A common strategy for Somali pirates is to select a geographical area and launch several attacks within a short period of time (Hansen, 2009). These boosts in piracy incidents begin in areas known to pirates, their "hunting grounds" (Hansen, 2009, p. 22; Bahadur, 2011, p. 141; De Wijk, Anderson, and Haines, 2010). The campaigns may have varying duration, but if this tactic is common to all pirates' groups in Somalia, a pattern of spatially and temporally interdependent incidents should emerge. As described by Hansen (2009:22):

> *The pirates began to initiate pirating campaigns, a multitude of attacks within a short time span often in a limited geographical sectors […] scouting and selecting opportune targets within their "hunting grounds", and returning to their bases when they ran out of supplies and patience.*

Contrary to what is commonly thought about pirates selecting targets in advance, attacks are more based on patrolling instead of intentionally pursuing specific vessels (Hansen, 2009). Roger Middelton, Chatham House expert, paralleled piracy to "walking down the street, looking through windows: you see one that has a single glazing so you smash the window, go in and steal the TV" (Bahadur, 2011, p. 54). Patrolling, however, does not mean that pirates wander at sea waiting for vessels to find them. Instead, those anecdotes suggest, pirates patrol specific location based on what they have learnt from previous campaigns. Hence, acting as rational hunters, pirates attempt to maximize profit with the least effort, namely by reducing travelling time and increasing the likelihood of success. One of the factors explaining the return of pirates is familiarity and knowledge of the environment. More knowledge and familiarity increases the likelihood that pirates will return to the same locations and its surroundings as this information is used to reduce uncertainty and increase expectations of success. This strategic calculus should result in patterns of reinforcement (i.e. return to same location) and spatial contagion to nearby locations. Consequently, the following hypotheses are formulated:

H1a. *The intensity of piracy in a location is positively associated to incidents in the previous month (contagion by reinforcement).*

H1b. *The intensity of piracy in a location is positively associated to previous incidents in neighbouring locations (contagion by contiguity).*

In addition to reinforcement and contiguity, pirates can use information from the outcomes of previous attacks to inform future selection of locations. This mechanism implies learning from experience. As in a Bayesian learning process, actors accumulate new information consistent with a previously hypothesized relationship. As in the case of burglars, if offenders assess a high rate of success in a given area, then they are more likely to return. Information about previous successes is immediately available to the pirates that actually carried out attacks. Besides within-group learning, other groups could gather the same information and learn by observing other groups. If these groups succeed, observers are encouraged to adopt the same behaviour, in this case increasing piracy activity in proximity of locations with higher rates of success. There is evidence of links among pirate groups, supporting the hypothesis that they might learn from each other's practices. Piracy networks are fluid; some overlap and occasionally cooperate (Monitoring Group on Somalia, 2008). The two main pirates networks of Somalia, namely the Puntland and the Hobyo-Hardheere networks, have collaborated since 2005 and some senior pirates also travelled around Somalia as instructors and head-hunters (Eichstaedt, 2010; Hansen, 2009). Cooperation and overlapping membership favour the

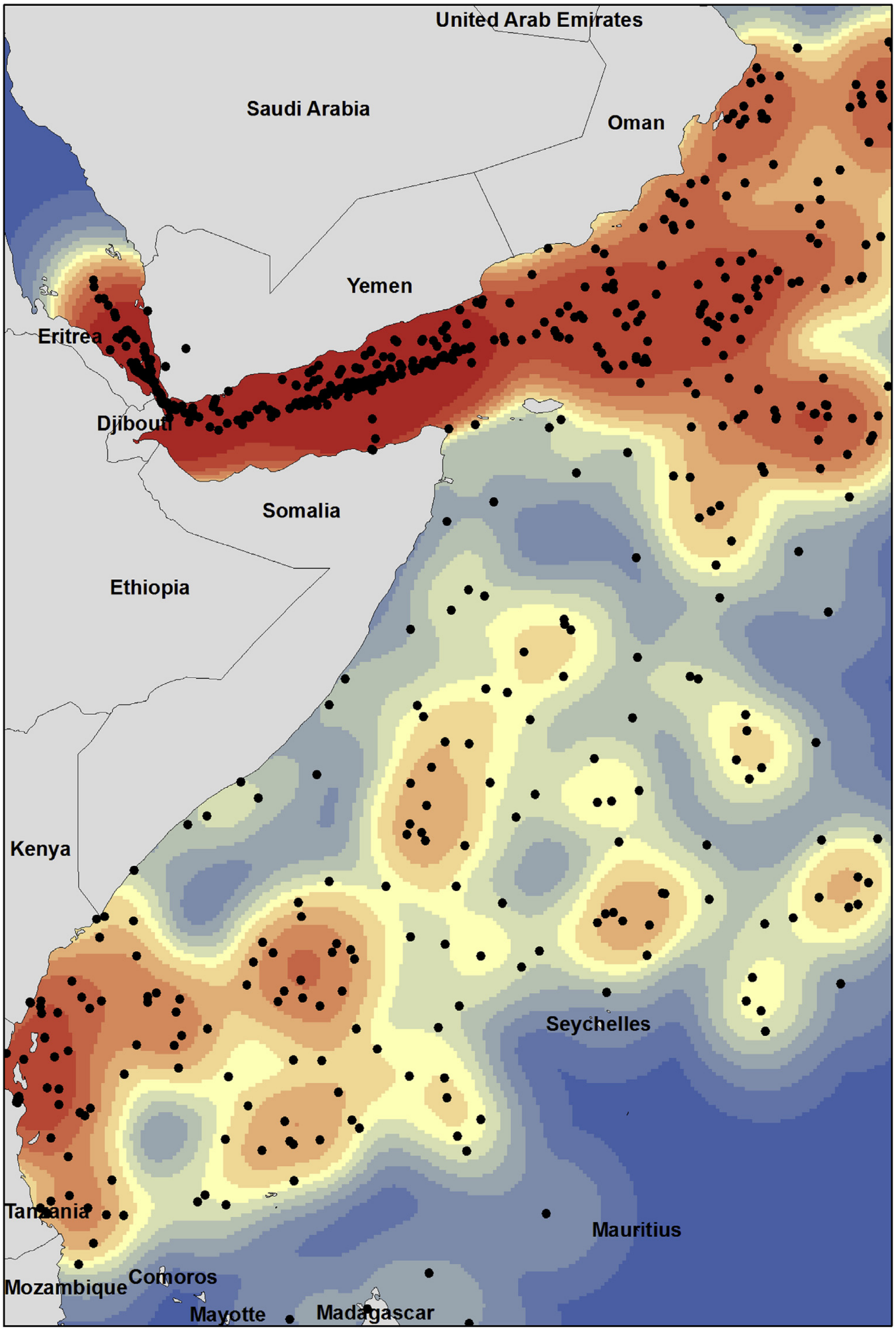

Fig. 1. Kernel density of attacks from 2005 to 2013. Spatial patterns of piracy in Somalia.

flow of information among groups and support the hypothesis that pirates learn not only from their own experience but also observing other groups' successes.[4]

The tacit coordination among pirate groups also explains why success would not lead to competition and thus dispersion rather than concentration of attacks. As groups learn about each others' successes, we could expect that more groups will end up operating in the same area; competition over scarce resources may drive to two possible scenarios. One, pirate groups will fight over specific areas. The coordination mechanisms mentioned above reduce competition and are often enforced by clan elders (Hansen, 2009). For example, pirates are forbidden to re-hijacked released vessels on their way off Somalia (Shortland & Varese, 2016). More likely, pirate groups will operate in those locations that are just proximate to those known to be successful, both to avoid frictions with other groups and to avoid attracting EU

[4] Unfortunately, distinguishing between contagion driven by learning from one's own experience from *observational* learning (Bandura, 1973) is impossible with existing piracy data. Such data does not identify piracy groups and/or networks carrying out attacks.

navy attention by overcrowding shipping lanes with pirates skiffs. So pirates will prefer operating in nearby areas (thus contagion will occur) and not precisely in the same exact area where successful attacks occurred.

Both within- and between-group learning are relevant and expected to have the same effect on piracy incidence. I propose the following hypothesis on learning:

H1c. *The intensity of piracy in a location is positively associated with rates of success in the same location and its surroundings (contagion by learning)*

If Hypotheses 1a, 1b and 1c find empirical support, it can be argued that location and timing of piracy attacks are strategically selected instead of being opportunistic and completely unplanned. All three hypotheses outline decision mechanisms that explain different parts of the spatio-temporal clustering of piracy incidents found in the literature. As will be clarified in the operationalization of the variables, the crucial difference between H1b and H1c is that the former explains contagion as result of geographical proximity, while the latter focuses on rational evaluation of previous attacks and success rates in each location.

Another important clarification concerns the null hypothesis. If there are several factors that explain clustering besides learning, contiguity, and reinforcement, we would see clustering even if no contagion is occurring. This point relates, again, to the fundamental Galton's Problem. If clustering of piracy is still present *after* controlling for risk factors that are similar in nearby units (e.g. distance from land), there is likely an interdependent data generating process that needs to be modelled. Hence, the main null hypothesis here is “no spatial interdependence” rather than “no clustering”, which could still be present in absence of contagion. Indeed, even in absence of interdependence and contagion, we may still observe clustering but what occurs in each unit is independent and does not affect others.

