Income Opportunities and Sea Piracy in Indonesia: Evidence from Satellite Data

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The effect of climatic variation on conflict and crime is well established, but less is known about the mechanism through which this effect operates. This study contributes to the literature by exploiting a new source of exogenous variation in climate to study the effect of fishermen's income opportunities on sea piracy. Using satellite data to construct a monthly measure of local fishing conditions it is found that better income opportunities reduce piracy. A wide range of approaches are employed to ensure that these effects are driven by income opportunities rather than other mechanisms through which climate could affect piracy.
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A large and growing literature in economics has established that adverse weather conditions can cause violent crime and conflict.[1] Despite the large number of studies, the mechanism through which this effect operates is not fully understood (Hsiang, Burke and Miguel, 2013; Dell, Jones and Olken, 2014). One of the primary links emphasized is that climatic shocks affect individual income and thus the opportunity costs of conducting illegal activities, in line with the theories proposed by Becker (1968) and Collier and Hoeffler (1998). However, the climatic shocks exploited in the literature could potentially affect violent crime and conflict through several other mechanisms. Government revenues could, e.g., be negatively affected by climatic shocks that affect the overall economy, which in

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[1] Rainfall shocks has been shown to cause conflict in sub-Saharan Africa - see Miguel, Satyanath and Sergenti (2004), Ciccone (2011) and Miguel and Satyanath (2011) - as well as a wide range of criminal and violent activity within countries. These include witch killings in Tanzania (Miguel, 2005), violent and property crime in 19th century Germany (Mehlum, Miguel and Torvik, 2006), peasant revolts in China (Jia, 2014), occupation of landholdings in Brazil (Hidalgo et al., 2010), as well as Hindu-Muslim riots (Bohlken and Sergenti, 2010), dowry deaths (Sekhri and Storeygard, 2014) and crime (Iyer and Topalova, 2014) in India. Higher temperatures have also been linked with both civil war (Burke et al., 2009) and crime (Jacob, Lefgren and Moretti, 2007). For additional papers in this literature, see the two recent reviews by Hsiang, Burke and Miguel (2013) and Dell, Jones and Olken (2014).

turn could change institutions and the crime prevention capacity of the state.[2] Returns from criminal activity may also change, which could incentivize predatory behavior and thus increase conflict and crime.[3] In addition, weather shocks could directly affect the feasibility of both committing and fighting illegal activities.[4] The aim of this paper is to contribute to the understanding of the relationship between climatic shocks and illegal activity by exploiting a new setting that enables a more direct investigation of the income opportunity channel.

The issue studied is the effect of changes in environmentally determined income opportunities for fishermen on the amount of sea piracy in Indonesia. This particular illegal activity has seen a revival in many developing countries since the beginning of the 21^{st} century and has contributed to substantial human suffering and economic costs (Elleman, Forbes and Rosenberg, 2010). Estimates suggest that the costs of sea piracy to the international economy could range between 7 and 12 billion U.S. dollars per year and that the welfare losses are considerable (Bowden, 2010; Besley, Fetzer and Mueller, 2015).[5] Hence, understanding the determinants of this activity is of considerable importance. The focus on the income opportunities of fishermen follows from an extensive contemporary as well as historical literature claiming that some fishermen may turn to piracy when incomes from fishing are low (Ormerod, 1924; Mo, 2002; Frécon, 2006; Elleman, Forbes and Rosenberg, 2010). Recent interviews with pirates in Indonesia confirm this and bear witness about recruitment from unemployed fishermen and sailors (Frécon, 2006). This may not be surprising given that the skills and capital required for piracy are similar to those required for fishing.[6] This is in line with a theoretical model similar to Becker (1968), where the returns from piracy outweighs the returns from fishing for some individuals during some specific time periods.

In order to identify how climate-induced changes in income opportunities affect sea piracy, this study introduces a new source of exogenous variation in local income. This measure is based on the reasoning that a fisherman's legal income opportunities are largely determined by changes in the amount of fish available in nearby waters. The measure relies on a marine biological literature which has shown that the amount of fish in a specific location can be estimated with satellite data on specific oceanographic conditions in that area. These conditions are

[2] This link between economic conditions and conflict is emphasized by e.g. Fearon and Laitin (2003). Recent studies have also found that climatically induced economic shocks affect political institutions (Brückner and Ciccone, 2011; Chaney, 2013).

[3] Support for this mechanism is found in the literature investigating the effect of commodity price shocks on conflict (see e.g. Angrist and Kugler, 2008; Dube and Vargas, 2013).

[4] Recent work has e.g. found that rainfall could have a direct effect on conflict (Sarsons, 2015) or affect conflict through transport costs (Rogall, 2014). Crime levels also seem to be affected by the weather in ways that cannot be explained by changes in income (see e.g. Jacob, Lefgren and Moretti, 2007) - potentially due to a direct biological effect on violent behavior (Tiihonen, Räsänen and Hakko, 1997).

[5] Besley, Fetzer and Mueller (2015) find that the generation of 120 million U.S. dollars of revenue for Somali pirates led to a welfare loss between 0.9 and 3.3 billion U.S. dollars.

[6] As highlighted by Elleman, Forbes and Rosenberg (2010) a large number of pirates use small fishing skiffs when operating.

in turn determined by complex environmental interactions of sunlight, temperature and nutrients in the water. Hence, given a set of time and location fixed effects as well as controls for local weather conditions, this measure is arguably an exogenous determinant of the income opportunities for fishermen.

The benefit of this approach is not only that it solves the common identification challenges that exist when estimating the effect of income on criminal activity, such as reverse causality and omitted variable bias, but it also enables isolating the effect of income opportunities from other effects of climate on piracy.[7] As discussed above, it is often hard to isolate the effect of climatically induced income opportunities from other mechanisms. These could be factors such as the returns from illegal activities, the feasibility of crime or the crime prevention capabilities of the government. In this paper, the particular setting exploited as well as the use of specific oceanographic climatic variation mitigates most of these concerns. First, returns from crime are not likely altered by changes in the local availability of fish since returns are determined by the number of potential targets, which are mainly international cargo ships passing through the Indonesian waters. This differs from most other setting in which the returns from crime are typically determined by local economic conditions. Second, oceanographic conditions in the water are not likely to affect the feasibility of conducting piracy. Even if such factors correlate with local weather conditions, which might make it easier or harder to conduct piracy, such an explanation can be ruled out since the local weather can be directly controlled for - something that has not been possible in the earlier literature. Third, local short term fluctuations in fishing conditions are unlikely to affect the government's crime prevention capacity. Incomes from marine fishing constitute less than 2 percent of GDP and resources directed towards fighting piracy have been very limited in Indonesia during the period of consideration. This can be compared with previous studies that have primarily focused on rainfall shocks in countries where agriculture compose a substantial part of the overall economy.

The main result shows that good fishing conditions reduce the mean number of piracy attacks by about 40 percent. Several steps are taken to provide support for these effects being driven by changes in local income opportunities for fishermen. In a first step the findings in the marine biological literature are reconfirmed, providing evidence that the measure of fishing conditions captures the local availability of fish. This is done by investigating the effect of changes in fishing conditions on the local price of fish. Second, the results are shown to be robust to controlling for different functions of local weather conditions, that may affect both fishing conditions and the possibility to conduct piracy. Third, by ex-

[7] Reverse causality in this case would occur if an increased likelihood of being attacked by pirates prevent fishermen from going to sea. In fact, this channel was highlighted by Lim Kit Siang, a member of the Malaysian parliament, who claimed that "fishermen . . . dare not go out to sea because of the lawlessness in the Straits of Malacca [in Indonesia]" (Siang, Lim Kit. 2004. "DAP call on government to set up a special squad to end the reign of fear of terror paralyzing Malaysian fishermen as a result of the latest abduction of three Kuala Sipitang fishermen by Indonesian pirates." Democratic Action Party.).

ploiting local labor market data an improvement of fishing conditions is shown to increase the income of fishermen in Indonesia significantly. Heterogeneity analysis provides additional support for the proposed mechanism by showing that effects are driven by areas that experienced slow growth during the sample period. This suggests that the availability of other income sources makes piracy less sensitive to fluctuations in fishing conditions. In addition, results are substantially stronger when the returns from fishing are higher - estimated by exogenous demand shocks to Indonesian fish exports. Finally, an investigation of the way in which income opportunities from fishing affect piracy indicate that the effect is primarily driven by changes in the opportunity cost of conducting piracy, rather than through a direct income effect from fishing.

In an additional analysis, the consequences of the typical policy response to piracy are investigated. This part of the paper focuses on a step up of military patrols in the Malacca Strait that increased the risk for pirates of getting caught. It is shown that the number of piracy attacks were substantially reduced as a result of these patrols. In a heterogeneity analysis the differential effect of these patrols with regards to fishing conditions is investigated. This analysis shows that patrols were much more effective at reducing piracy in areas with poor fishing conditions, which could plausibly be explained by a larger number of potential pirates in these areas. More importantly, these results provide additional support for the main mechanism emphasized in the paper since they clearly suggest that better fishing conditions does not make fighting piracy easier.

Except for some of the papers mentioned above, previous studies on the relationship between both economic and climatic conditions and conflict have extensively relied on cross country analysis (Blattman and Miguel, 2010; Hsiang, Burke and Miguel, 2013). This is also the case for the recent literature that focuses on the determinants of piracy. The main part of this literature have addressed the role of state capacity in determining piracy, but a few recent papers also partly address the issue of income opportunities empirically (see Cariou and Wolff, 2011; Jablonski and Oliver, 2012; Daxecker and Prins, 2012; Ludwig and Flückiger, 2014).[8] These studies tend to find a negative correlation between different income measures and the number of piracy attacks. The negative correlation also holds when focusing on the aggregate fishery production in a country, suggesting that income opportunities among fishermen might have an important causal impact on the number of piracy attacks. This study contributes to the above literature by ex-

[8] Most closely related to this paper is the simultaneous, but independent, paper by Ludwig and Flückiger (2014). They find a positive correlation between a country's yearly level of phytoplankton and fish catches; and a negative correlation between phytoplankton and piracy for a subsection of the years included in this study. In contrast to Ludwig and Flückiger (2014), this paper uses a more refined source of exogenous variation by exploiting a two dimensional measure of fishing conditions based on previous marine biological studies in Indonesia. The micro approach in this study also enables the use of local labor market data for fishermen as well as seasonal and within country geographical variation resulting in a more than 60 times larger sample size. In addition, the focus of this paper is broader by looking not only at changes in income opportunities but how these effects vary with other determinants of piracy as well as the role played by piracy patrols.

ploiting an as-if random assignment using fishing conditions to enable a credible identification of the causal effect of income opportunities. It also adds to the previous literature by using very detailed geographic variation and local labor market data.

The paper is organized as follows. The next section provides an overview of sea piracy as well as the fishing industry in Indonesia. Section II describes the marine biological motivation for the construction of the measure of fishing conditions as well as the data used for this. The subsequent section discusses the validity of this measure by investigating the effect of changes in fishing conditions on the local price of fish and labor market outcomes for fishermen. Thereafter, Section IV addresses the relationship between piracy and fishing conditions. The section starts with describing the construction of the sample used in the main analysis, then reports on a graphical analysis of the relationship between fishing conditions and piracy and finally outlines the empirical strategy employed to estimate the causal effect. Section V reports the main results on piracy attacks as well as the heterogeneity of these results. The following section investigates the impact of increasing anti-piracy patrols in the Malacca Strait. Section VII addresses the robustness of the results, and section VIII offers a summarizing discussion and concluding remarks.

I. Background

A. Piracy in Indonesia

During the last 15 years the waters around the Indonesian archipelago have been ranked among the most pirate prone in the world. The number of attacks have varied substantially over this period, from more than a hundred attacks a year in 2000-2004 to a record low number of less than 50 in 2009 (ICC International Maritime Bureau, 2013; Elleman, Forbes and Rosenberg, 2010, Chapter 7). However, since 2009 the number of attacks has been on the rise again and Indonesia is taking over as the most pirate prone country in the world. According to the International Maritime Bureau (IMB), Indonesia accounted for more than a quarter of all global piracy incidents in 2012 with a total of 81 attacks. In these attacks, 73 vessels were boarded and 47 crew members were taken as hostage (ICC International Maritime Bureau, 2013).

Piracy attacks in Indonesia are often carried out using simple technology such as skiffs, knives and small arms. The typical attack is carried out by a group of 5-10 pirates targeting an international cargo or bunker ship and involves stealing the personal belongings of the crew members and/or the vessel's safe (Elleman, Forbes and Rosenberg, 2010, Chapter 4). However, more violent attacks in which the crew gets kidnapped or the ship gets hijacked does also exist. On some occasions attacks are also carried out towards smaller vessels such as fishing boats or yachts. There are substantial revenues to be made from piracy. It has, e.g., been documented that an attack in Indonesia typically results in rewards between

10,000 - 20,000 U.S. dollars (Elleman, Forbes and Rosenberg, 2010, Chapter 7). This implies an individual return from an attack that corresponds to about 7 to 30 times the average monthly income for fishermen.[9]

Despite the large number of piracy attacks in the Indonesian waters, there have been few interventions aimed at reducing piracy and the authorities have been criticized for their inaction. Lack of funding has prevented the Indonesian government from supplying enough patrol ships and the government has been resistant to joining international agreements on anti-piracy in the region as well as allowing other countries to patrol their Exclusive Economic Zone. This has partly been due to disputes about their territorial waters (Elleman, Forbes and Rosenberg, 2010, Chapter 7). It has also been claimed that the relatively low domestic losses from pirate activity compared to other illegal activities (such as logging or fishing), has contributed to limited resources being spent to prevent it (Storey, 2008). An additional potential explanation for this is the fact that searching for pirates is a costly activity with typically low returns, since it is very hard to arrest someone for suspected piracy (Mo, 2002). Searching for pirates is particularly difficult in Indonesia with more than 18,000 islands that could provide cover and make it hard for large patrol ships to navigate.