Countering contagion: counter-piracy in Somalia

Contagion is not only instigated by what others do but can also be “inhibited by the information [units] receive through time about one another's behaviour and its consequences” (Pitcher, L Hamblin, & Miller, 1978). Hence, while some factors are expected to favour the contagion of piracy (i.e. rate of success in close locations), there are also factors that inhibit and contain contagion. One important factor that has potentially inhibited pirates' activity and altered their *modus operandi* off Somalia is the European Union Naval Force Atalanta (EUNAVFOR). EUNAVFOR was established in late 2008 to reduce the incidence and contagion of maritime piracy in the Gulf of Aden and the Somali basin. The deployment of warships from European countries has been extended until December 2018 with the objective of protecting vulnerable vessels (especially those carrying food aid), deterring and disrupting piracy and monitoring fishing to support international organization which are building maritime security and capacity in the area (EUNAVFOR webpage).

The presence of warships is expected to have a decreasing effect on piracy. I distinguish between deterrence and compellence effects. Deterrence occurs when an actor is discouraged to initiate an action because he or she fears the threat of retaliation; compellence describes a situation where the cost-benefit calculation of action is altered after the cost has been imposed (Schelling, 1966). I argue that EUNAVFOR deployment has both a deterrence effect (overall reduction of attacks following the deployment of warships) and a compellence effect (reduction of risk of attacks in location where the navy has imposed costs on pirates by disrupting attacks). In line with this, hypotheses on contagion inhibitors are:

H2a. *EUNAVFOR patrolling in the Indian Ocean has decreased the risk of piracy attacks (deterrence)*

H2b. *Rescue intervention reduces the risk of piracy in the same location and its nearby (compellence)*

Analysis: data and method

The availability of spatially and temporarily disaggregated data on incidents allows for an empirical analysis of micro-level theories of violent actors' behaviour. In order to test the hypotheses on how pirates select locations to perpetrate attacks, I use a time-series cross-sectional dataset with grid cells-month as unit of analysis. Particularly for the Somali case, most events do not occur in ports but at high sea. This introduces the problem of defining what a “location” is at sea since there is no natural or administrative boundary separating different areas. The spatial unit I refer to with the term “location” is a cell from the PRIO-GRID (Tollefsen, Forø, Strand, & Buhaug, 2012). The PRIO-GRID consists of 0.5 × 0.5 decimal degrees cells and covers the maritime areas where Somali pirates attack vessels. This includes the Somali coast, the Gulf of Aden and the Somali basin (see Fig. 1). The data include 2964 cells observed monthly from 2005 to 2013, for a total of 320,112 observations. I use months as the temporal unit in order to better identify contagion processes and immediate effects of counter-piracy. About 10% of the cells (397) experienced at least one attack in the period under consideration. I use a dataset on maritime piracy (Maritime Piracy Event & Location Database, MPELD, Daxecker, Prins, & Salvatore, 2018), which collects information on attacks combining reporting from International Maritime Bureau (IMB), Anti-Shipping Activity Messages (ASAM) and International Maritime Organization (IMO). While reporting of attacks in the 1990s was geographically unprecise, reporting significantly improved in 2000s. Only 6 out of almost 1300 incidents off Somalia from 2005 to 2013 have no clear geographical reference, thus were excluded. Duplicates of incidents reported in both sources were also removed. The analysis includes actual and attempted attacks since the main research question focuses on pirates' strategic selection of favourable environments, rather than explanations of success. Incidents are self-reported by crew or ship owners; however incentives for reporting attacks are likely independent from where they occur, thus should not substantially alter geographical patterns. The dependent variable is the monthly number of piracy incidents in each cell.

I first present a logistic regression that estimates the effect of contextual risk factors (stability, economic conditions, geographical features, and weather patterns). The logit model sets the baseline risk based uniquely on cells' features, thus the model excludes spatial variables. The count models build on this baseline. They only include variables that were significant in the logit model with the addition of the contagion-related covariates. More specifically, I test hypotheses 1a, 1b and 1c on contagion by reinforcement, contiguity and learning using a zero-inflated negative binomial (ZINB) to model the intensity of piracy. Hypotheses 2a and 2b on counterpiracy are examined thereafter. H2a focuses on deterrence effect in the aftermath of EUNAVFOR deployment. To test the compellence in hypothesis 2b, I examine the effect of EUNAVFOR actual intervention against pirates to rescue vessels rather than EUNAVFOR's mere presence. Since rescuing operations and intensity of piracy are endogenous, I perform a seemingly unrelated estimation (SUR) that allows me to combine a ZINB and logistic regression to test hypothesis H2b.

Main independent variables

Reinforcement, contagion and learning

To measure reinforcement, I use the temporal lag of the dependent variable to test the hypothesis that number of incidents in the previous month has a positive effect on the likelihood of future ones *within the same unit*. Second, contagion requires that what occurred in a proximate unit j at time t-1 has an effect on the nearby unit i at time t. Consequently, I calculate the spatial lag of incidents occurring in neighbouring units and also include its time lag. The neighbourhood of a cell is defined by the eight contiguous grid cells sharing a border or vertex with the cell. This is called a queen matrix of order 1, which means contagion can occur from one cell to any of the eight cells immediately adjacent to it. Third, the learning mechanism implies that pirates will operate again around areas where they carried out mostly successful attacks. For example, if most attacks near the Gulf of Aden were successful, it is more likely that pirates will operate there in the future. I measure the rate of success for each cell in the previous month as a simple proportion of actual attacks over the total number of incidents in the cell in the previous month. I also calculate the spatial lag of success to assess whether there is an increase in attacks nearby successful locations.[5]

Deterrence and compellence

Information on the location of EUNAVFOR Atalanta mission ships is not publicly available. It is known, however, that locations where EU ships intervened were scattered across the Somali basin as shown in Fig. 2, suggesting that no matter where originally deployed, ships were able to intervene in the whole area under analysis, though not always promptly as some unsuccessful rescues indicate. The support of air patrols and drones surveillance along the coast improved the mission's capacity to operate in this vast region. Importantly, pirates are not informed about where EUNAVFOR ships are located at different times, so they cannot purposely avoid specific areas based on the expectations that warships will be patrolling. To measure deterrence, I thus add a dummy variable for the EUNAVFOR Atalanta deployment that takes value of 1 for all grids after 2008. To avoid conflating Atalanta with the introduction of Best Management Practices and private security on board, I control for these two factors separately (see below on control variables).

The compellence mechanism suggests that locations where pirates have previously confronted EUNAVFOR ships are less likely to be selected for subsequent attacks. The EUNAVFOR website provides data on the rescue of vessels, but the location of the operation is vague and refers only to Gulf of Aden or Somali basin. In order to identify cells where the mission intervened to disrupt an ongoing attack, I cross the information reported by the EUNAVFOR on the exact date and type of rescued vessels with MPELD data. Using the exact date and type of vessel, I can match incidents with rescues and accordingly locate EUNAVFOR interventions.[6] I account for pirates' strategic adaptation after confrontation with EU warships by including a time-lagged dummy for grids where the EU intervened to rescue a vessel. Linking incidents to rescue is crucial for testing EUNAVFOR effectiveness. Jablonski and Oliver (2013) operationalize this variable as a count of patrolling vessels, but they cannot actually locate their activities. They find no effect for this variable, but since incidents are not linked to international counter-piracy efforts it is problematic to completely rule out any effect. In fact, Jablonski and Oliver mention that a local deterrent effect can be at place, which is also consistent with the findings in Shortland and Vothknecht (2011). Such local effect can only be observed with disaggregated data that previous studies lacked.

As a summary, Table 1 reviews hypotheses and operationalizations.

Control variables

Most of the control variables are calculated and assigned to each cell using ArcGIS. I proxy institutional capacity (strength of local governance and the degree of instability) with the number of monthly killings along Somali coast reported in the Armed Conflict Location and Event Data project (ACLED, Raleigh, Linke, Hegre, & Karlsen, 2010).[7] I expect that both very stable and very unstable territories are associated with fewer pirate attacks close to the coast, as posited by the institutional capacity argument. I include a square term for this inverse-U relationship. Non-linear effects are also expected for measures of distance from ports and density of shipping traffic. Pirates will attack more often in areas where many vessels transit, yet too high density may be a problem as the crew may call for close ships' help. Distance from ports should also have a non-linear effect. Since pirates try to maximize gain and reduce effort, travelling too far is not ideal. Yet, vessels actively avoid the Somali coast. Consequently, pirates are forced to move a bit further while still preferring to be as close as possible to land. Squared distance from ports and density of traffic are included to account for these non-linearities. Distance from ports is calculated with ArcGIS while data on shipping density are from the European Commission Maritime Forum yet, unfortunately, available only for 2010.[8] Because of this limitation, traffic density is included in the ZINB inflation stage because locations without transit will never experience piracy. Assigning a low probability of attack to locations with low traffic is the best way to make use of available information on sailing vessels. I also include a dummy for cells within 200 nautical miles from the Bab-el-Mandeb chokepoint and a dummy for monsoon seasons (South-West monsoon in summer and North-East in winter). To show that piracy is also a function of labour opportunities, I interact the monsoon season with a dummy for the Gulf of Aden; more specifically, the growth in fishing production brought by the summer monsoon in the Somali Basin should reduce piracy in this area but less pronouncedly in the Gulf of Aden. Finally, the introduction of Best Management Practices (BMP) document in 2009 and on-board private security can also be argued to have had an impact on the intensity of piracy off Somalia. I use EUNAVFOR data to calculate the time lagged number of rescued vessels that implemented BMP and the number of vessels with private security on board for each cell-month.

Estimation and results

Before focusing on the ZINB model, Model 1 in Table 2 reports the logit model including only the control variables and the time lag of the dependent variable. This model identifies the baseline risk of experiencing one attack in a grid cell-month. Most variables behave as hypothesized. Shipping density is associated positively with incident occurrence; hence the likelihood of piracy is higher where there are more potential targets available. Increasing distance from ports reduces the odds of attacks. The square term for traffic density and distance, however, is not significant. Being in proximity of the Bab el-Mandeb strait is also very risky for vessels as it is easier for pirates to identify target, attack and then quickly escape to the coast. Higher density of traffic in these areas also allows pirates to choose more vulnerable targets. Meteorological conditions also affect the risk of attacks, though only the South-Western monsoon curbs piracy, while the winter monsoon has no significant impact. Because of its intensity and high temperature, coastal communities benefit from the summer monsoon; its upwelling increases the presence of sea nutrient and makes fishing more attractive than going out at high sea to rob or hijack vessels (Wiebinga, W Veldhuis, & W De Baar, 1997). The interaction term between summer monsoon and the Aden region shows that risk of incidents is lower during the summer monsoon but this effect is more moderate in the Gulf of Aden. Here the increased marine productivity is half than in the Somali basin so, as consequence, fishery does not sufficiently substitute for piracy nor it increases the opportunity cost of using boats for piracy instead of fishery. Hence, few attacks still occur. Finally, the number of battle-related deaths along Somali coasts measures the degree of instability and local governance. According to the results, instability but not complete chaos provides advantages for illicit activities such as piracy. The baseline model confirms that quality of

[5] Notice that attacks are defined as attempted or successful in the IMB, ASAM and IMO reports depending on whether pirates managed to either board or hijack a vessel.

[6] For example, EUNAFOR reports four rescued vessels on 01/01/2011, namely two tugs, a chemical tanker, an oil tanker. Similarly, MPELD records five incidents on the same date, four of which involving exactly the same type of vessels. A fifth vessel is reported as hijacked by MPELD and, consistently, is recorded as pirated in the EUNAVFOR.

[7] This includes all casualties reported in ACLED within coastal Somali second order administrative units (Global Administrative Units http://www.gadm.org).

[8] Available here: https://webgate.ec.europa.eu/maritimeforum/en/node/1473.

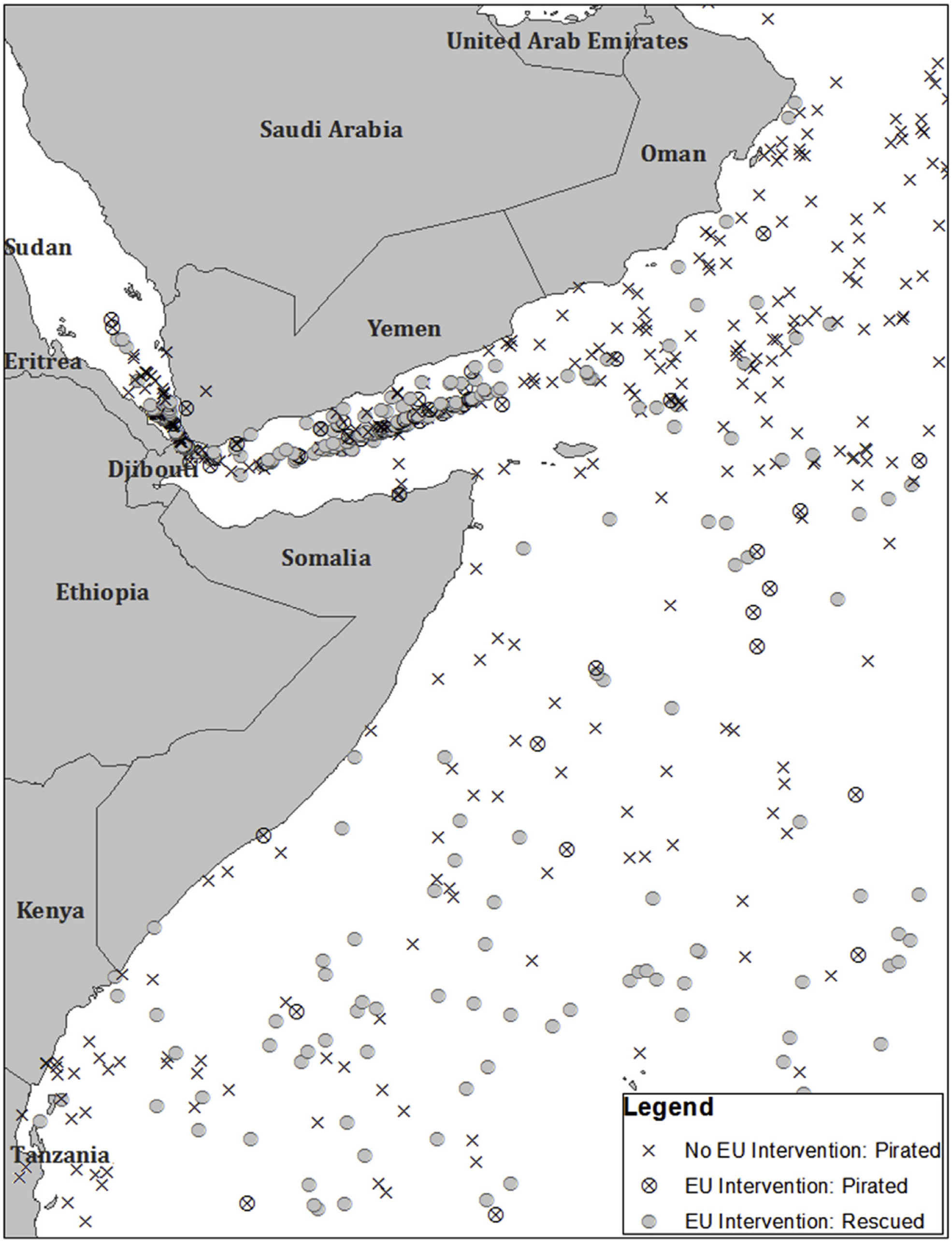

Fig. 2. Piracy incidents and EUNAVFOR intervention from December 2008 to 2013.

Table 1
Summary of mechanisms and measurements.

HYPOTHESES	Mechanism	Operationalization
H1: Contagion	(a) by Reinforcement: More incidents after one occurred in the same location *i* at *t-1*	DV_{t-1}
	(b) by Contiguity: More incidents after one occurred in neighbouring locations *j* at *t* and *t-1*	$W{*}DV_t^j W{*}DV_{t-1}^j$
	(c) by Learning: More incidents if the location or nearby have high rate of successful attacks	$\left(\frac{\text{Successful Attacks}}{\text{Total Attacks}}\right)_{t-1}^{i} W{*}\left(\frac{\text{Successful Attacks}}{\text{Total Attacks}}\right)_{t-1}^{j}$
H2: Inhibitors of Contagion	(a) Deterrence: Less risk of incidents after EUNAVFOR deployment	Dummy Atalanta
	(b) Compellence: Less risk of incidents after confrontation with EUNAVFOR	Dummy Rescue *t-1* within cell

governance, economic opportunities, weather and geographic factors affect the location of attacks not only at the state level.

The logit model neglects the contagion mechanisms and does not disentangle simple geographic clustering from actual contagion. It also does not account for how many times locations experience piracy. As main model, I estimate a ZINB to explore channels of contagion. There

Table 2
Logit and count models for piracy contagion.