However, during the 2000s some progress has been made to combat piracy in the Malacca Strait - one of the most piracy prone areas in Indonesia. One of the main catalysts behind this development was the decision by the Joint War Committee (JWC) to classify the Malacca Strait as a high risk area in July 2005, which affected insurance premiums for ships passing through these waters and put international pressure on the Indonesian government and its neighbors to take actions to prevent piracy attacks (Elleman, Forbes and Rosenberg, 2010, Chapter 5). Indonesia initiated Operation Octopus to combat piracy in the Malacca Strait in the same month - an operation that has since reoccurred annually. The operation involved patrolling of navy ships, helicopters, aircraft as well as troops on land and it has been put forward as an explanation to why the number of piracy attacks decreased in the end of 2005 in the Malacca Strait (Storey, 2008). Following this operation; Indonesia, Singapore and Malaysia also introduced joint air patrols over the strait in September 2005 (Elleman, Forbes and Rosenberg, 2010, Chapter 5). The purpose of these patrols is to identify suspected vessels from air, which can later be approached by navy ships for searching and investigation. Hence, the success of such operations likely depend on the number of ships at sea as well as current visibility, which in turn may depend on local weather conditions. This may be of particular importance for Indonesian anti-piracy operations since these are typically carried out with low technology equipment (Storey, 2008). All in all it has been claimed that the countries bordering the strait invested 1 billion U.S. dollars to improve security in the strait, which lead to the removal from the JWC's list in August 2006 (Khalid, 2006). The effect of these efforts to combat

[9] This calculation is based on the average monthly income of fishermen in 2011 of 1,176,675 rupiah per month (BPS, 2012*b*), which correspond to approximately 134 U.S. dollars per month.

piracy is investigated in section VI below.

B. Indonesian Fishing Industry

Indonesia is the third largest fishing nation by quantity produced and a major exporter of fish (FAO, 2013). The fishing industry is also a vital part of the Indonesian economy, accounting for 21 percent of Indonesia's agricultural economy, 3 percent of national GDP and providing over six million people with direct employment.[10][11] Marine fishery captures, the focus of this paper, correspond to the majority of fishery production in Indonesia and contribute about 1.9 percent to GDP (Lymer et al., 2008). About half of the captured fish, and by far the largest group, are the so called small pelagic fishes. This group includes species such as sardine and mackerel and is the group considered in the next section when constructing the measure of fishing conditions (Lainez del Pozo, 2013).

Marine fishing is carried out by traditional as well as commercial fisheries. Traditional fishing is conducted in small vessels in trips lasting one to two days close to the shoreline, mostly for subsistence by fishers and their families. Commercial fishing on the other hand is carried out further from the shoreline (4 nautical miles and beyond), but is also usually conducted from small boats. This makes fishing sensitive to changes in weather and environmental conditions.

Fish catches are largely determined by the different fishing seasons in Indonesia, which are in turn influenced by the two monsoons present in the area; the western and south-eastern monsoon. The primary boat fishing season is during the south-eastern monsoon, which occurs from June to September. Pelagic fishes are typically abundant during this part of the year (Hendiarti and Aldrian, 2005). From December through March the western monsoon occurs. During this period winds are typically stronger and rains heavier. This makes boat fishing more difficult and fishing is therefore often carried out closer to the shore. Although these patterns are evident all over Indonesia, the monsoonal system affects the coastal processes in each region differently (Hendiarti and Aldrian, 2005).

Several studies document high variability in the income of fishermen in Indonesia (see, e.g., Sugiyanto, Kusumastuti and Donna, 2012; Verité, 2012). In a recent study of the income of poor households in Yogyakarta by Sugiyanto, Kusumastuti and Donna (2012, p. 7) it was, e.g., noted that:

> "The largest fluctuation [among all surveyed occupations] occurred in the income and consumption of the fishermen. Due to the seasonal nature of their profession, they achieved the highest maximum income and the lowest minimum income. If the season was good and there was a large catch, fishermen would take in especially large incomes, but

[10]FAO. 2013. "Indonesia, FAO to strengthen fisheries and aquaculture cooperation." October http://www.fao.org/news/story/en/item/176776/icode/

[11] These numbers are probably lower bounds since they exclude illegal fishing, which is estimated to be substantial in Indonesia.

usually this season only lasts about three months. For the rest of the year the southern coastal fishermen tend to be unemployed because they are unable to go fishing due to the seasonal weather changes that limit the possibility of catching a profitable number of fish."

There is also evidence that the income of fishermen depends on how successful fishing trips are and that fishermen may not receive any payment if catches are not sufficient to cover expenses (Verité, 2012). Environmental and weather conditions affect fishermen's income, not only by determining the amount of fish in the water and hence how successful fishing trips are, but also by influencing the number of trips that can be carried out in a given month. During periods of extreme weather, fishermen may be forced to stay on shore, which, e.g., happened during the 2011 western monsoon in Indonesia.[12] These facts, combined with low income levels, put many fishermen in an economically vulnerable situation which requires them to adopt strategies to supplement their income in periods when fish catches are low (Anna and Fauzi, 2010).

II. Constructing Fishing Conditions

This study exploits oceanographic data to construct a measure of fishing conditions that affect the income opportunities of fishermen. This measure is determined by complex environmental interactions that, given a few conditions discussed below, are likely to be exogenous to piracy. The construction of the measure is based on a marine biological literature, which has found that satellite data can be used to estimate the abundance, migration patterns, distribution, and growth of fish in a given area (see, e.g., Hendiarti and Aldrian, 2005; Semedi and Dimyati, 2009; Nurdin, S; Lihan, T; Mustapha, 2012; Semedi and Hadiyanto, 2013).[13] The measure used in this paper exploits satellite data on the chlorophyll-a concentration and sea surface temperature of the ocean. The chlorophyll-a concentration provides information about the amount of phytoplankton in a location since it is used for the photosynthesis. Phytoplankton, in turn, is the base of the ocean food web and thus the primary food source of all small pelagic fish. The sea surface temperature of the ocean determines the development and survival of eggs as well as migration and distribution patterns of fish (Laevastu and Hayes, 1981). This paper will rely on the findings of Semedi and Hadiyanto (2013), who study the relationship between the catch per unit of effort of small pelagic fishes and oceanographic conditions in the Makassar Strait in Indonesia between 2007 and 2011. They find that all captures were made in waters with a chlorophyll-a concentration of 0.3 mg/m^3 to 2.8 mg/m^3 and a sea surface temperature (SST) between 26 °C to 30 °C. Based on this finding the following equation is used to

[12]Ministry of Marine Affairs and Fisheries. 2012. "Bad weather, Fishermen Economy Worsen." http://kkp.go.id

[13] These studies typically collect daily data from vessels on fish captures and then correlate this with in situ as well as satellite data on different characteristics of the waters, such as the sea surface temperature, chlorophyll-a concentration and salinity.

construct the measure of fishing conditions for a particular month (t) and area (a):

$$f_{at} = \frac{\sum_{i=1}^{n_a} \mathbb{1}[26 \leq SST_{iat} \leq 30 \wedge \ 0.3 \leq chlorophyll_{iat} \leq 2.8]}{n_a}, \tag{1}$$

where $\mathbb{1}[.]$ is an indicator function. This function takes on the value 1 when the observational point i in area a and month t satisfies the requirements established in Semedi and Hadiyanto (2013), i.e. when fishing conditions are good, and zero otherwise. In order to make the measure comparable between units, the sum of all good points in area a is divided by the total number of observational points (n_a) in that particular location (see Panel C of Figure A1 for an illustration of this).[14] This produces a ratio between 0-1 for each geographical and time unit, which has the intuitive interpretation that it estimates the share of good fishing spots in a particular area at a given point in time.[15] The benefit of this measure is that it is determined by processes exogenous to piracy. Growth of phytoplankton, e.g., depends on the availability of sunlight, temperature and the nutrients in the water. These are in turn determined by environmental processes such as upwellings, during which ocean currents bring cold and nutrient rich water from the bottom of the ocean to the surface (NASA Earth Observatory, 2013). The data used for constructing this measure is derived from the NASA Modis Aqua satellite and is available for every month from July 2002 to June 2013 at a 0.05 degree spatial resolution (Acker and Leptoukh, 2007).

III. Validating Fishing Conditions

As discussed above, previous qualitative evidence suggests that the amount of fish caught is an important determinant of income. To validate that the measure defined in this paper is capturing relevant changes in the amount of fish that affect the income opportunities of fishermen, two different approaches are taken to address both the availability of fish and the labor market outcomes for fishermen. This section describes the data employed for constructing the two samples used in these analyses. The geographical distribution of these samples is presented in Figure A2 and summary statistics are reported in the first two panels in Table A1. Results are reported in the end of this section.

[14] The number of observational points for each area (n_a) is determined by the spatial resolution of the satellite data, the size of the unit as well as the share of an area that is covered by water.

[15] Since this measure is based on a study in a particular area in Indonesia and is focusing on small pelagic fishes, the external validity of this measure might be a concern. In order to investigate this, it has therefore been compared to a measure of "good fishing spots" derived by experts at the Institute for Marine Research and Observation in Indonesia (see figure in the online appendix). These measures are positively correlated, also after conditioning on time and cell fixed effects.

First, the impact of fishing conditions on the availability of fish is investigated by studying the local price of fish in 16 coastal markets in Indonesia.[16] The location of these markets is illustrated in Panel A of Figure A2. For this analysis, data on the average monthly price of fish for January 2008 to April 2012 is collected for each market from the monthly reports produced by the Indonesian Directorate General of Processing and Marketing of Fishery (DJ PPHP).[17] These include the price for a wide range of fish species in different local markets (DJ PPHP, 2012). Species that occur at least 5 times during the sample period and markets that have data for at least 10 time periods are included.[18] From Table A1 it can be seen that the average monthly price of fish is 22,713 rupiah per kilo, which corresponds to approximately 2.4 U.S. dollars per kilo. The price of fish varies considerably over this time period both between markets and within markets over time.

Second, the labor market outcomes of marine fishermen in coastal districts are studied using data from the Indonesian Labor Market Survey (SAKERNAS). This data is available for at most 260 out of the 285 coastal districts in Indonesia as illustrated in Panel B of Figure A2. The sample used for this analysis relies on data from 7 survey rounds of SAKERNAS, carried out each February and August from 2007 to 2010. These rounds are chosen since they include detailed industry and occupation information, which enables the identification of marine coastal fishermen. Additional information in the survey on the district location of jobs makes it possible to match each coastal fisherman surveyed in a particular month to the fishing conditions in the coastal area of that district the same month. During this time period a total of 12,285 such fishermen responded to the survey. For these fishermen the share of total working hours dedicated to fishing the previous week is constructed as well as the number of hours dedicated to other jobs. In Table A1 it can be seen that fishermen tend to spend as much as 97 percent of their working hours fishing, working on average 41 hours per week. Information on the income the current month is available for those fishermen that are self-employed, which constitute about 53 percent of the previous sample. Using the response from these individuals the total income per month as well as the income per working day is calculated. Self-employed fishermen earn on average 780,631 rupiah per month and 41,949 rupiah per working day.

[16] Investigating the quantity of fish caught would have been preferred over the price of fish for the reasons discussed below in this section. However, a credible analysis of the quantity of fish is not possible since reliable disaggregated data on fish captures is not available.

[17] The average price is used to capture the total abundance of fish in a particular location. This is done since the composition of the species in the catch may vary between seasons as well as markets.

[18] Species that are used in fish farming are excluded from the analysis as well as markets that are not located in coastal fishing communities.

B. Validation Results

This section describes how fishing conditions affect the above defined validation outcomes. In order to do this, these outcomes have been regressed on fishing conditions, controlling for location (fish market/coastal district) as well as month by year fixed effects. Results are reported in Figure 1 for several distances from the shore using either the linear measure of fishing conditions as it is defined above or a dummy variable indicating if fishing conditions are above or below the median in the sample. The preferred specification uses the above median definition and considers fishing conditions in a relatively large zone ranging up to 50 nautical miles (approximately 93 km) from the shore.[19] The results from this specification are presented in Table 1.

Column (1) in Table 1 shows the result for the average monthly price of fish. An improvement of fishing conditions significantly reduces the price of fish. This is also the case when calculating wild cluster bootstrap p-values to deal with the small number of clusters, as suggested by Cameron, Gelbach and Miller (2008). A shift from below median fishing conditions to above, i.e., from relatively poor to good conditions, corresponds to a reduction of about 10 percent of the mean price of fish. Panel A in Figure 1 reports the results from running the same specification, but considering the two definitions of fishing conditions at different distances from the coast. Both of these specifications show very similar results, indicating that the effect of fishing conditions on the price of fish is significant for distances greater or equal to 20 nautical miles from shore and seems to stabilize at around 50 nautical miles. This finding highlights the importance of considering a sufficiently large area in order to adequately capture the relevant fishing zone.