	Model 1	Model 2	Model 3	
	Logit	NB	ZINB Main Model	
			NB	Inflation
Reinforcement	2.751***	1.257***	1.135***	
	(0.184)	(0.348)	(0.333)	
Contiguity ($t-1$)		0.143	0.110	
		(0.125)	(0.118)	
Contiguity		0.993***	0.928***	
		(0.121)	(0.114)	
Rate of Success ($t-1$)		4.856***	4.790***	
(Space lag)		(1.411)	(1.358)	
Rate of Success ($t-1$)		0.882**	0.905**	
		(0.396)	(0.356)	
Density	0.054***	0.037***	0.004	−1.715***
	(0.017)	(0.009)	(0.014)	(0.433)
Density (sq)	−0.001	−0.0004	−0.0001	
	(0.001)	(0.0003)	(0.0001)	
Distance ports	−0.07**	−0.039	−0.037	
	(0.034)	(0.034)	(0.034)	
Distance ports (sq)	−0.003	−0.004**	−0.005**	
	(0.002)	(0.002)	(0.002)	
Chokepoint	1.185***	0.843***	0.771***	
	(0.215)	(0.197)	(0.213)	
Summer monsoon	−1.160***	−0.593***	−0.592***	
	(0.180)	(0.112)	(0.112)	
Winter monsoon	−0.036			
	(0.1)			
Gulf of Aden	−0.540***			
	(0.199)			
Summer monsoon*Aden	1.031***			
	(0.228)			
Winter monsoon*Aden	0.076			
	(0.139)			
Killed ($t-1$)	3.691***	2.808***	2.821***	
	(0.531)	(0.692)	(0.674)	
Killed ($t-1$) (sq)	−1.781***	−1.343***	−1.349***	
	(0.264)	(0.343)	(0.335)	
Constant	−6.938***	−6.875***	−6.171***	0.479**
	(0.327)	(0.322)	(0.320)	(0.241)
Observations	320,112	320,112	320,112	
LnAlpha			1.797***	1.514***
Vuong Statistics			4.75***	
10,720				
10,891				
AIC		10,816		
BIC		10,965		

Clustered Standard Errors.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

are locations with very low or even zero chances of attacks, for example if vessels never cross that cell. Now, what explains immunity from piracy is likely different what explains concentration of piracy. The ZINB models these two processes separately,[9] differently from count models such as negative binomial (NB). For comparison, I report also the results from a NB model in Table 2 (Model 2); all key statistics (AIC, BIC and Vuong test) suggest that the ZINB model perform significantly better than the NB, although the point estimates are not very different. My decision to select the ZINB model relies on both statistical and theoretical reasons. First, I believe that shipping density affects both intensity and probability that an incident will ever occur in a location. This is effectively modelled by the ZINB. Second, the seemingly small differences between NB and ZINB (which nonetheless are statistically important in terms of goodness-of-fit) do tell us something about the proposed theory of piracy contagion, namely that locations with high number of attacks do not have specific features that differentiate them from locations with extremely low risk.

ZINB estimates are shown in Model 3 (Table 2). The covariate for the inflation equation is shipping density: locations where vessels never transit are expected to be less (if never) targeted. Also, mechanisms of contagion by reinforcement, contiguity and learning are tested in this model. The increase in expected count of incidents after at least one occurred in the previous month is indicative of a reinforcement process. The intensity of attacks increases 211% when an attack already occurred in the same location (Table 3). If the attack occurred in surrounding locations, the intensity is heightened by 152%, meaning the number of attacks more than doubles. The significance of the spatial lag and the non-significance of the spatio-temporal lag suggest that this neighbourhood effect occurs in the short run, namely within the same month. Incidents that occurred in the surroundings are not affecting the intensity of piracy in the following months. This is likely the result of short campaigns often carried out by Somali pirates that generate chains of attacks close in space within a short period. Near-repeat analysis discussed below confirms this interpretation.

A third contagion mechanism suggests that pirates learn for previous attacks and return to locations where more successful attacks were carried out. The model supports this explanation, as the positive and significant coefficients for the learning variables show. A 10% increase in the rate of success results in 9% more incidents in that unit and, more importantly, 62% more in the surrounding locations. The control variables retain significance and direction as estimated in the logit and NB models, except for density, which is only significant in the inflation equation. As expected, less trafficked areas are important predictors of no incidents, meaning they are not selected by pirates.[10]

Fig. 3 plots the probability of an attack after one has occurred in nearby cells, as estimated by the ZINB. The likelihood of attacks increases as more incidents occur in the surrounding units, regardless of whether the cell has already experienced an attack in the previous time period. The risk of piracy is higher when both surrounding units and the location itself were targeted previously (solid line, approximately 3%) but is halved when only neighbouring cells have been previously attacked (dashed line, approximately 1.5%). This suggests that piracy both spreads to new locations and re-occur in those that already experienced it. Predicted probabilities in Fig. 4 refer to similar scenarios where pirates have successfully carried out attacks in neighbouring units in the previous month. Again, the likelihood of piracy increases as success rate grows, and doubles when an incident occurred in the previous month too. Note that the highest success rate is 0.75, hence the difference between the two lines is significant for most observed variation in the sample.

I explore the finding on the short-term versus long-term contagion by contiguity further by moving to a higher level of temporal disaggregation, namely daily variation in attacks. Near-repeats analysis can be used to identify daily patterns of contagion. Near-repeats are events that occur close in time and space in a non-random way. Full results are not included to preserve space (results available upon request), there is a clear pattern of near-repeats with the first piracy attack being followed by a rapid increase of risk in nearby cells for a short temporal span.[11] Indeed, after several attacks the risk of getting caught is higher because vessels might have alerted authorities so the campaign has to stop. It follows that pirates can carry out multiple attacks in close areas for a short period; they will then have to either move away or retreat. Fig. 5 maps the location of near-repeats. The longest

[9] The model estimates two separate equations, one for the data-generating process of the zeros and another for the positive counts. The inflation equation is a logistic model for 0s, the other model is a negative binomial. So the two equations are: $\log it(\Pr(Y_{it}=0)) = \text{intercept} + \gamma_1 Z_{it}$, $NB(\Pr(Y_{it}>0)) = \exp(\text{intercept} + \beta_1 X_{it} + \beta_2 W_{it})$, Where $\boldsymbol{Z_{it}}$ are covariates for inflation stage (only density in this case), $\boldsymbol{X_{it}}$ is a vector of the main independent variables (Table 1) and $\boldsymbol{W_{it}}$ are the set of control variables.

[10] Recall that the inflate equation predicts the likelihood of 0s.

[11] Software for Near-Repeat analysis: http://www.cla.temple.edu/cj/misc/nr/.

Table 3
Incident rate ratio (Model 3, 4 and 5).

Mechanism	Variable	IRR	% Change Piracy
Reinforcement	Count ($t-1$)	3.111	+211%
Contiguity	Count (Space lag)	2.530	+152%
Learning	Rate of Success ($t-1$) (Space lag)	1.049	+61%
	Rate of Success ($t-1$)	1.009	+10%
Deterrence	Atalanta2011	1.3	+30%
	Atalanta2012	0.507	−49%
	Atalanta2013	0.123	−88%
Compellence	$\text{Success}_{(max)}$*Rescue ($t-1$)	0.51	−89%

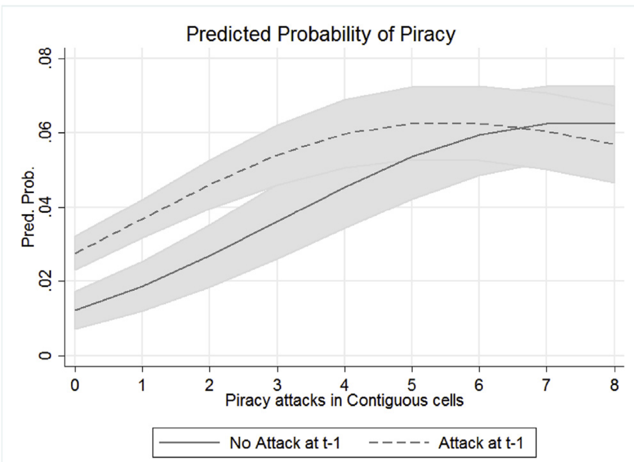

Fig. 3. Predicted Probability of Piracy after piracy in nearby cells.

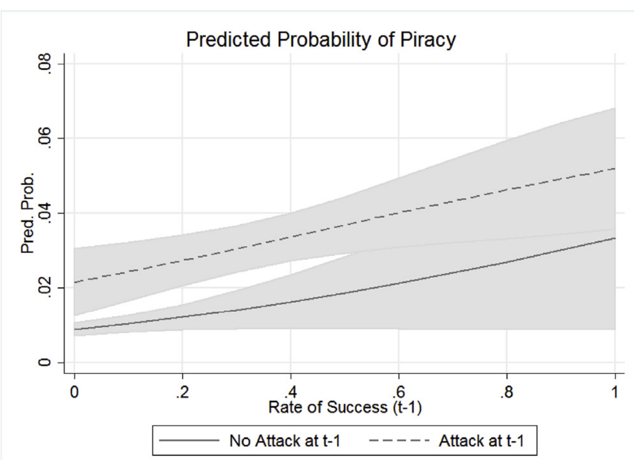

Fig. 4. Predicted Probability of Piracy after successful piracy in nearby cells.

chains (> 10 attacks) are in the Gulf of Aden, close to the straits. Here, the conjunction of favourable geographic conditions probably allows pirates to attack multiple targets in a short amount of time (one day interval).

In sum, results in Table 2 reveal that piracy spreads in space, also to previously immune locations. This contagion is driven not only by spatial contiguity but also by a learning process through which pirates update their belief about successful areas. The same argument holds for reinforcement, that is to say, the expectation that pirates return to locations they are familiar with.