Overall these results provide further support for the findings in the marine biological literature, namely that changes in oceanographically determined fishing conditions do affect the amount of fish available. These results should, however, be interpreted with caution for several reasons. First, some of the fish sold in these markets might not have been caught locally, despite the choice of the relatively large 50 nautical mile fishing zone. Instead, fish could have been transported to the market from other areas where fishing conditions may be different. These estimates are therefore likely to capture only part of the effect of changes in fishing conditions on the price of fish. Second, since the structure of demand for fish is unknown it is hard to infer from these estimates exactly how the quantity of fish is affected. With these caveats in mind, it is still reassuring that this analysis provides robust significant results in the expected direction.

The effect of fishing conditions on different labor market outcomes for fishermen is presented in the following 4 columns in Table 1. These regressions control for

[19] 50 nautical miles has been chosen to adequately capture as much of the relevant fishing conditions as possible and also roughly correspond to the distance from shore of the area studied by Semedi and Hadiyanto (2013). The above median fishing conditions definition is preferred since it does not require making structural assumptions about the relationship between fishing conditions and the outcomes (see discussion in Section IV.C).

Table 1—Validating measure of fishing conditions

Outcome:	Price	Share of Work	Hours not Fishing	Income	Log(Income)
	(1)	(2)	(3)	(4)	(5)
Above Median Fish.	-2167.5	0.0099	-0.39	8026.5	0.13
	(870.4)**	(0.0035)***	(0.15)***	(2411.8)***	(0.039)***
		[0.0035]***	[0.15]***	[2746.0]***	[0.037]***
Observations	448	11780	12285	6563	6559
R-Squared	0.19	0.092	0.083	0.16	0.25
Mean of Outcome	22713.3	0.97	1.09	41949.2	10.4
Wild Cluster P-value	0.022				
Location FE	Yes	Yes	Yes	Yes	Yes
Month * Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No

Note: This table reports the effect of above median fishing conditions in a 50 nautical mile fishing zone from the coast on the average price of fish in 16 coastal markets and a set of labor market outcomes in 250-260 coastal districts (depending on the availability of data). All regressions include fixed effects for each month-year combination and market/coastal district. Robust standard errors clustered on the local markets or coastal districts are reported in parenthesis. P-values using the Wild Clustered Bootstrap procedure suggested by Cameron, Gelbach and Miller (2008) are also reported for the price sample and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) are reported in brackets for the labor market outcomes.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

250-260 coastal district fixed effects (depending on the sample) as well as 7 month by year fixed effects. Columns (2) and (3) show how fishing conditions affect the time allocation decision of fishermen. A shift from below to above median fishing conditions increases the share of hours spent on fishing by about 1 percentage point according to column (2) and reduces the amount of time spent on other income generating activities by 0.4 hours per week (about 36 percent of the mean) as shown in column (3). Columns (4) and (5) further show that good fishing conditions lead to a 13 percent increase in the income of self employed fishermen. All results are highly statistically significant at the 1 percent level, but the time allocation effect sizes are relatively modest. A potential explanation for this is that changes in fishing conditions are not likely to affect all fishermen equally. In particular, fishing conditions is presumably a more important determinant of labor market outcomes in areas with lower economic activity and infrastructure. To investigate this claim the effects have also been estimated for the areas in the sample with the lowest economic activity, as proxied by lights at night, and fishermen in these areas indeed experience a much stronger labor market response to changes in fishing conditions.[20] Panels B-D in Figure 1 show how the labor

[20] The sample has then been split by an area's average stable lights at night within 50 km from the coast in the year before the sample period starts. In the lowest decile fishermen experienced a 47 percent increase in income, a 6 percentage point increase in the share of time spent fishing and a 2.4 hour decrease of time spent on other income generating activities every week. These results are reported in the online appendix.

market results differ by the size of the fishing zone considered and whether fishing conditions are defined as a dummy or a linear measure. Estimates using the linear definition tend to be larger, but less precisely estimated. Also for these specifications, results tend to stabilize around 50 nautical miles.

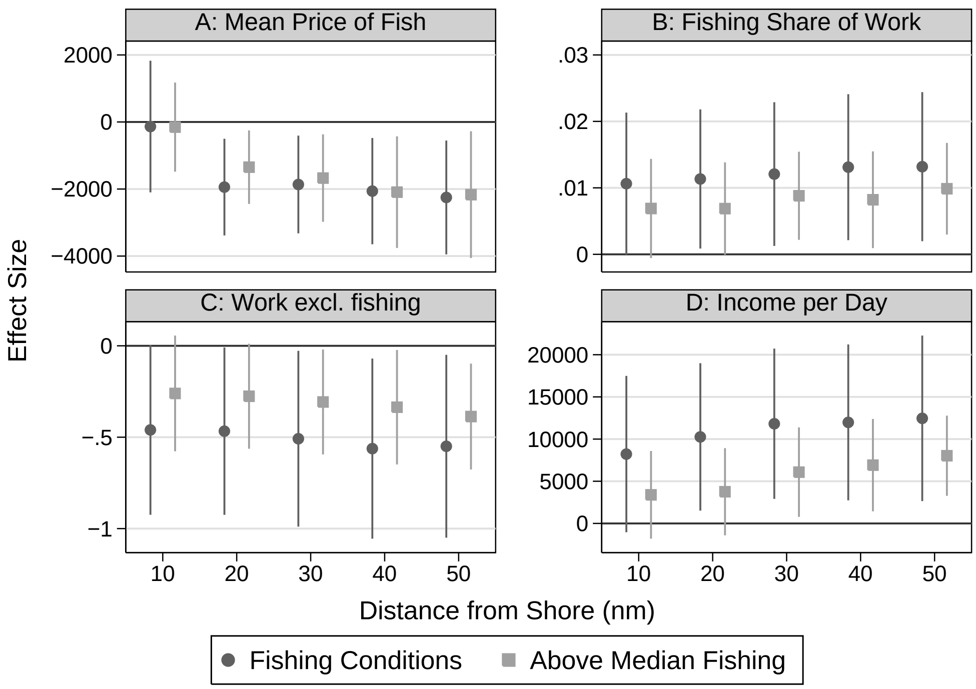


Figure 1. Point estimates for validation analysis by distance from coast

Note: This figure shows the point estimates and the 95 percent confidence intervals of the impact of fishing conditions on the four validation measures by the distance (in nautical miles) from shore that fishing conditions are considered. All regressions include location fixed effects as well as month by year fixed effects (i.e. the 50 nm specification correspond to the results reported in Table 1). Points illustrate results for regressions using the measure of fishing conditions as defined in equation (1), whereas squares illustrate results for a dummy variable equal to one if this measure is above the median. Standard errors are clustered on 16 coastal markets for the price regressions and on 250-260 coastal districts (depending on the availability of data) for the labor market regressions.
Source: Figure is based on Author's own calculations.

To sum up, this analysis suggests that fishing conditions has clear labor market consequences for fishermen.[21] Notably, better fishing conditions substantially and robustly increases the income from fishing per day worked. Hence, results

[21] The empirical specification used in this analysis corresponds to the specification used in columns (2) and (7) in Table 2 that investigate the effect on sea piracy. This differs from the baseline specification used in the piracy analysis (equation 2). The reason for this is limitations in the price and labor market data, which samples some of the districts only once in a particular month. Hence, including a large

are consistent with oceanographic conditions being an important determinant of the returns from fishing and thereby affecting the opportunity costs of engaging in illegal activities.

IV. Piracy and Fishing Conditions

This section describes the details of the main analysis carried out in the paper. It starts with providing information about the piracy data used and how this is combined with fishing conditions to construct the two main samples. The geographic and temporal relationship between fishing conditions and piracy is then investigated in a graphical analysis. Finally, the identification challenges are discussed together with the econometric specification in the last part of the section.

A. Piracy Data and Sample Construction

Geo-coded data on piracy attacks is combined with fishing conditions in two different samples. The first sample consist of 2×2 degree cells (approximately 200 km by 200 km) covering the whole Exclusive Economic Zone (EEZ) of Indonesia. The choice of this cell size naturally follows from the validation analysis above, since fishing conditions extending approximately 50 nautical miles in all directions are allowed to matter for an attack carried out in the centroid of a cell.[22] In the second sample, attacks carried out at different distances from the shore are linked to the fishing conditions in all 285 coastal districts in Indonesia.

For the construction of these samples (illustrated in Figure A2) data on piracy attacks from the National Geospatial-Intelligence Agency (NGA) has been collected. This data include detailed information about the type of attack, aggressor, victim, date of occurrence, as well as a short description of the event. The dataset covers attacks that occurred from 1978 until today. The NGA combines data from several agencies that monitor and report on piracy incidents (such as the International Maritime Bureau (IMB) and the UK Maritime Trade Operation) and it is thus likely to be one of the best source available to capture the amount and location of piracy attacks. Pirate attacks are broadly defined in this study and include both attacks that have been carried out, attempted attacks that were avoided as well as suspicious approaches. Further, in the aggregate number of

number of month by location fixed effects as in equation 2 would result in removing important variation. However, in order to facilitate comparisons with the labor market and price effects, results using the same specification as in equation (2) are reported in the online appendix. Overall, these results show a consistent pattern. The income effects are of an almost identical magnitude and highly statistically significant, whereas the results on prices and time allocation are smaller and no longer statistically significant.

[22] The choice of this relatively large cell size is important since it reduces the problem of potential spillovers between cells. This would occur if fishermen choose to fish in a neighboring area when fishing conditions deteriorate at home. Hence, choosing smaller units of analysis would risk attenuating the true effect as suggested by the validation analysis where fishing conditions closer to shore produce smaller and less precisely estimated effects.

attacks both ships that were on route and anchored when the attack was carried out are included. However, since much of this data rely on self-reporting by ships, some attacks are likely to go by without being recorded. Hence, the data used in this study is still likely to underestimate the true number of attacks. The IMB, e.g., believes that its reports only capture about half of all attacks that occur (Bowden, 2010).

During the period of interest in this study, from July 2002 to June 2013, a total of 1,062 attacks were carried out in the cell sample covering the EEZ of Indonesia, of which most have been attacks on merchant or international cargo ships. Compared to other countries' EEZ the number of attacks in Indonesia is substantial and varies considerably over time, as can be seen in Figure A3. From high levels in the beginning of the 2000's, the total number of attacks in Indonesia decreased substantially in the second half of the first decade, only to increase again during the beginning of the second decade.

B. Graphical Analysis

The temporal and geographical variation of fishing conditions and piracy attacks, is illustrated in figures 2 and 3. Figure 2 shows that fishing conditions as well as the number of piracy attacks vary substantially by location. There is a clustering of attacks in all months in the Malacca strait, which is a vital shipping lane for vessels traveling from Europe and the Middle East to East Asia. However, during months when fishing conditions in the strait are particularly poor, such as in April, there is a substantial increase in the number of attacks. Overall, the map suggests that local fishing conditions can explain an important part of the variation in piracy attacks.

To further examine the role of seasonal changes, Figure 3 shows how average fishing conditions and the mean number of attacks over all cells vary by months within a year. A clear pattern emerges from this graph, namely that months with poor fishing conditions tend to experience a large number of attacks and vice versa. In April, for example, fishing conditions on average reach their lowest level at the same time as the number of piracy attacks spike and are 60 percent higher than the mean. However during the primary boat fishing season from June to September, when fishing conditions are relatively good, the number of attacks are kept at a comparably low level. This clearly suggests a negative seasonal relationship between fishing conditions and piracy.

The next sub-section outlines the strategy used to control for such seasonality and exploit the random variation in fishing conditions to determine whether the relationship between fishing conditions and piracy can be given a causal interpretation.

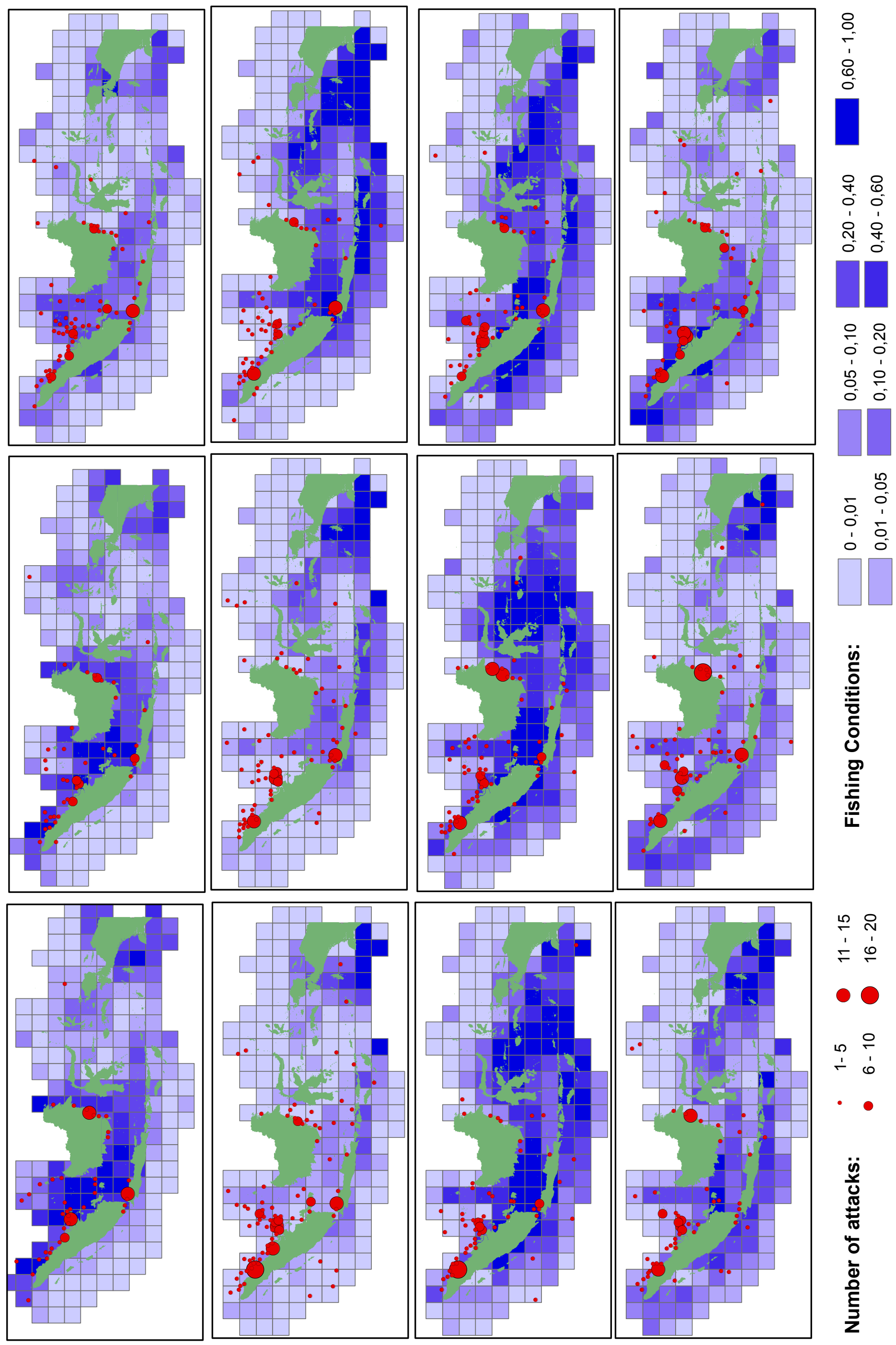


Figure 2. Total piracy attacks and average fishing conditions by month

Note: This figure shows the total number of attacks each month (from January in the top left corner to December in the bottom right) during the whole sample period (July 2002-June 2013) and the average fishing conditions during that month in each cell.
Source: Figure is based on Author's own calculations using the data presented in Table A1.