Now, I assess the effect of EU counterpiracy in terms of deterrence and compellence (H2a and H2b). The deployment of EU warships for the Atalanta mission should alter pirates' decision-making and contain the contagion of piracy. Model 4 (Table 4) tests the effect of EUNAVFOR deployment on the intensity of piracy activity using year dummies that equals 1 for years after 2008. Model 4 reveals that the deterrent effect only started in 2012, with a 49% reduction of monthly attacks and became even stronger afterwards, with an 88% decrease in 2013 (Table 3). Piracy activity off Somalia did not drop immediately after the deployment, but the mission became a more effective deterrent later. Indeed, in 2012 EUNAVFOR was allowed to expand its operations to Somali territorial waters and coastline and established cooperation with the Somali Transnational Federal Government (European Council, 2012). In May 2012, EUNAVFOR conducted its first raid against a pirates' base on Somalia's coast, during which boats and weapons were completely destroyed (BBC News, 2012). Models with one single dummy variable for Atalanta mission (not shown) do not capture this gradual improvement and report a positive coefficient. Furthermore, the implementation of BMP and use of on-board private security does not significantly reduce attacks, while more likely reduce their success.

Moving to compellence, I test the effect of EU rescue operations on pirates' strategic selection of locations. More specifically, I measure whether pirates faced EUNAVFOR in a location in the previous month to test the compellence effect. Disrupting attacks does not simply threaten, but actually imposes costs on pirates. Since the strategic interaction between pirates' activity and EU intervention is endogenous, I use a seemingly unrelated regression (SUR) to test the hypothesis. The SUR model estimates two separate equations allowing correlation between disturbances. To ensure consistency with the main model presented earlier (ZINB, model 3) the two seemingly unrelated models are a ZINB and a logit model. I expect the intensity of piracy to be related to EU activity in given units in the last month; hence I use the ZINB with the number of attacks as the dependent variable and previous EUNAVFOR rescue interventions as the independent variable. At the same time, EU interventions are a function of piracy actually occurring, which is why the logit model uses a dummy for EUNAVFOR intervention in the previous month as the dependent variable, and the previous number of attacks and success rate as covariates. I interact success rates and EU rescues in the ZINB equation because compellence can be conditional on learning. If pirates attack a vessel in a cell that has 100% failure rate, they are less likely to return to the location independently from EUNAVFOR intervention. A compellence effect occurs when successful areas become dangerous for pirates because of EU disruption. Indeed, models without the interaction term report no significant effect of intervention on future piracy incidents (not shown).

The results are reported in Model 5 (Table 4). The logit estimation shows that interventions are strongly and positively related to piracy activity not only in a specific unit but also in its proximity. Also rates of success in the location increase the probability of EU intervention, suggesting a learning effect also for counterpiracy operations. Focusing on the ZINB model, it is interesting to see that the disruption of attacks by EUNAVFOR reduces piracy incidence and discourages attacks even when the success rate is high. As reported in Table 3, when success rate is at its maximum, piracy is reduced by 89% by EU intervention. However, this compellence only lasts for one month. It disappears after 2 months as reported by the lags for rescue operations carried out at *t-2* and *t-3*. Eventually, pirates go back to that location. This short-term effect has two main reasons. On the one hand, we know from the logit equation of the SUR estimation that EUNAVFOR intervenes more in areas where more successful attacks occurred. On the other hand, this intervention is not followed or complemented by constant patrolling of these areas. After the rescue of vessels, warships move away. Thus, it is

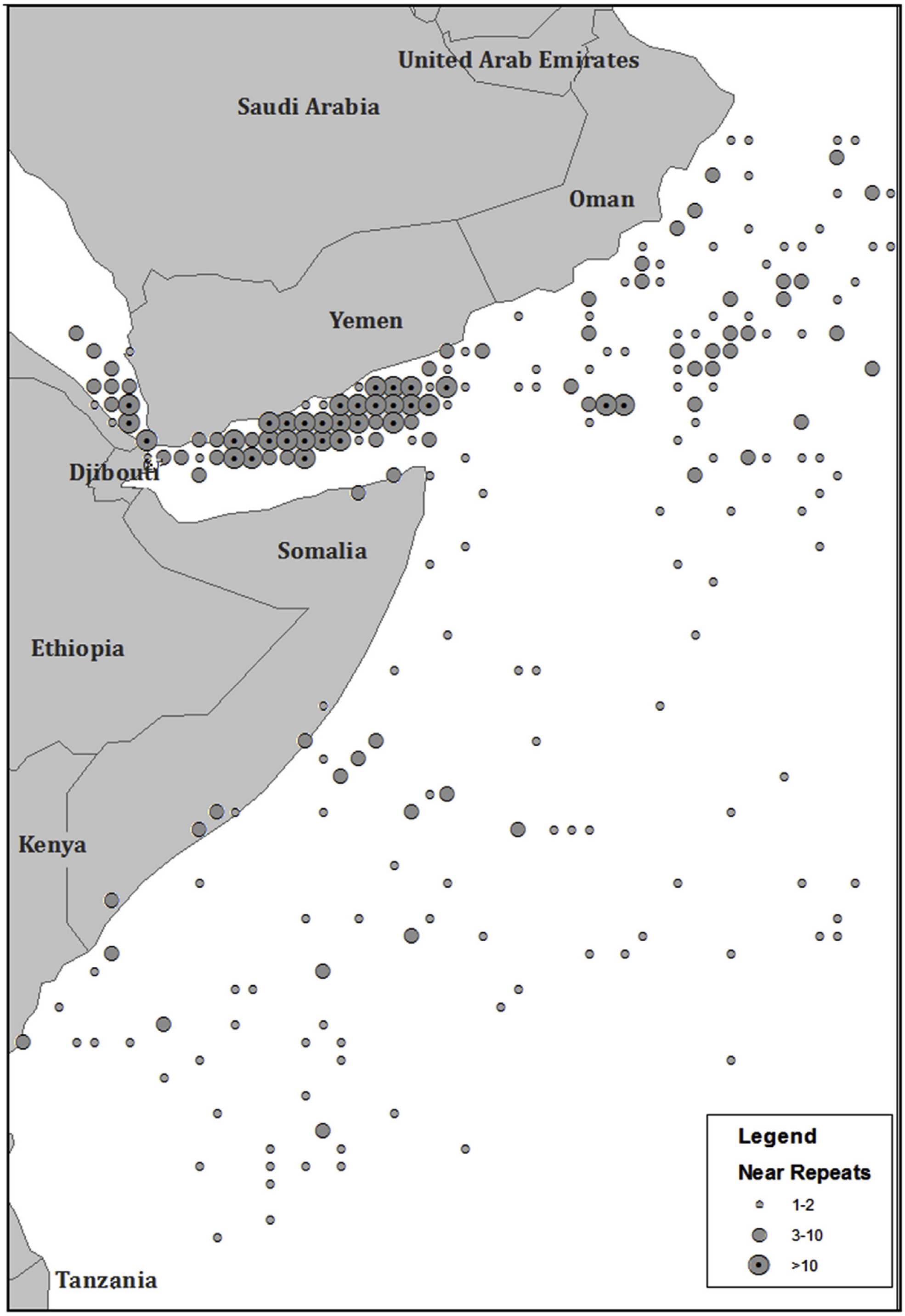

Fig. 5. Location of incidents occurring within near repeat chains.

possible that pirates wait approximately one month, according to my analysis, and then again return to these areas because of their high success rates.

The predicted effect of the interaction between success rates and EU intervention is plotted in Fig. 6. Very interestingly, success increases likelihood of contagion only when attacks did not trigger EU rescue (solid line). Indeed, the risk of attacks increases from almost 2% to more than 10% when most previous attacks were successful and the EU did not disrupt them. Conversely, EUNAVFOR interventions decrease probability of piracy spreading to new locations regardless of success rates. The dashed line in Fig. 6 is indicating that pirates are less likely to operate in locations where their success led to EU intervention, even less so when they were very successful. A plausible explanation for this is that more effective piracy attacks attract much more attention and robust military deployment, thus posing significant constraints on pirates' capacity to operate in such areas in the following month.

Table 4
ZINB and SUR models for counter-contagion.

Variables	Model (4)	Model (5)	
	ZINB	SUR Rescue	
	Atalanta	ZINB+	Logit
Reinforcement	1.210***	0.601**	4.696***
	(0.335)	(0.286)	(0.657)
Contiguity ($t-1$)	0.805***	0.902***	
	(0.108)	(0.120)	
Contiguity	0.0193	0.403***	
	(0.121)	(0.0821)	
Rate of Success ($t-1$)	1.128	3.901***	17.65***
	(0.759)	(1.049)	(1.560)
Rate of Success ($t-1$) (Space Lag)	4.496***		
	(1.445)		
Atalanta2010	0.214		
	(0.141)		
Atalanta2011	0.261**		
	(0.118)		
Atalanta2012	−0.680***		
	(0.160)		
Atalanta2013	−2.098***		
	(0.261)		
Success ($t-1$)*Rescue ($t-1$)		−7.331***	
		(2.180)	
Rescue ($t-1$)		2.600	
		(0.946)	
Rescue ($t-2$)		1.623***	
		(0.221)	
Rescue ($t-3$)		1.535***	
		(0.202)	
BMP	−0.0420	−0.152	
	(0.282)	(0.391)	
Private Security	−0.122	0.124	
	(0.365)	(0.576)	
Constant	−2.887***	−5.034***	−8.761***
	(0.800)	(0.749)	(0.405)
Observations	177,840	177,840	177,840

Other control variables are included in the estimation.
Clustered standard errors.
***p < 0.01, **p < 0.05, *p < 0.1.
+Inflation stage with Density (***) not reported.