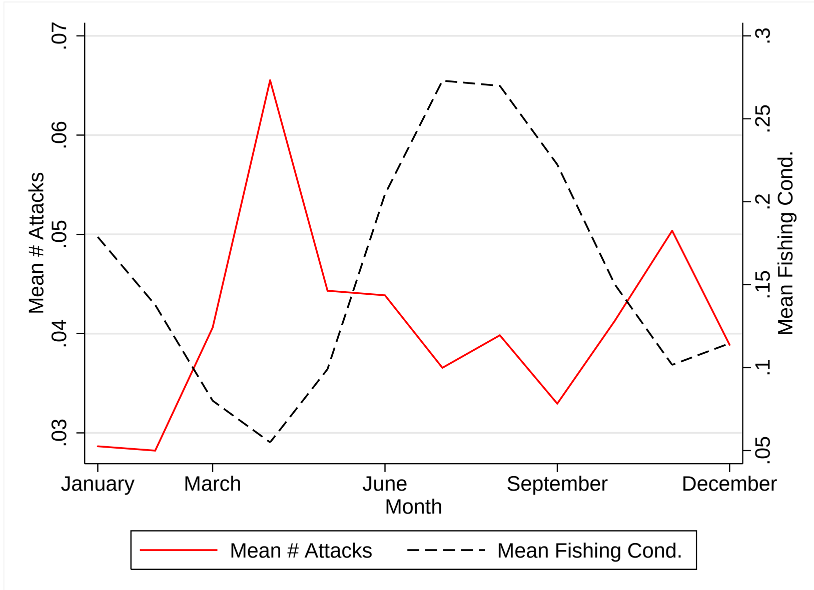


Figure 3. Monthly fishing conditions and piracy attacks

Note: This graph shows the average fishing conditions and number of attacks for each month over all years and cells during the sample period. The graph has been constructed using the cell sample covering the whole EEZ of Indonesia.
Source: Figure is based on Author's own calculations.

C. Econometric Specification

Even if fishing conditions are determined by factors that are out of control of the fishermen, the previous section clearly implies that it is not randomly assigned. This is because certain areas or time periods may simply have better fishing conditions on average as well as characteristics that make them more or less prone to piracy attacks. A location close to the shore may, for example, experience oceanographic processes that produce better fishing conditions at the same time as this location is easier to access for pirates, making piracy attacks more common. Time specific factors could also be important. In particular the seasonal patterns of piracy and fishing may differ between locations as suggested by Figure 2. Hence, in order to exploit the as good as random variation in the fishing conditions variable, the following fixed effect model is the preferred specification:

$$p_{aym} = \beta f_{aym} + \delta_{am} + \gamma_y + \lambda \mathbf{X_{aym}} + \epsilon_{aym}, \quad (2)$$

where p_{aym} is a measure of the amount of piracy attacks in area a in year y and month m, δ_{am} corresponds to location by month fixed effects included to capture local seasonality, γ_y to year fixed effects and $\mathbf{X_{aym}}$ is a vector of environmental control variables that includes second degree polynomials of wind speed, wave height and rainfall.[23] Controls are added to address a potential threat to identification, namely that there are other climatic factors that covariate with fishing conditions that could affect piracy through other mechanisms than income opportunities. In the previous literature it has, e.g., been highlighted that high wind speeds may prevent pirates from navigating their small skiffs (see e.g. Besley, Fetzer and Mueller, 2015) which is likely to affect the feasibility of conducting attacks. Since wind patterns could also affect oceanographic processes that influence fishing conditions, controlling for wind speed could be of importance. There are also other environmental factors that in a similar fashion could affect both fishing conditions and piracy, namely the height of waves as well as the amount of rainfall.[24] To construct these control variables additional environmental satellite data on average monthly accumulated rainfall, average monthly wind speed and average monthly wave height has been collected for the same time period and geographical units as above.[25]

The fishing conditions variable, f_{aym}, is entered into the specification in a number of different ways in order to take the potential non-linearity of this relationship into account. However, the preferred specification is a dummy variable coded as 1 if fishing conditions are above the median, i.e. when fishing conditions are good, and 0 otherwise - the same as in the validation analysis above.[26] This definition has been chosen to facilitate the interpretation of the coefficient and to avoid making strict assumptions on the structure of the relationship between fishing conditions and piracy.[27] Under the assumption of strict exogeneity conditioned on the fixed effects, β would identify the true causal impact of fishing conditions on piracy. Robust standard errors that are clustered at the area level to take into account serial correlation of the errors over time are reported as well as standard errors following Conley (2008) and Hsiang (2010). The latter are adjusted both for serial correlation over time as well as spatial correlations within 1,000 km from the centroid of an area. This cut-off has been chosen following a literature investigating the spatial correlation patterns of coastal environmental processes and fish stocks, which typically finds that these measures are no longer correlated

[23]Results are robust to controlling for month by year fixed effects instead of year fixed effects, as reported in the results section.

[24] Even if it is warranted to control for these factors, it may not be fully desirable since these controls may capture parts of the income effect and therefore generate attenuated effects. However, to rule out other potential mechanisms they are included in the preferred specification.

[25] The rainfall data comes from the Tropical Rainfall Measuring Mission and the wind speed and wave height data from the reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ERA ECMWF). All of this data has a 0.25 degree spatial resolution and has been chosen since it provides the longest possible time series on these variables for Indonesia.

[26] Such changes in fishing conditions are frequent and occur on average 2.3 times in every cell in every year.

[27]An additional reason for preferring this specification is that it deals with the skewness of the fishing conditions variable and thus reduces the weight given to outliers in the fishing conditions distribution.

after a distance of approximately 1,000 km (see e.g. Mueter, Ware and Peterman, 2002).[28]

V. Main Results

This section reports the main results from estimating equation (2) and is divided into two parts. The first part carries out the analysis for the two samples defined above. The cell sample is used to get at the overall impact of changes in fishing conditions on piracy in the Indonesian EEZ. However, in order to be able to more easily compare the results to the above findings on labor market outcomes; allow for attacks and fishing to be carried out in different locations; and investigate how effects vary by conditions on land, results are also reported for the 285 coastal districts in Indonesia. The second part of this section investigates the heterogeneity of the results in both of these samples with regards to income determinants.

A. Impact on Piracy Attacks

Table 2 shows the main results from the cell sample. The number of attacks is used as outcome in Panel A, whereas the outcome has been recoded as a dummy variable in Panel B. This has been done to capture the extensive margin effect of whether an attack occurred or not. Column (1) shows a positive unadjusted correlation between piracy attacks and fishing conditions. This is not surprising since areas with on average better fishing conditions are likely to have a greater number of fishermen and thus a larger pool of potential pirates (see Figure 2). However, controlling for time and location invariant factors by introducing cell and month by year fixed effects in column (2) produces a robust and highly statistically significant negative estimate of the impact of fishing conditions on piracy. This is the natural fixed effect specification and is thus comparable to the validation results in Table 1.

The estimate becomes smaller for the extensive margin effect but is of a similar magnitude for the number of attacks when including year and month by cell fixed effects in column (3). Hence, controlling for potential differences in seasonality between cells produces consistent results, despite including a large number of fixed effects. This specification includes 2,363 month by cell fixed effects and 12 year fixed effects and thus solely exploits variation for the same month and cell between years that is distinct from the common time effect in that year. The results from the preferred specification (equation 2) which also includes polynomial environmental controls for wind speed, wave height and rainfall is presented in column (4).[29] These show that good fishing conditions reduces the mean number

[28]Choosing both shorter and longer cut-off distances typically generates smaller standard errors as reported in the online appendix.

[29]Note that the wave height data is not available for some observations since one cell does not have overlapping satellite data. Results are identical when including a missing dummy for these observations.

Table 2—Impact of fishing conditions on piracy

	(1)	(2)	(3)	(4)	(5)
Panel A: # Attacks					
Above Median Fish.	0.023	-0.022	-0.019	-0.017	-0.017
	(0.011)**	(0.0069)***	(0.0077)**	(0.0078)**	(0.0079)**
	[0.011]**	[0.0070]***	[0.0077]**	[0.0080]**	[0.0081]**
Wind Speed				-0.0063	-0.013
				(0.0095)	(0.011)
Wind Speed Sqr				0.00075	0.0014
				(0.00078)	(0.00085)
Accumulated Rainfall				0.034	0.021
				(0.052)	(0.065)
Accumulated Rainfall Sqr				-0.044	-0.022
				(0.092)	(0.11)
Wave Height				-0.080	-0.10
				(0.047)*	(0.046)**
Wave Height Sqr				0.021	0.026
				(0.012)*	(0.012)**
Pabel B: Attack (1 or 0)					
Above Median Fish.	0.017	-0.010	-0.0060	-0.0055	-0.0057
	(0.0063)***	(0.0029)***	(0.0031)**	(0.0031)*	(0.0031)*
	[0.0065]***	[0.0029]***	[0.0031]**	[0.0031]*	[0.0031]*
Wind Speed				-0.0022	-0.0058
				(0.0050)	(0.0055)
Wind Speed Sqr				0.00038	0.00072
				(0.00045)	(0.00047)
Accumulated Rainfall				0.012	0.014
				(0.030)	(0.035)
Accumulated Rainfall Sqr				-0.0099	-0.011
				(0.052)	(0.058)
Wave Height				-0.033	-0.049
				(0.024)	(0.025)*
Wave Height Sqr				0.0069	0.011
				(0.0059)	(0.0063)*
Observations	25948	25948	25948	25860	25860
Mean # Attacks	0.041	0.041	0.041	0.041	0.041
Mean Attack (1 or 0)	0.027	0.027	0.027	0.027	0.027
Cell FE	No	Yes	No	No	No
Cell * Month FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No
Year * Month FE	No	Yes	No	No	Yes

Note: This table reports the effect of above median fishing conditions on sea piracy using the cell sample. Panel A report the effect for the number of attacks, whereas Panel B report the effect for a dummy variable indicating whether an attack occurred or not. Robust standard errors clustered on the cell level in parenthesis and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

of attacks by about 40 percent and the baseline probability of an attack occurring at all by 20 percent. Results for the number of attacks are significant at 5 percent, but the extensive margin coefficient is only significant at the 10 percent level. Adjusting standard errors for spatial correlations does not alter any of these results. Finally, results are largely unaffected by adding additional fixed effects and controlling for month by year invariant factors in column (5).

Since fishing conditions are determined by complex environmental interactions and weather conditions is a potentially important determinant of the feasibility of piracy, it is important to rule out that the above results are driven by variation in other weather variables. This is the reason for including a polynomial of weather controls in the main specification. To ensure that these are correctly specified, Table 3 report the results of running the main specification for each of the weather controls separately. As expected, we see that increases in wind speed and in particular wave height lead to significant reductions in the number of piracy attacks. This is in line with previous literature suggesting that rough waters makes it difficult for pirates to carry out attacks (Besley, Fetzer and Mueller, 2015). Plotting the relationship between the number of piracy attacks and these climatic controls suggests that a second degree polynomial is the correct functional form. However, to ensure that this choice does not have any implications for the results, the last three columns in Table 3 instead include the weather controls linearly, as a 3$^{\text{rd}}$ degree polynomial and by including dummy variables for each quartile of the variables. This produces very similar results to those reported in Table 2.

The above analysis assumes that piracy attacks are carried out within the same area as fishing. This is a reasonable assumption that follows from the literature discussed above that claims that fishermen's skills and capital are exploited for piracy. However, to test this claim more directly and investigate the locality of these effects Table 4 reports results for estimating equation (2) for coastal areas. This analysis allows for attacks to be carried out both further and closer to shore than where fishing is conducted. The table reports the effect of fishing conditions within 50 nautical miles from the shore (following the approach applied in the validation analysis) on piracy attacks 20 - 60 nautical miles from the shore. Results are shown both for the number of attacks and for whether an attack occurred or not. A clear pattern emerges from this analysis, namely that fishing conditions tend to more strongly affect the extent of piracy within the fishing zone than beyond it. The effect size for the number of attacks as share of the mean is more than twice as large for attacks carried out within 20 nautical miles (30 percent) from the shore than those carried out within 60 nautical miles (12 percent) from the shore. Effects closer to the shore are also more precisely estimated, whereas attacks 50 to 60 nautical miles from the shore are not significant when taking spatial correlations into account. The latter is likely a result of some attacks being attributed to several fishing zones with this approach, due to partly overlapping attack zones. All in all this analysis provides support for the approach taken in this paper since attacks carried out within the fishing zone respond substantially stronger to changes in fishing conditions.

Although intuitive to understand, a shift from below to above median fish-

Table 3—Piracy and the Weather

Outcome:	# Attacks					
	Without Fishing Conditions			Alternative Weather Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Above Median Fish.				-0.018 (0.0078)** [0.0080]**	-0.017 (0.0079)** [0.0081]**	-0.017 (0.0077)** [0.0079]**
Wave Height	-0.098 (0.044)**			-0.011 (0.017)	-0.26 (0.12)**	
Wave Height Sqr	0.027 (0.013)**				0.17 (0.075)**	
Wave Height Qub					-0.034 (0.015)**	
Wind Speed		-0.019 (0.010)*		-0.0016 (0.0035)	0.032 (0.032)	
Wind Speed Sqr		0.0015 (0.00087)*			-0.0067 (0.0059)	
Wind Speed Qub					0.00045 (0.00036)	
Accumulated Rainfall			0.049 (0.049)	0.0086 (0.018)	-0.0058 (0.085)	
Accumulated Rainfall Sqr			-0.076 (0.090)		0.092 (0.26)	
Accumulated Rainfall Qub					-0.14 (0.25)	
Observations	25860	25948	25948	25860	25860	25860
R-Squared	0.0046	0.0045	0.0043	0.0049	0.0054	0.0054
Mean of Outcome	0.041	0.041	0.041	0.041	0.041	0.041
Cell * Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Quadratic	Quadratic	Quadratic	Linear	Cubic	Quartile

Note: This table reports the effect of weather conditions on sea piracy. The first three columns report the effects of weather on sea piracy separately for each weather type, specified in the same way as in the main specification (i.e. a second degree polynomial). The following three columns implement the main specification, but controls for different functions of the weather variables (linear, cubic polynomial and dummy variables for each quartile of each weather variable). Robust standard errors clustered on 196 cells in parenthesis and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

ing conditions will not be informative about any potential non-linearity in the

Table 4—Fishing Conditions and Sea Piracy in Coastal Areas

Distance	20 nm	30 nm	40 nm	50 nm	60 nm
	(1)	(2)	(3)	(4)	(5)
Panel A: # Attacks					
Above Median Fish	-0.017	-0.019	-0.020	-0.020	-0.017
	(0.0061)***	(0.0078)**	(0.0080)**	(0.0085)**	(0.0088)**
	[0.0079]**	[0.010]*	[0.011]*	[0.013]	[0.014]
Observations	37571	37571	37571	37571	37571
R-Squared	0.0073	0.0094	0.011	0.013	0.016
Mean of Outcome	0.054	0.071	0.091	0.11	0.14
Pabel B: Attack (1 or 0)					
Above Median Fish	-0.0096	-0.0098	-0.011	-0.010	-0.0076
	(0.0029)***	(0.0032)***	(0.0035)***	(0.0040)**	(0.0040)*
	[0.0040]**	[0.0048]**	[0.0054]**	[0.0062]	[0.0069]
Observations	37571	37571	37571	37571	37571
R-Squared	0.0079	0.011	0.013	0.016	0.019
Mean of Outcome	0.037	0.048	0.059	0.072	0.085
District * Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic

Note: This table reports the results from estimating equation (2) using fishing conditions in the 50 nautical mile coastal zone of all 285 coastal districts. The columns report the effects for attacks carried out in a given distance from the coast (corresponding to 20, 30, 40, 50 or 60 nautical miles from shore). Panel A reports results for the number of attacks and Panel B for a dummy variable indicating whether an attack occurred or not. All regressions include second degree polynomials of wind speed, wave height and accumulated rainfall. Robust standard errors in parenthesis are clustered on 285 coastal districts and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

relationship between fishing conditions and piracy. To deal with this, Figure 4 plots the response functions from linear regressions as well as second and third order polynomials using a more fine tuned division of the fishing conditions variable defined in section II. Instead of splitting the variable at the median, the fishing condition measure is percentile ranked and used to estimate equation (2) for both the cell and district samples.[30] In addition to the predicted response, the graphs also show the 95 percent confidence intervals of these estimates. Results are consistent with the estimates from the main specification, but effect sizes are larger and less precisely estimated - especially for the linear regression for which results are just above marginal significance (p-value 0.13 for the cell sample). These graphs suggest that the relationship between fishing conditions and piracy is non-linear and therefore provides an additional reason for using the above median definition as the preferred specification.

[30] Using a percentile rank is preferred over using the variable as defined in section II to deal with the skewness of the variable. Results using the unadjusted measure show a similar pattern, but are smaller and less precisely estimated when using the main specification with a large number of fixed effects. These results are reported in the online appendix together with the distribution of the variable.

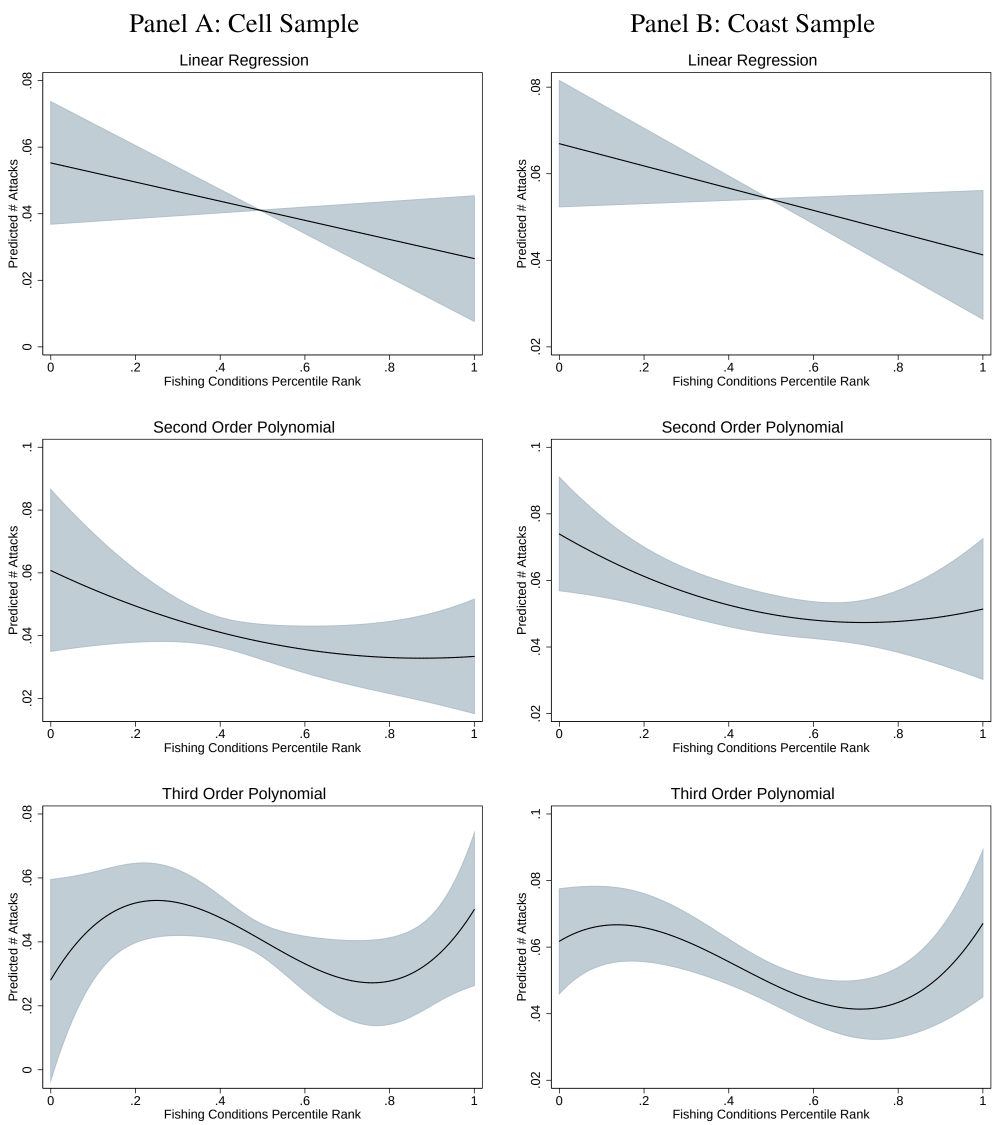


Figure 4. Percentile rank regressions for fishing conditions

Note: This figure plots the response function of linear and polynomial regressions using the percentile rank of fishing conditions. All regressions control for location by month fixed effects, year fixed effects as well as for a second degree polynomial of wind speed, wave height and accumulated rainfall. The three figures in Panel A report the result for the cell sample, whereas the figures in Panel B report the corresponding regressions for the coastal district sample (with the number of attacks within 20 nautical miles as outcome). The shaded areas illustrate the range of 95 percent confidence intervals based on standard errors clustered at the geographical unit of analysis (cell/coastal district).
Source: Figure is based on Author's own calculations using the data presented in Table A1.

B. Testing for an Income Effect

The above section shows that an improvement of fishing conditions robustly reduces the number of piracy attacks the same month. As discussed, results point towards this finding being driven by changes in local income opportunities for fishermen. Theoretically, such an effect could work through either or both of the following two channels. First, changes in the returns from fishing could make it relatively more beneficial to go fishing and therefore alter the *opportunity cost* of engaging in piracy - following the theoretical reasoning discussed above. However, an improvement of income opportunities could also raise the *income* of fishermen so that they can select away from piracy and still have enough to cover expenses. Plausibly, income from fishing during the previous high season could be particularly important for the number of piracy attacks in the lean season, since fishing follows a clear seasonal pattern. In order to test for this latter effect, a variable for previous fishing conditions is added to the main specification. This variable captures the income opportunities from fishing in previous periods, which should affect piracy only through the *income effect* when controlling for contemporaneous fishing conditions.

Table 5 reports the results from this analysis for a number of different measures of previous fishing conditions. The reason for including different definitions is that the best way to capture the income effect is a priori unknown - the previous fishing period that will be most important for current available funds depends on factors such as to what extent fishermen are able to save their income and local differences in seasonality.[31] In the first two columns, the share of good (above median) fishing months immediately preceding the month of interest is investigated. This is done for the last 6 and 12 months, considering both the full sample as well as focusing solely on the two lean months when piracy is common (April and May).[32] The reasoning behind using this definition is that the last few months will matter the most if fishermen are unable to save for periods far into the future. However, given the seasonality in fishing it may not be the preceding months that are most important, but rather a particular time period. Therefore, the share of good fishing months during the previous calendar year, as well as the previous main fishing season (June to September), are reported in columns (3)-(4). Finally, since fishing seasons differ locally, the last column also reports results using the share of good months during the local high season. This has been done by considering the conditions in the on average best month in a cell as well as the preceding and succeeding month.

[31] Unfortunately, the survey data available does not allow for a test of this, since it only includes reported income for the past month.

[32] Results are unaffected by including both shorter and longer time periods, as well as focusing on other lean periods.

Table 5—Testing for an Income Effect

Outcome:	# Attacks				
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Above Median Fish.	-0.017	-0.018	-0.017	-0.017	-0.016
	(0.0075)**	(0.0079)**	(0.0076)**	(0.0076)**	(0.0066)**
	[0.0076]**	[0.0080]**	[0.0077]**	[0.0077]**	[0.0069]**
Abovemedian (t-1 to t-6)	0.0048				
	(0.017)				
	[0.017]				
Abovemedian (t-1 to t-12)		-0.0088			
		(0.024)			
		[0.025]			
Abovemedian prev. year			-0.0071		
			(0.017)		
			[0.018]		
Abovemedian prev. season				-0.0037	
				(0.014)	
				[0.014]	
Abovemedian prev. local					0.00091
					(0.0065)
					[0.0064]
Observations	24684	23508	24688	24688	23369
Mean of Outcome	0.040	0.039	0.040	0.040	0.037
Pabel B: Main lean season					
Above Median Fish.	-0.042	-0.037	-0.043	-0.043	-0.034
	(0.018)**	(0.016)**	(0.018)**	(0.018)**	(0.015)**
	[0.017]**	[0.016]**	[0.018]**	[0.018]**	[0.015]**
Abovemedian (t-1 to t-6)	-0.021				
	(0.018)				
	[0.015]				
Abovemedian (t-1 to t-12)		-0.041			
		(0.038)			
		[0.046]			
Abovemedian prev. year			-0.042		
			(0.032)		
			[0.040]		
Abovemedian prev. season				-0.0027	
				(0.028)	
				[0.028]	
Abovemedian prev. local					-0.0076
					(0.011)
					[0.013]
Observations	4312	3920	4312	4312	4092
Mean of Outcome	0.055	0.051	0.055	0.055	0.050
Cell * Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic

Note: This table reports the results from including previous fishing conditions when estimating equation (2). Panel A report the results for the full sample and Panel B report the results for the main lean season for fishing (April and May). Column (1) includes a variable capturing the share of good fishing months during the previous 6 months, column (2) does the same for the previous 12 months, column (3) reports the results for the share of good fishing months during the previous calendar year and column (4) does it for last year's high season for fishing (June to September). Finally, the last column reports the effect for the share of good months during last year's cell specific high season (defined as the on average best month together with the previous and following month - i.e. an average over 3 months). Robust standard errors in parenthesis are clustered at the cell level and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

From Table 5 it can be seen that none of these specifications estimate a significant income effect on piracy and that effect sizes are typically small. This is particularly the case for the specifications that focus on the high season (the last 2 columns) - i.e. those that would arguably best capture potential income effects. In contrast, the estimates for the contemporaneous month are large and statistically significant in all specifications. The only specifications for which previous fishing conditions has a similar size are those that focus on the lean season and include that season the previous year. As discussed in the robustness section below, this may be due to persistence in the effect a particular month - i.e. that fishermen decide to enter into piracy since fishing conditions for the same month the previous year were poor. The robustness section also reports that estimating the main specification and including previous months separately yields the same conclusion as the results presented in Table 5.