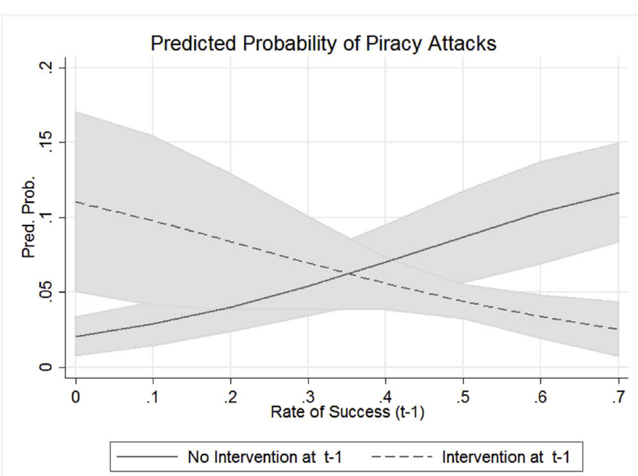

Fig. 6. Predicted Probability of Piracy after EUNAVFOR intervention against successful attacks.

Robustness and model fit

How much does the inclusion of contagion and counter-contagion variables improve predictive performances of a model of piracy risk?

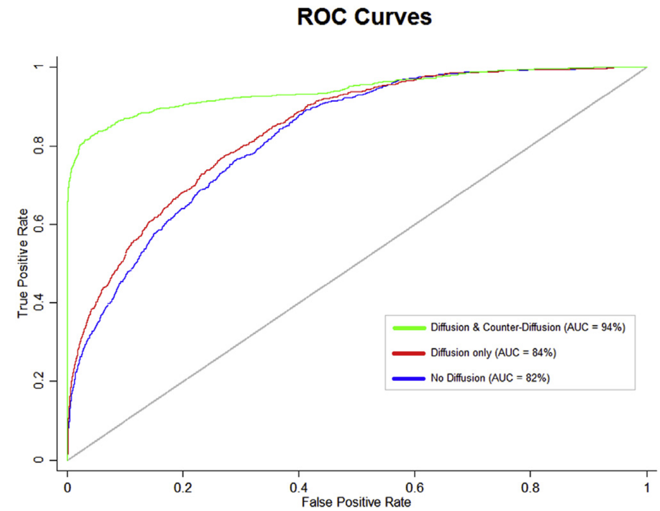

Fig. 7. Receiver-Operating Characteristic Curves for piracy attacks (2005–2013).

Fig. 7 plots the Receiver-Operating Characteristic (ROC) curves that compare the in-sample predictions of three different piracy models. The larger the area under the curve (AUC), the higher the model's predictive power. The blue curve refers to a model that only includes what I referred to as contextual factors, namely all covariates except variables related to contagion and counter-contagion, as listed in Table 1. The red curve refers to a model that includes variables measuring contagion by contiguity and learning. Finally, the green curve refers to the full model where both contagion and counter-contagion variables are included. As indicated in the Figure, the contagion model already improves the prediction of a simple model where spatial interdependences are not accounted for, moving the AUC from 82% to 84%. Furthermore, the largest improvement on predictive power results from the inclusion of counter-contagion factors, which contributes to a 10-point increase in the AUC (94%). Since this is the first study using such spatially and temporally fine-grained data, there is no existing model against which I can compare these ROC curves. The only available in-sample prediction exercise is provided by Daxecker and Prins (2015). Using country-year as unit of analysis, their model for all piracy incidents has an AUC of 92%. While differences in the unit of analysis and geographical scale make these results not fully comparable, this still suggests that considering contagion and counter-contagion factors increases the in-sample fit of risk models of piracy. In addition to this, I map the predicted risk of piracy in the Appendix (Fig. AI) to show that the estimated geographic patterns of risk are more similar to the observed geography of attacks in the counter-contagion model. Taken together, the risk maps in Appendix and the ROC curves corroborate the claim that predictions on pirates' behaviour do improve when models account for both factors that boost and contain the spatial spread of piracy.

In the Appendix, I present additional empirical results to assess the robustness of my findings. First, I did not include month or grid cell fixed effects in the main model because the ZINB already captures some heterogeneity. Indeed, the standard estimation of a ZINB model in Stata does not allow the use of fixed effects. In Table AI (Appendix) however, I show consistent results of a ZINB model with the inclusion of month fixed effects. Table AII shows the estimates of separate ZINB models for the contagion variables, and results are comparable to the main model presented in the manuscript. In addition, Table AIII reports results using the leads for the main independent variables, namely contiguity and learning. The lead of reinforcement is simply the dependent variable, since reinforcement is its time lag so it is obviously not included. If contagion is occurring, then the lead of the covariates driving contagion would have no significant effect on the number of incidents. Consistently, I find that leads are not significantly associated with piracy attacks. The Appendix also includes robustness tests using only successful piracy attacks (Table AIV), models specification with a dummy variable for the grid-cells within the Internationally Recommended Transit Corridor (IRTC) just outside the Gulf of Aden (Table AV), models with quarterly aggregated data (Table AVI) and finally models with four-month lags of the independent variables. The last two tables in particular aim at providing support to the expectation that pirates do return to some locations and their surroundings months after the successful attacks and the identified contagion patterns are not only the results of a single campaign. Finally, Table A VIII reports the result of a Markov-Chain logit model to provide a more conservative test of the contagion process. The model shows that the probability that previously safe locations experience piracy is higher when nearby successful attacks are perpetrated, while contiguity affects both the likelihood of spread in nearby cells and re-occurrence of piracy in the same cell.

Discussion and conclusions

It could be argued that contagion at sea is more challenging to identify compared to land-based contagion because socio-economic and environmental drivers of the phenomenon are not present on water. This claim seems to misunderstand contagion. First, if socio-economic and environmental features are sufficient for explaining the spatial and temporal clustering of events, clustering is very likely the result of the initial spatial distribution of these features rather than an interdependent process of contagion. This is the difference between spatial interdependence and common exposure. Second, pirates are very land-based actors and carefully select locations to sail from. For example, they seek local tribes' protection and relatively secure ports. Hence, the decision of where to sail from and to is not independent from land-based conditions. In other words, piracy occurs at sea but it is not a uniquely and purely maritime activity.

Another important points concern how confident we can be on mechanisms behind contagion of piracy and other forms of violence and crime. Violence during civil wars spreads because actors attempt to establish control over contested areas. Starting from their home base, each party uses violence in surrounding areas whenever necessary to gain relevant territories. In the case of sea-based crime, however, is it possible to identify the origin of the contagion? Pirates have to move on water to commit attacks and each time they try to identify areas suitable for attacks. Possibly, they go back to the last location they operated within and then move to its immediate surroundings. Given the availability of GPS and other technologies, pirates have at least the opportunity to do so. While conflicts escalate or relocate from a point of origin, piracy has no fixed beginning point. For contagion patterns to emerge, it is necessary that pirates decide to go in a location to start their campaigns. If they simply hunt specific targets, this behaviour would not result in spatio-temporal clustering. Once the campaign ends or at least one attack is carried out, pirates have to go back to shores again. Then, when a new campaign starts, they may decide to go back to already areas that are known and 'successful'. In this sense, the dynamics of Bayesian learning that are used to explain behaviours of other violent actors (terrorist or rebel groups), is particularly explicit and strategic in pirates' decision-making. The fact that these actors carry out their attacks at sea simply facilitates the isolation of such mechanisms that are more difficult to disentangle in land-based phenomenon. The problem of many confounders and common exposure, while still of some relevance, should be less severe for the inferences made here.

Moving from existing work on contagion of political and criminal violence, the analysis presented here shows that violent actors strategically select location for violence and adapt their decision-making according to learning and counter-violence factors. Using the case of Somali maritime piracy as strict test of such claims, I show that, along with contextual factors that increase the profitability and attractiveness of piracy (economic opportunities, instability, geography and weather), pirates base their decision making on three important factors that explain why piracy exhibits pattern of spatial interdependence. This pattern can be described as outbursts of activity followed by a contagious period, which is limited in time (within one month) and space (within 250 km). After this period, the contagion in the area stops. Additionally, successes may drive pirates to return to locations where they failed less. Interestingly, the learning process does not exclude the possibility that those who recognize the advantages of operating in a location are the same who achieved the first success. Practices, which also involve ways of carrying out attacks, may diffuse "in virtue of the signal they send" (Gilardi, 2016), rate of success in this case. Unfortunately, the data available does not allow distinguishing among groups and identifying contagion processes due to observational learning.

The identification of the sources of clustering has crucial implications for counter-piracy policy. Counter-crime interventions usually refer to hotspot maps to identify areas considered to be at risk. However, a static map of hotspot may result in misinformed strategies. Indeed, not all hotspots are constant over time and it is easy to misinterpret a temporary high concentration of piracy with a stable hotspot (Johnson & Bowers, 2004; Johnson, Lab, & Bowers, 2008). The near-repeat analysis, for example, has shown that an "originator" event may start a chain of correlated attacks only because of event-dependency and contagion. This means that a hotspot may be the result of an occasional outburst of activity following a precipitating event but this does not imply that the areas is always at high risk of piracy. In such instances, constant patrolling by navy forces (as in the transit corridor) is not efficient, whereas rapid interventions to disrupt activities are more appropriate. Stable hotspots, on the other hand, record high intensity of piracy over time, not just occasionally. This is due not to contagion but to location characteristics that are particularly favourable for piracy. Such hotspots are localized around the Gulf of Aden and Northern Somali coast, where concentration of piracy is reported throughout the whole 2005–2013 period. Hence, the distinction between risk heterogeneity and contagion made in this article is extremely policy-relevant and necessary to properly inform intervention strategies. Understanding the determinants of piracy clustering in specific locations is central for planning appropriate counter-piracy strategies as it would allow to distinguish between areas that needs to be constantly patrolled and those where the risk of attack is temporarily heightened for a limited period.

Acknowledgment

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.polgeo.2018.07.004.

Appendix

Table AI
ZINB with Month Fixed Effects

Variables	Model with Month Fixed-Effects	
	ZINB	Inflation stage
Reinforcement	1.182***	
	(0.317)	
Contiguity (t-1)	1.941***	
	(0.707)	
Contiguity	0.563***	
	(0.0786)	
Rate of Success (t−1)	0.975***	
	(0.110)	
Density	0.0244**	−1.633***
	(0.0121)	(0.417)
Density (sq)	−0.000260**	
	(0.000103)	
Distance port	−0.191***	
	(0.0388)	
Distance port (sq)	0.000756	
	(0.00153)	
Distance chokepoint	0.000367	
	(0.000294)	
Killed	5.361***	
	(0.924)	
Killed (sq)	−2.618***	
	(0.459)	
Constant	−5.165***	0.604***
	(0.250)	(0.210)

Clustered standard errors.
***p < 0.01, **p < 0.05, *p < 0.1.

Table AII
ZINB Models with Diffusion variables separately

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Reinforcement only	Inflation stage	Contagion only	Inflation stage	Learning only	Inflation stage
Density	0.0286**	−1.626***	0.0273**	−1.612***	0.0270**	−1.556***
	(0.0122)	(0.428)	(0.0136)	(0.458)	(0.0121)	(0.450)
Density (sq)	−0.000338*		−0.000279**		−0.000317*	
	(0.000183)		(0.000109)		(0.000167)	
Distance port	−0.218***		−0.201***		−0.222***	
	(0.0378)		(0.0432)		(0.0382)	
Distance port (sq)	0.00219		0.000914		0.00245	
	(0.00151)		(0.00161)		(0.00151)	
Summer Monsoon	−0.607***		−0.575***		−0.547***	
	(0.115)		(0.123)		(0.123)	
Distance chokepoint	0.000256		0.000393		0.000258	
	(0.000279)		(0.000339)		(0.000285)	
Killed	3.948***		3.112***		3.778***	
	(0.571)		(0.632)		(0.607)	
Killed (sq)	−1.904***		−1.492***		−1.818***	
	(0.284)		(0.314)		(0.302)	

(continued on next page)

Table AII (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Reinforcement only	Inflation stage	Contagion only	Inflation stage	Learning only	Inflation stage
Contiguity			1.216*** (0.109)			
Contiguity (t−1)			0.832*** (0.0786)			
Reinforcement	2.481*** (0.137)					
Rate of Success ($t-1$)					5.870*** (0.282)	
Constant	−4.791*** (0.209)	0.797*** (0.205)	−5.113*** (0.263)	0.619*** (0.215)	−4.788*** (0.217)	0.819*** (0.198)
Lnalpha		1.835*** (0.195)		2.171*** (0.210)		1.785*** (0.268)
Observations	320,112	320,112	320,112	320,112	320,112	320,112

Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table AIII
ZINB with main IVs' lags and leads.

Variables	ZINB Inflation stage	
Reinforcement	0.505*** (0.148)	
Contiguity	−0.0948 (0.0915)	
Contiguity (t-1)	0.0546 (0.0702)	
Rate of Success (t−1.)	15.71*** (0.558)	
Rate of Success (t+1)	0.532 (0.387)	
Contiguity (t+1)	−0.0665 (0.0430)	
Density	0.000183 (0.00932)	−1.432*** (0.125)
Density (sq)	−0.000132 (0.000210)	
Distance port	−0.0413*** (0.0154)	
Distance port (sq)	0.00114* (0.000659)	
Distance chokepoint	−0.0951 (0.139)	
Summer Monsoon	−2.21e-05 (9.81e-05)	
Killed	−8.044 (6.440)	
Killed (sq)	3.956 (3.170)	
Constant	−7.013*** (0.615)	−17.13*** (0.114)

Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table AIV
ZINB Models with Successful Piracy Attacks only

Variables	(1)	(2)	(3)	(4)
	Successful attacks	Inflation stage	Successful attacks	Inflation stage
Density	0.0312	−2.339***	0.0334	−2.370***
	(0.0244)	(0.580)	(0.0241)	(0.577)
Density (sq)	−0.000198		−0.000221	
	(0.000156)		(0.000154)	
Distance port	−0.313***		−0.308***	
	(0.0626)		(0.0632)	
Distance port (sq)	0.00182		0.00177	
	(0.00257)		(0.00257)	
Summer Monsoon	−0.733***		−0.757***	
	(0.171)		(0.172)	
Distance chokepoint	0.00128***		0.00120**	
	(0.000492)		(0.000498)	
Killed	2.536*		2.561*	
	(1.317)		(1.373)	
Killed (sq)	−1.245*		−1.254*	
	(0.655)		(0.683)	
Reinforcement	0.618**		2.418***	
	(0.281)		(0.350)	
Rate of Success ($t-1$)	4.651***			
	(0.510)			
Contiguity ($t-1$)	0.538***		0.813***	
	(0.126)		(0.191)	
Contiguity	0.910***		1.047***	
	(0.123)		(0.156)	
Constant	−6.537***	0.989***	−6.489***	0.963***
	(0.398)	(0.339)	(0.380)	(0.346)
Lnalpha		2.324***		2.855***
		(0.442)		(0.499)
Observations	320,112	320,112	320,112	320,112

Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table AV
ZINB Models with Transition Corridor dummy

Variables	(1)	(2)	(4)	(5)
	Corridor Diffusion	Inflation stage	Corridor Counter-diffusion	Inflation stage
Density	0.0180	−1.668***	0.00679	−1.478***
	(0.0140)	(0.400)	(0.0116)	(0.420)
Density (sq)	−0.000175**		−0.000156	
	(7.82e-05)		(0.000108)	
Distance port	−0.186***		−0.0839**	
	(0.0398)		(0.0359)	
Distance port (sq)	0.000343		−0.00232	
	(0.00158)		(0.00178)	
Summer Monsoon	−0.542***		−0.858***	
	(0.116)		(0.163)	
Distance chokepoint	0.000440		0.000299	
	(0.000308)		(0.000226)	
Killed	2.779***		12.26	
	(0.770)		(7.727)	
Killed (sq)	−1.437***		−6.096	
	(0.385)		(3.801)	
Reinforcement	1.153***		1.641***	
	(0.313)		(0.371)	

(continued on next page)

Table AV (*continued*)

Variables	(1)	(2)	(4)	(5)
	Corridor Diffusion	Inflation stage	Corridor Counter-diffusion	Inflation stage
Rate of Success ($t-1$)	1.803***		1.409	
	(0.689)		(0.987)	
Contiguity ($t-1$)	0.497***		0.368***	
	(0.0750)		(0.0812)	
Contiguity	0.969***		0.850***	
	(0.119)		(0.131)	
IRTC	0.853***		1.009***	
	(0.207)		(0.249)	
Rescue ($t-1$)			−1.031**	
			(0.476)	
Rescue ($t-2$)			1.429***	
			(0.264)	
Rescue ($t-3$)			1.369***	
			(0.218)	
Atlanta	1.006***			
	(0.268)			
Constant	−5.234***	0.577***	−5.262***	0.573***
	(0.255)	(0.215)	(0.747)	(0.212)
				1.356***
Lnalpha		1.595***		(0.319)
		(0.220)		
Observations	320,112	320,112	177,840	177,840

Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table AVI
ZINB Models with data aggregated by quarter.