To sum up, this analysis finds no evidence of a significant income effect from previous fishing periods. This does not necessarily mean that there is no instantaneous income effect. The reason for this is that previous fishing conditions may not adequately affect the amount of available funds during the lean season, e.g. if fishermen are unable to save for the future. Hence, even if a direct income effect from fishing cannot be ruled out, the analysis in this section suggests that the main results are driven by changes in the opportunity costs of conducting piracy.

C. Heterogeneity by Income Determinants

Guided by the theoretical crime literature, one would expect factors that affect the opportunity costs as well as the returns from fishing to influence the response of pirate activity to changes in fishing conditions. This section investigates the heterogeneity of the main results along these dimensions. Two additional data sources are required for these two analyses. The first analysis uses data on average visible stable lights at night for 2002 and 2012 from the National Oceanic and Atmospheric Administration (NOAA). In the latter analysis, data on monthly commercial fish landings and fishery imports in the US have been collected from NOAA's national marine fisheries service. The summary statistics of the constructed variables are reported in Table A1.

First, if other legal income opportunities are available to fishermen, one would expect less of a response in piracy to changes in fishing conditions since fishermen could more easily turn to other income generating activities. The opportunity costs of piracy would in this case be less affected by changes in fishing conditions. To get a proxy for local legal income opportunities this study follows a recent literature in economics that has shown that satellite data on lights at night is a strong predictor for local economic activity (see e.g. Michalopoulos and Papaioannou, 2013; Henderson, Storeygard and Weil, 2012). To get a measure of how economic opportunities have developed in the coastal areas used in the analysis above, the average stable lights at night in a 50 km radius around the coast is calculated for 2002 and 2012. Thereafter the growth in lights during the sample period is determined for each coastal district. This data is then used to split the sample from the coastal district analysis into high growth and low growth areas (above and below the median growth in the sample). The results from this analysis are presented in Table 6.[33] It is shown that areas where growth was slow or negative during the period are substantially more sensitive to changes in fishing conditions and are in fact driving the main results with a point estimate that is about 70 percent larger than in the full sample. The point estimates in slow and high growth areas are significantly different at the 5 percent level with clustered standard errors and at the 10 percent level with Conley (2008) standard errors. This is consistent with other local income sources mitigating the impact of a fishing condition induced income shock on piracy. It also provides additional support for fishing conditions affecting sea piracy through changes in income opportunities. Growth in lights at night has been chosen as the proxy for local income opportunities since it provides information about whether economic conditions have improved or deteriorated during the sample period. For a given location, this should be more informative about the dynamics of the economy and the availability of alternative income opportunities than a measure of the aggregate size of the economy.[34] However, a potential concern with this approach is that growth in economic activity is correlated with other factors that affect piracy or fishing, such as the local resources available for patrolling. Hence, these results should be interpreted with caution.

To overcome the concerns with the above approach and more directly capture how the relative returns from fishing matter, this section also investigates the heterogeneity of the main effects depending on exogenous demand shocks to Indonesian fish exports. When there is a high demand for fish, one would expect a stronger response in income to fluctuations in fishing conditions and therefore also a larger change in the number of piracy attacks. In other words, the opportunity costs of conducting piracy would be more heavily affected. If demand is low and fishermen are not able to sell the fish they have captured, changes in fishing conditions should matter relatively less.[35] To estimate demand shocks to Indonesian fishery exports, this analysis exploits detailed information on monthly fish catches in the US. The US is by far the largest importer of Indonesia fish in terms of value, with imports amounting to 1.1 billion US dollars in 2012 constituting about 30 percent of the total value of Indonesian exports (BPS, 2012*a*). The reasoning behind this approach is that months with low fish catches in the US would

[33] Two coastal districts did not have any light in 2002 and are therefore dropped from the analysis, since growth rates could not be calculated for these 2 areas. This should not be a major concern, however, since they only corresponds to about 0.7 percent of the sample.

[34] In addition, level based measures of income opportunities are likely to introduce bias, since a larger economy around a fishing port reasonably implies that more ships are traveling to that particular location. As shown in an earlier version of the paper, a larger number of potential targets increases the response in piracy to changes in fishing conditions, which could attenuate the effect of alternative income opportunities. This attenuation bias is possibly less of a concern for the growth analysis, since the relationship between growth and shipping traffic is likely weaker.

[35] Note that there may still be more piracy attacks during these periods, as indeed the data suggests.

Table 6—Heterogeneous Effects by Income Determinants

Outcome:	# Attacks				Import
	Slow Growth	High Growth	High Demand	Low Demand	
	(1)	(2)	(3)	(4)	(5)
Above Median Fish.	-0.029	-0.0017	-0.030	-0.0070	
	(0.011)***	(0.0037)	(0.0085)***	(0.013)	
	[0.014]**	[0.0044]	[0.0087]***	[0.013]	
US Low Catch					1117264.0
					(431324.2)**
Observations	18843	18464	13325	12535	132
R-Squared	0.014	0.0046	0.0061	0.0055	0.055
Mean of Outcome	0.088	0.020	0.035	0.048	9739469.0
Location * Month FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Controls	Quadratic	Quadratic	Quadratic	Quadratic	No

Note: This table reports heterogeneity of the main results by other income determinants. The first two columns report the results of estimating the main specification in the coastal sample (i.e. corresponding to column (1) in Panel A in Table 4) for areas with high and low growth during the sample period (proxied by the local growth in lights at night in a 50 km area surrounding the coast between 2002 and 2012). The first column reports the estimated effect for coasts that experienced below median growth and the second column for coasts that experienced above median growth. Columns (3)-(4) report the results of estimating the main specification (i.e. corresponding to column (4) in Table 2) in a sample split by months during which there was a strong demand for Indonesian fish exports, proxied by low catch levels in the US in that particular month. Column (3) reports the effect for months where the US catch was below the median in that particular month (i.e. demand was high) during the sample period, whereas column (4) reports the effect for months with above median catch (i.e. low demand). The last column shows the unadjusted correlation between the US import of Indonesian fish and the above definition of an unusually low catch. Robust standard errors in parenthesis are clustered on coastal districts or cell and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

generate a larger demand for importing fish from Indonesia. This claim is tested in the last column of Table 6 which correlates US fish imports from Indonesia on a dummy variable equal to one if the US fish catch during a particular month is below the median during the sample period for that month. As expected, lower fish catches in the US are associated with larger US fish imports from Indonesia. Relying on this finding Table 6 also reports the results from splitting the sample into months during which there was a high demand for Indonesian fish (below median domestic catch in the US) and months with low demand (above median domestic catch). Results show substantially larger effects (with point estimates being significantly different at the 10 percent level) for months during which there is high demand for Indonesian fish, providing additional support that income opportunities from fishing is the driving mechanism.

VI. Evaluating Anti-Piracy Efforts

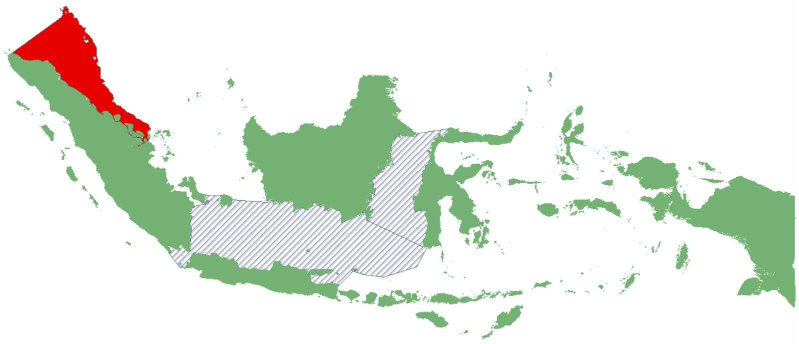
As discussed above, Indonesia initiated efforts to combat piracy in the Malacca Strait in July 2005 following increased international pressure. In particular, a large military operation under the code name Operation Octopus was carried out from July to September 2005 and joint air patrols were initiated from September 2005 onwards. This section aims to evaluate both how effective these efforts were in reducing piracy as well as whether these effects differ by local fishing conditions. Panel A of Figure 5 shows the area where actions were taken to reduce piracy (Malacca Strait, colored red) as well as the control area used for this analysis (Makassar Strait and Java Sea, colored gray). The South China Sea, which is neighboring the Malacca Strait, has been excluded from the analysis since piracy in the area could have been indirectly affected.[36] Panel B of Figure 5 shows the number of attacks each month in the two areas. Before the counter piracy efforts were initiated the number of attacks in both areas seems to follow roughly similar trends, but with strong seasonality. However, following July 2005 there is a significant decrease in the number of attacks in the Malacca Straits. This drop persists for some time, but after a few years the number of attacks seems to revert back to similar levels as in the control area. To investigate this pattern more formally the following difference-in-differences specification is estimated for the cell sample:

$$p_{aym} = \beta(d_{ym} * o_a) + \delta_{am} + \gamma_{ym} + \lambda f_{aym} + \theta \mathbf{X_{aym}} + \epsilon_{aym}, \tag{3}$$

where p_{aym} are the number of piracy attacks in cell a in year y and month m, d_{ym} is a time dummy that switches on from July 2005 onwards. The sample has been limited to the areas illustrated in Figure 5 and the dummy variable o_a indicates if a particular cell is covered by the operation. The variables δ_{am} and γ_{ym} represent cell by month and year by month fixed effects. These are included to capture both differences in seasonality between locations and short term fluctuations that could affect all areas. Finally, a dummy for above median local fishing conditions is also included (f_{aym}) as well as the same second degree polynomials of weather controls as in the baseline specification ($\mathbf{X_{aym}}$). Under the key assumption of parallel trends in the absence of treatment conditional on the fixed effects, β captures the effect of increased patrolling on the number of piracy attacks. Panel A of Table 7 shows the results from estimating equation (3). The results show a strong immediate reduction in the number of attacks during the year after the patrols were put in place. These effects seem to decrease but persist over time, suggesting that increased patrolling had persistent effects on the

[36] Not only are spillovers possible from the neighboring areas, but the exact geographical coverage of the operations is unknown.

Panel A: Patrolled and non-patrolled areas



Panel B: Number of attacks in the two areas

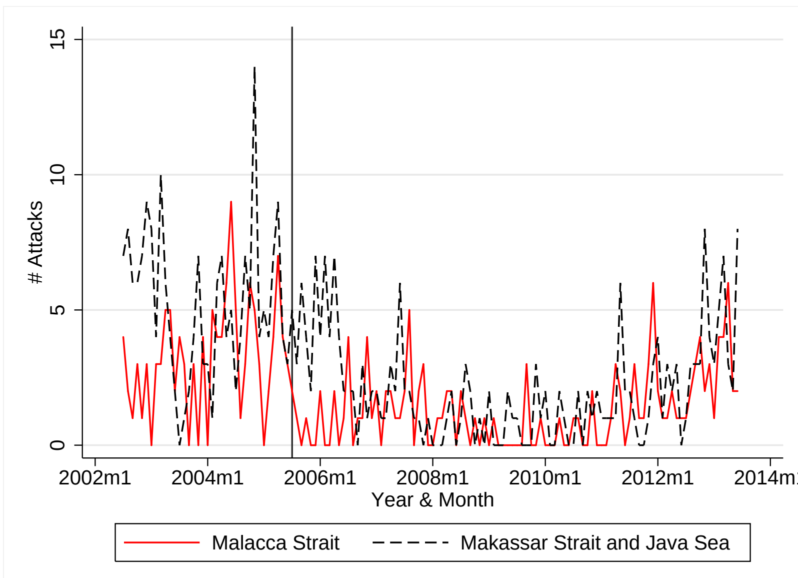


Figure 5. Anti-Piracy Patrols

Note: This figure shows the variation used for the evaluation in Section VI of the anti-piracy operations carried out in the Malacca Strait. Panel A shows the areas affected by the operation (Malacca Strait, in red) and those unaffected (Makassar Strait and the Java Sea, dashed). Panel B shows the number of attacks in these two waters, where the vertical line represents the initiation of anti-piracy patrols in the Malacca Strait.
Source: Figure is based on Author's own calculations using the data presented in Table A1 and the map is constructed by the Author.

amount of piracy.[37] This could be because of incapacitation effects or deterrence