Variables	(1)	(2)	(3)	(4)
	Quarterly Diffusion	Inflation stage	Quarterly Counterdiffusion	Inflation stage
Density	0.0311***	−2.722***	0.0324***	−1.925***
	(0.00970)	(0.369)	(0.0105)	(0.262)
Density (sq)	−0.000526**		−0.000524**	
	(0.000214)		(0.000214)	
Distance port	−0.0881***		−0.0784***	
	(0.0224)		(0.0238)	
Distance port (sq)	−0.000520		−0.000931	
	(0.00109)		(0.00120)	
Summer Monsoon	−0.360***		−0.263***	
	(0.0840)		(0.0840)	
Distance chokepoint	0.000125		2.67e-05	
	(0.000118)		(0.000127)	
Killed	0.153***		0.211***	
	(0.0300)		(0.0313)	
Killed (sq)	−0.00789***		−0.0104***	
	(0.00208)		(0.00198)	
Reinforcement	0.830**		1.091***	
	(0.386)		(0.337)	
Rate of Success ($t-1$)	23.62***		24.36***	
	(2.299)		(2.013)	
Contiguity ($t-1$)	−1.059**		−0.926**	
	(0.448)		(0.430)	
Contiguity	1.202**		1.104**	
	(0.479)		(0.456)	

(*continued on next page*)

Table AVI (*continued*)

Variables	(1)	(2)	(3)	(4)
	Quarterly Diffusion	Inflation stage	Quarterly Counterdiffusion	Inflation stage
Rescue ($t-1$)			−0.295	
			(0.247)	
Rescue($t-2$)			−0.0886	
			(0.131)	
Rescue ($t-3$)			−1.509***	
			(0.248)	
Constant	−5.585***	−17.65***	−5.764***	−16.97***
	(0.141)	(0.252)	(0.163)	(0.222)
Lnalpha		0.248**		0.104
		(0.0974)		(0.0927)
Observations	106,704	106,704	106,704	106,704

Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table AVII
ZINB Models with Diffusion covariates at 4 months lag

Variables	(1)	(2)
	4 Months Lag	Inflation Stage
Density	0.0246**	−1.589***
	(0.0114)	(0.421)
Density (sq)	−0.000294*	
	(0.000152)	
Distance port	−0.202***	
	(0.0385)	
Distance port (sq)	0.00156	
	(0.00153)	
Summer Monsoon	−0.609***	
	(0.134)	
Distance chokepoint	0.000289	
	(0.000275)	
Killed	3.576***	
	(0.559)	
Killed (sq)	−1.733***	
	(0.279)	
Reinforcement ($t-4$)	1.527***	
	(0.207)	
Rate of Success ($t-4$)	3.230***	
	(0.482)	
Contiguity ($t-5$)	0.544***	
	(0.0872)	
Contiguity($t-4$)	0.526***	
	(0.0809)	
Constant	−4.835***	0.723***
	(0.218)	(0.199)
Lnalpha		2.106***
		(0.227)
Observations	308,256	308,256

Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Markov-Chain Logit

The first column in Table A VIII shows the likelihood that piracy will occur in a locations that has not experiences piracy at *t-1*, in other words it tests the spread of piracy to new locations. Column two in Table A VIII shows the likelihood that piracy will occur again in locations that experienced attacks at *t-1*, thus testing the likelihood of repeated activity in a cell-month. First thing to highlight is that the spatial lags of piracy behave similarly in both models, indicating that cells contiguous to attacked locations are more likely to experience both diffusion *and* re-occurrence of piracy; to put it otherwise, they are at risk regardless of whether they have already experienced piracy in the previous month. However, it is noteworthy that previous successes lead to higher likelihood of spread to new, surrounding locations but lower likelihood of re-occurrence in previously targeted areas. This result is statistically significant only at 0.1 level, but it points out that successes also bear costs in terms of attracting EU counter-piracy attention. When pirates successfully board or hijack a vessel, they may prompt EU reaction and, in turn, are forced to move away from these areas. This means that success will reduce chances of repeated attacks in the following month, but increase odds of attacks in surrounding areas. Differently from the learning mechanisms, contiguity does not tell us about the success of attacks, which explains why occurrence of attacks in surrounding areas can still lead to both spread and reoccurrence as attempted attacks are less likely to draw attention and being reported.

While testing spread of piracy as a Markovian process may provide a more conservative test for the diffusion hypothesis, the underlying assumptions of Markov-Chain logit models may pose too many restrictions on the data generating process. For example, the Markovian logit assumes that all units have a probability of transitioning from no-piracy to piracy greater than 0, so it is not possible to account for the zeros inflation. Also the stationarity of the transition probabilities is debatable if we consider seasonal variation and, probably more important, the deployment of the EU navy as a structural shock.

Table AVIII
Markov-Chain logit models.

Variables	Transition from No Piracy → Piracy	Transition from Piracy → Piracy
	Diffusion of Piracy	Recurrence of Piracy
Rate of Success($t-1$)	6.815**	−3.921*
	(3.820)	(1.725)
Contiguity ($t-1$)	0.448***	0.454***
	(0.0717)	(0.165)
Contiguity	0.791***	0.743***
	(0.0931)	(0.161)
Density	0.0770***	0.0737*
	(0.0159)	(0.0426)
Density (sq)	−0.00102**	−0.000927
	(0.000472)	(0.000797)
Distance port	−0.173***	−0.139
	(0.0364)	(0.158)
Distance port (sq)	0.000775	0.000550
	(0.00152)	(0.00888)
Distance chokepoint	0.000291	0.000646
	(0.000264)	(0.000689)
Killed	2.434***	4.919**
	(0.702)	(2.366)
Killed (sq)	−1.148***	−2.529**
	(0.349)	(1.177)
Summer Monsoon	−0.698***	−0.146
	(0.113)	(0.313)
Constant	−5.838***	−1.068
	(0.195)	(0.925)
Observations	319,245	867

Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Predicted geography of piracy risk

It is also useful to look at how the risk of piracy varies in space, compared to where actual attacks occurs. Given the high number of units in the sample, it is difficult to compare predictions for each location over time. Alternatively, I present the average risk of piracy as estimated in the main models for the manuscript, namely the ZINB with diffusion variables and the ZINB with both diffusion and counter-diffusion variables. These are the same models whose ROC curves are compared at the end of the article. Fig. AI compares the risk of piracy as predicted by the diffusion-only model (left panel) and by the counter-diffusion model (right panel) with the actual density of piracy incidents shown in the manuscript (central panel) for the year 2005–2013. Both right and left panels show similar geographic patterns, although the right-hand map that includes EU counter-piracy efforts seems to be more precise at identifying high risk areas (darker red shades), which in turns provide a more accurate prediction compared to the actual risk areas. For example, according to the diffusion-only predictions, the whole Somali coastline is predicted to have extremely high risk of piracy also in areas where very few incidents occurred (e.g. north-west Somali basin). Accounting for factors that have reduced the incidence of piracy in some areas, however, only identifies few hotspots along the Somali coast, and even fewer within the Somali basin.

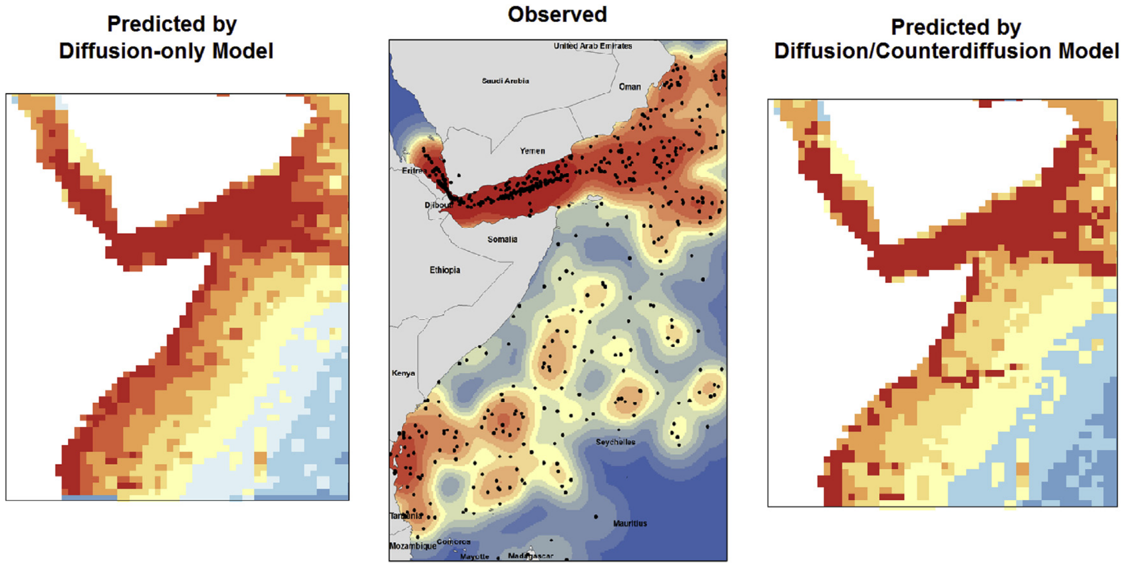

Fig. A1. Average probability of piracy attacks by grid-cell.1

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