[37] Attributing these effects to increased patrolling could be problematic if the change in insurance premiums by the reclassification of the Malacca Strait also disproportionately affected shipping patterns,

effects due to a higher perceived risk of getting caught. The reduction roughly corresponds to 1.8 times the mean number of attacks in the control group.[38]

Table 7—Effect of Piracy Patrols

Outcome:	# Attacks			
Sample included after July 2005:	1 year	2 years	3 years	4 years
	(1)	(2)	(3)	(4)
A: Direct effect of Patrols				
Patrolled * Post	-0.29	-0.19	-0.15	-0.16
	(0.13)**	(0.077)**	(0.064)**	(0.069)**
	[0.13]**	[0.083]**	[0.074]**	[0.082]**
B: Heterogeneous effects by fishing conditions				
Patrolled * Post	-0.48	-0.42	-0.39	-0.40
	(0.22)**	(0.14)***	(0.13)***	(0.13)***
	[0.18]**	[0.11]***	[0.11]***	[0.12]***
Patrolled * Post * Above Median	0.24	0.30	0.32	0.32
	(0.25)	(0.17)*	(0.16)**	(0.14)**
	[0.20]	[0.13]**	[0.13]**	[0.12]**
Observations	1823	2279	2733	3189
Mean of Control	0.16	0.14	0.12	0.11
Cell * Month FE	Yes	Yes	Yes	Yes
Year * Month FE	Yes	Yes	Yes	Yes
Controls	Quadratic	Quadratic	Quadratic	Quadratic

Note: Panel A in this table reports the results from estimating equation (3). The columns present the estimate for including data one, two, three or four years after the patrols were initiated. Panel B implement a triple difference strategy where the DID variables from Panel A are interacted with the measure of good fishing conditions. All regressions control for above median fishing conditions as well as second degree polynomial function of accumulated rainfall, wind speed and wave height. Robust standard errors in parenthesis are clustered on the cell and Conley (2008) standard errors that are adjusted for both spatial and temporal correlations (assuming a distance cut-off of 1,000 km) in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

To be able to say something about how the effectiveness of the operation varies by local income opportunities, the heterogeneity of this effect is investigated with regards to fishing conditions. This is done by interacting all DID variables in equation (3) with the above median fishing conditions variable. Hence, this creates a triple difference equation that estimates the effect of the operation by contemporaneous fishing conditions. Results from this analysis are presented in Panel B of Table 7. A clear pattern emerges from this analysis, namely that the effect of the operation is substantially stronger in areas with poor fishing conditions.[39] A likely explanation for this is that there is a larger number of potential pirates when fishing conditions are poor (since piracy is relatively more profitable

which could in turn affect the number of potential target. However, the persistence of these effects suggest that they are driven by patrolling since the Malacca Strait was removed from the JWC's list in 2006 and effects persist long after that.

[38] Estimating this regression for the coastal district sample instead produces very similar results. These results are reported in the online appendix.

[39] The effect for areas with poor fishing conditions can be read straight of the table as the coefficient of

during these time periods), which makes the operation more successful. The validity of the results from this analysis hinges on the assumption that patrols do not respond to contemporaneous shocks in fishing conditions. This is a reasonable assumption since the navy does not have the capability of predicting local fluctuations in oceanographic conditions.[40]

VII. Robustness Checks

This section addresses the sensitivity of the results presented above. The identification assumption as well as other potential mechanisms and the estimation strategy are discussed.

The main identification assumption in the analysis is that fishing conditions are as good as randomly assigned conditional on the fixed effects. To investigate this, leads and lags have been included in the main specification, i.e. column (4) in Table 2. The point estimates of these and their respective confidence intervals are presented in Figure 6. As can be seen from the figure the point estimate on the main variable of interest is largely unaffected and the estimates of these controls are typically small and insignificant. The only estimate with a similar magnitude and significance is the 12 months lag of the fishing conditions variable. This could potentially be explained by fishermen taking past experiences from the same month the previous year into account when deciding on moving into piracy.

Even if fishing conditions are as good as randomly assigned, there could potentially be other reasons than changes in income opportunities that explain why an improvement of fishing conditions reduces the amount of piracy. The most likely such scenario would probably be extreme weather conditions affecting both oceanographic conditions and the possibilities of engaging in piracy. As discussed above, the effects are very robust to the inclusion of different functions of local controls for wind speed, wave height and rainfall. This should mitigate concerns about the effects of interest being driven by other factors than changes in fishing conditions.

Another potential concern is that an improvement of fishing conditions increases the number of fishermen at sea, and that this may have a direct effect on piracy attacks. Such a mechanism may work in either, or both, of the following two directions. On the one hand, an increase in the number of fishing boats may increase the number of potential targets for pirates, since fishing boats are also sometimes attacked. This would tend to attenuate the effect of income opportunities, given that a larger number of attacks would be carried out when fishing

the first interaction. For areas with good fishing condition the effect is the sum of the triple and the first interaction, since the triple interaction estimates the difference between the effects for good and poor conditions.

[40] If anything, one would expect the navy to target areas with previously high piracy levels. As shown from the unadjusted correlation between fishing conditions and piracy in the main analysis, these tend to be areas with on average better fishing conditions. Hence, such targeting would likely generate a bias towards finding effects for areas with better fishing conditions and therefore suggest that the above results are lower bounds.

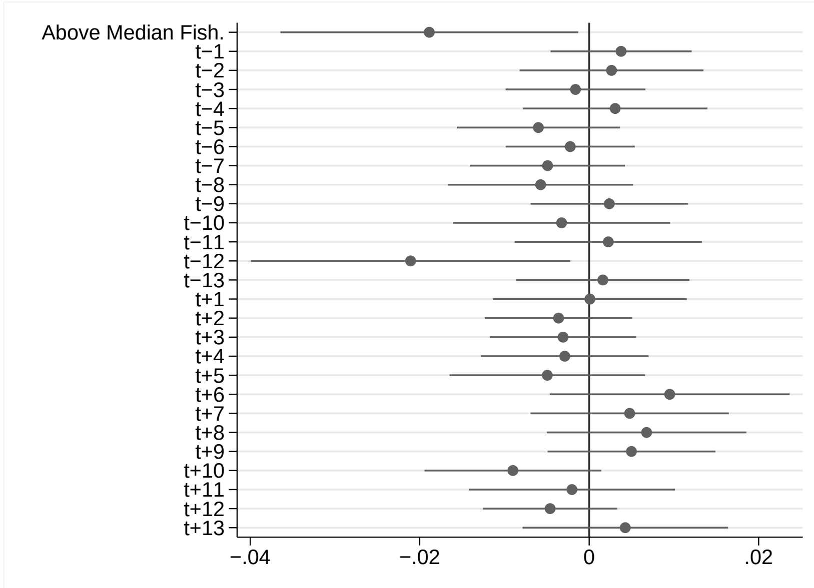


FIGURE 6. POINT ESTIMATES AND CONFIDENCE INTERVALS OF LAGS AND LEADS

Note: This figure shows the point estimates and the 95 percent confidence intervals of the impact of lags and leads of above median fishing conditions on the number of piracy attacks. These coefficients are simultaneously estimated in a single regression corresponding to column 4 in Table 2, i.e., controlling for second degree polynomial functions of wind speed, accumulated rainfall, wave height as well as month by cell and year fixed effects. The number of observations are 20,764 and standard errors are clustered on 196 cells.
Source: Figure is based on Author's own calculations using the data presented in Table A1.

conditions are good. However, very few fishing boats are attacked in this sample and excluding them from the analysis produces identical results. On the other hand, an increase in the number of fishing boats at sea may provide monitoring and could thus potentially make it easier to catch pirates or prevent them from carrying out attacks. There are a number of reasons why this is not likely to be a major concern. First of all, anecdotal evidence from the Malacca Strait suggest that more vessels at sea make piracy easier, rather than harder, to carry out since it helps pirates to blend in and therefore harder to detect.[41] Hence, if there are more boats at sea due to better fishing conditions, pirates could more easily approach a target without raising suspicion. In addition, field studies suggest that pirates live among the fishermen and that no one dares to talk about them in the local communities - further suggesting that monitoring is unlikely.[42] Finally, two results from the empirical analysis also speak against the results being driven by

[41]Kemp, Ted. 2014. "Crime on the high seas. The world's most pirated waters" CNBC, December 15. http://www.cnbc.com/2014/09/15/worlds-most-pirated-waters.html.
[42]Frécon, Eric. 2005. "Piracy in the Malacca Straits: notes from the field." IIAS Newsletter 36. March

monitoring. To start with, the unadjusted correlation between fishing conditions and piracy is positive. This suggests that more attacks are carried out in locations with better fishing conditions and more fishermen at sea, which should not be the case if monitoring by fishermen is a serious concern for the pirates. Secondly, the analysis of the anti piracy patrols above shows that it was more successful in areas with worse fishing conditions. This goes against what one would expected if results were driven by monitoring, since the operation should then have been more successful in areas with better fishing conditions (and more fishermen at sea). In addition, the analysis of labor market outcomes in Section III as well as the heterogeneity analysis in Section V.C clearly suggests that results are driven by changes in income opportunities. If anything, other potential mechanisms would likely go in the opposite direction.

To take into account the fact that the outcome variable in some of the analyses above is a count variable, fixed effect poisson and probit methods are also implemented to estimate equation (2). The results from these regressions are presented in Table A2. Overall, estimates with these non-linear models tend to be of a roughly similar magnitude as the OLS results. Results are highly statistically significant for the coast sample, but less precise for the cell sample.[43] This is in particular the case for the probit regressions including all month by location fixed effects, which is no longer statistically significant. Hence, this suggests that the extensive margin results in the paper should be interpreted with caution.

VIII. Discussion and Concluding Remarks

This study investigates the impact of changes in climatically determined income opportunities on piracy in Indonesia. The empirical strategy exploits exogenous changes in oceanographic fishing conditions and it is found that these affect the number of piracy attacks. This finding is robust to a wide range of different specifications using both an analysis focusing on the whole EEZ of Indonesia and one on coastal areas. The main result shows that good fishing conditions reduce the mean number of attacks by 40 percent of the mean. Compared to previous studies on the effect of climatic variation on crime and conflict the effect in this study is large, but within the range of earlier findings.[44]

[43] Note that these models drop all groups defined by the fixed effects for which there is no within variation in the outcome. Hence, the samples used for these estimations are substantially smaller, especially for the specification with month by location fixed effects. These models do therefore disregard potentially important variation when estimating control variables that could affect the precision of the estimates.

[44] The synthesis by Hsiang, Burke and Miguel (2013) reports that the median effect in the literature of a one standard deviation change towards more adverse climate is an increases in conflict by 14 percent of the mean and interpersonal violence by 4 percent. The largest reported point estimate for the former is a 93 percent increase and for the latter a 20 percent increase. Since the climatic variation used in this paper is defined in a different manner, results are not directly comparable. However, in order to make a very rough comparison the main effect in this paper could be scaled by the variability in fishing conditions. A shift from below to above median on average corresponds to a 1.2 s.d. increase in fishing conditions. Hence, a 1 s.d. shift in fishing conditions can be approximately compared to a 33 percent decrease in piracy.

An analysis of the impact of changes in fishing conditions on the price of fish as well as the income and working hours of fishermen provides support for the proposed mechanism, namely that the effects are driven by changes in income opportunities. This is also supported by heterogeneity analysis, which shows that effects are stronger in areas with slow growth and in time periods with a high demand for fish. Finally, an attempt to separate income effects from opportunity costs suggests that results are driven by the latter.

To get an approximate sense of the size of this effect, the change in income caused by improved fishing conditions can be compared with the change in the number of attacks. An indicative estimate suggests that a 1 percent increase in income per working day reduces the number of attacks by about 1-2 percent of the mean.[45] This estimate should be interpreted with considerable caution due to limitations in the labor market data, which only allow for an identification of the income effect for self employed fishermen during a limited time period. Nonetheless it gives a rough approximation of the importance of this effect.

Further, by evaluating the effect of stepping up piracy patrols in Indonesia it is found that they reduced the number of attacks substantially. Notably, these efforts affected piracy in a particular location differently depending on the contemporaneous fishing conditions in that area. In areas with poor fishing conditions, the patrols were much more successful at reducing piracy. A possible explanation for this is that lacking income opportunities contributed to a larger number of potential pirates in these locations. This finding also mitigates concerns that the results in the paper are driven by anti-piracy operations being more feasible during time periods when fishing conditions are better - e.g. by fishermen providing monitoring of pirates.

As discussed above, this study relates to the large literature showing that climatic factors can substantially affect criminal activity and conflict - a literature that has potentially important implications for interpreting the consequences of climate change. This is likewise the case for the findings in this paper, since fishing conditions are also projected to be altered by climate change. In fact, the fish catch potential in Indonesia may be particularly adversely affected. Cheung et al. (2010) show that the Indonesian EEZ will be the hardest hit of all countries studied, with a more than 20 percent decline in 10-year fish catch potential by 2055. Even if it is hard to make any extrapolations from the short term analysis in this paper, the findings are consistent with climate change having important implications for piracy.

Finally, compared to the previous studies on climatic variation and conflict, the setting in this study enables a more close investigation of the underlying mechanism. Therefore it may provide some important insights for policy. The findings suggest that improving income opportunities for fishermen in periods when fishing conditions are poor, could be a viable strategy to reduce the number

[45] This calculation uses the reduced form estimates from the coastal district sample in Table 4 and the first stage estimate using the corresponding specification (reported in the online appendix).

of piracy attacks. Additional research is needed in order to investigate how such policies could be designed.

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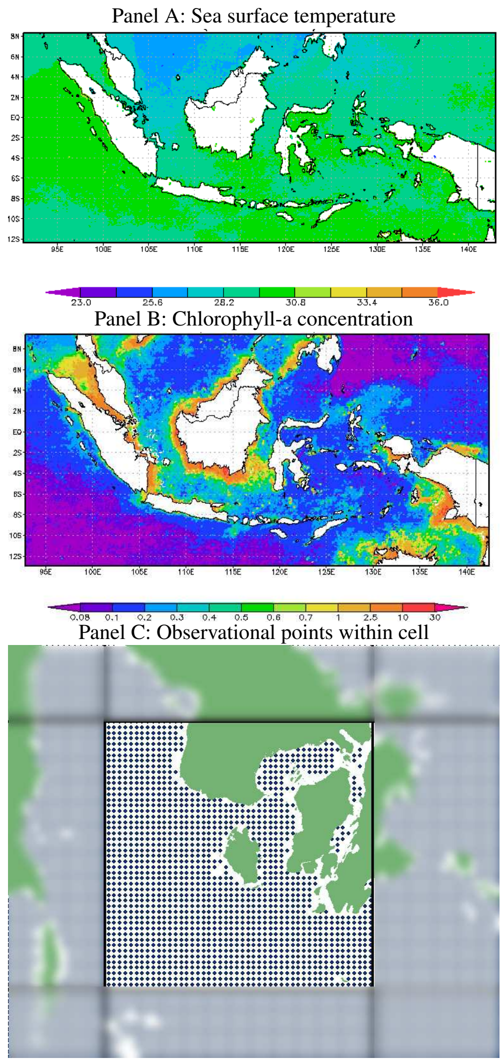


Figure A1. Constructing measure of fishing conditions

Note: This figure illustrates the construction of the measure of fishing conditions. The two top panels show the raw data from the NASA Modis satellite for a given month. Panel C clarifies how a particular unit of analysis has been constructed by illustrating the observational points within a cell.
Source: The figures in Panel A and B are produced using the Giovanni online data system (Acker and Leptoukh, 2007), whereas the figure in Panel C is constructed by the Author.

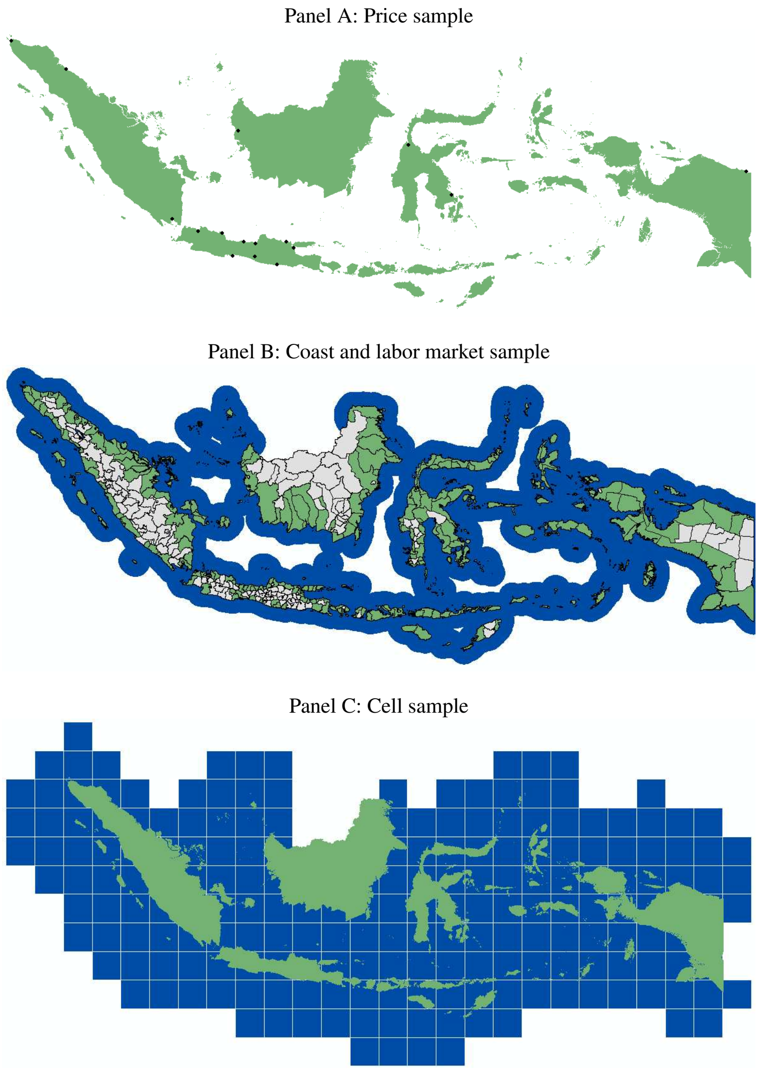
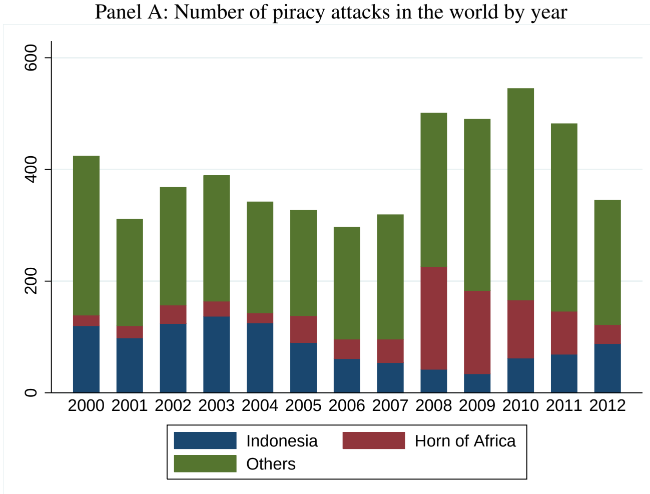


FIGURE A2. SAMPLES USED FOR ANALYSIS

Note: This figure shows the geographical distribution of the four main samples used in the analysis. Panel A shows the location of 16 coastal fish markets used in the price analysis. Panel B shows the 50 nautical mile fishing zone of the Indonesian districts used in the labor market and coastal district sample analysis. All green (dark) districts are included in the labor market sample, whereas gray (light) districts do not have any labor market data on marine coastal fishermen. Panel C shows the 2×2 degree cells covering the whole EEZ of Indonesia used in the main analysis.
Source: Maps are constructed by the Author.

Panel A: Number of piracy attacks in the world by year



Panel B: Total attacks in Indonesia by month

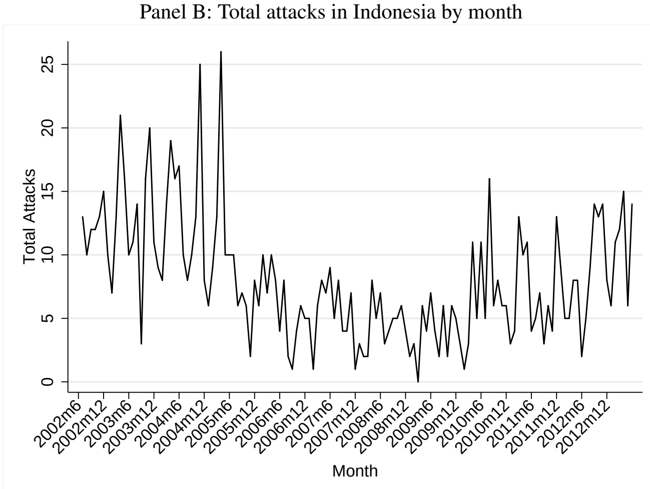


Figure A3. Piracy attacks in Indonesia and the world

Note: This figure shows the time variation in the number of piracy attacks in Indonesia and the world. The data is from the National Geospatial-Intelligence Agency. Panel A shows the total number of attacks in the world by year from 2000 until 2012. This graph also shows the share of attacks that were carried out in the EEZ of Indonesia as well as in the EEZ of Somalia and Yemen (Horn of Africa). Panel B shows the number of attacks by month in the EEZ of Indonesia from July 2002 to June 2013.
Source: Figure is based on Author's own calculations using the data presented in Table A1.

Table A1—Summary statistics

	MEAN	SD	MIN	MAX	OBS
Price Sample					
Fish Price	22713	8794	5613	62500	448
Above Median Fish	0.500	0.501	0.000	1.000	448
Fishing Conditions	0.227	0.286	0.000	1.000	448
Labor Market Sample					
Total Income	780631	749940	0	25000020	6607
Days needed for income	20.613	7.096	0.000	31.000	6607
Income per day worked	41949	45299	0	1250001	6563
Log of income per day worked	10.373	0.709	7.051	14.039	6559
Hours worked in fishing	40.720	19.907	0.000	98.000	12285
Hours worked excl. fishing	1.094	3.951	0.000	42.000	12285
Share of work hours in fishing	0.974	0.087	0.500	1.000	11780
Fishing Conditions	0.319	0.304	0.000	1.000	12285
Above Median Fish	0.502	0.500	0.000	1.000	12285
Cell Sample					
# Attacks	0.041	0.293	0.000	8.000	25948
Attack (1 or 0)	0.027	0.162	0.000	1.000	25948
Fishing Conditions	0.157	0.261	0.000	1.000	25948
Above Median Fish.	0.500	0.500	0.000	1.000	25948
Chlorophyll-a	0.562	1.036	0.028	14.916	25948
SST	29.539	1.304	24.270	32.628	25948
Wind Speed (m/s)	4.226	1.540	1.251	9.699	25948
Accumulated Rainfall (m)	0.201	0.132	0.000	0.992	25948
Wave Height (m)	1.088	0.633	0.092	3.035	25860
US Catch (Metric Ton)	139500	79306	35185	319833	132
US Low Catch (1 or 0)	0.5	0.5	0.0	1.0	132
US Import (kg)	9739469	2383342	3767130	15661289	132
Coast Sample (50nm)					
Fishing Conditions	0.226	0.273	0.000	1.000	37703
Above Median Fish	0.500	0.500	0.000	1.000	37703
Wind Speed (m/s)	3.535	1.142	1.225	7.925	37703
Accumulated Rainfall (m)	0.208	0.129	0.000	0.916	37703
Wave Height (m)	0.790	0.495	0.092	2.816	37571
Average Stable Lights 2002	1.789	2.795	0.000	18.323	37703
Average Stable Lights 2012	2.355	3.615	0.000	23.516	37703
Growth in Lights (2002-2012)	1.019	3.129	-0.862	46.197	37439

Note: This table reports summary statistics for the four main samples used in the analysis. Columns (1) through (4) reports the mean, standard deviation, minimum and maximum values of the listed variables, whereas column (5) shows the number of observations.
Source: The fishing condition variable is contructed by the author using satellite data on sea surface temperature and chlorophyll-a from the NASA Modis Aqua Satellite accessed through the Giovanni online data system, developed and maintained by the NASA GES DISC (Acker and Leptoukh, 2007). Fish pricses data has been collected and compiled by the author using the January 2008 to April 2012 monthly reports produced by the Indonesian Directorate General of Processing and Marketing of Fishery (DJ PPHP, 2012).The data for the labor market sample was constructed using the Indonesian Labor Market Survey (SAKERNAS) carried out each February and August from 2007 to 2010 (BPS, 2010). The rainfall data comes from the Tropical Rainfall Measuring Mission, which has also been accessed through the Giovanni online data system. Wind speed and wave height is from the reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (Dee et al., 2011). Data on average visible stable lights at night for 2002 and 2012 is from the National Oceanic and Atmospheric Administration (NOAA) (NOAA, 2012) as well as the data on monthly commercial fish landings and fishery imports in the US (NOAA National Marine Fisheries Service, 2013). The data on piracy attacks is from the National Geospatial-Intelligence Agency 2002-2013 (2013). Further details on variable and sample construction is outlined in sections II, III and IV.

Table A2—Poisson and Probit Regressions

Outcome:	# Attacks: Poisson			Attack (1 or 0): Probit		
	(1)	(2)	(3)	(4)	(5)	(6)
A: Cell Sample						
Above Median Fish.	-0.34***	-0.30**	-0.26*	-0.20***	-0.13	-0.11
	(0.13)	(0.13)	(0.14)	(0.064)	(0.082)	(0.085)
				[-0.010]	[-0.032]	[-0.027]
Observations	10287	3427	3427	10209	3427	3427
Mean of Outcome	0.10	0.31	0.31	0.068	0.20	0.20
B: Coast Sample						
Above Median Fish	-0.28***	-0.33***	-0.27***	-0.21***	-0.25***	-0.21***
	(0.068)	(0.094)	(0.099)	(0.045)	(0.063)	(0.061)
				[-0.018]	[-0.071]	[-0.055]
Observations	12910	5912	5912	12631	5912	5912
Mean of Outcome	0.16	0.34	0.34	0.11	0.24	0.24
Cell FE	Yes	No	No	Yes	No	No
Cell * Month FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Year * Month FE	Yes	No	No	Yes	No	No
Controls	No	No	Quadratic	No	No	Quadratic

Note: This table reports the effects of above median fishing conditions on piracy in the cell sample using poisson and probit estimation. Panel A report results for the cell sample and Panel B for the coastal district sample (considering attacks within 20 nautical miles from shore). The first three columns report the results on the number of attacks using poisson and the last three columns on a dummy variable indicating whether an attack occurred or not using probit. Robust standard errors clustered on the geographical location (cell/coastal district) in parenthesis. Outcomes that are constant within cells are dropped from the poisson and probit regressions, explaining the lower number of observations in these regressions. The marginal effect at the mean for the probit regression is reported in brackets.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.