Economic Shocks in the Fisheries Sector and Maritime Piracy

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Abstract

For a panel of 109 coastal countries we show that negative economic shocks in the fisheries sector are associated with an increase in maritime piracy. Our identification strategy uses the variation in the phytoplankton abundance off the individual countries' coasts, measured by satellite data, as a source of such shocks. We find that plankton abundance is positively related to fish catches but negatively associated with the incidence of piracy, onset and the absolute number of pirate attacks. Our instrumental variable estimates indicate that a one percent increase in fish catches reduces the risk of piracy occurring by one percentage point.

JEL classification: K42, Q22, D74, O18
Keywords: Maritime Piracy, Fisheries Sector, Instrumental Variable Regression

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1 Introduction

Even though the scale of piracy activity varies considerably by region, the occurrence of piracy attacks is a worldwide phenomenon. In the period from 2004 to 2009, more than 40 percent of all coastal countries experienced at least one piracy incident.[1] Such incidents have been shown to increase trade costs and to reduce the volume of traded goods.[2] Consequently, the widespread occurrence is seen as a major threat to international trade since more than 80% of all traded goods are transported by sea.[3] The identification of factors that drive the piracy activity is therefore of economic relevance. A commonly mentioned factor in the literature is the lack of legal income opportunities (Rosenberg (2009); Jablonski and Oliver (2012); Bateman (2009, p. 131)). In the view of the fact that the people who engage in piracy attacks frequently have a background in the fishing industry—which provides them with the necessary navigational skills and knowledge of local waters to carry out an attack—economic shocks affecting this population group are likely to play a particularly important role in explaining variation in piracy activity (Daxecker and Prins (2012); Burnett (2003); Frécon (2005); Murphy (2009)).

In this paper, we examine the link between economic shocks in the fisheries sector and the incidence of piracy. Our empirical analysis is based on a panel of 109 coastal countries that spans the years 2004–2009.[4] We extract information on the incidence of piracy—at least one piracy attack in a given year—as well as the number of pirate attacks from the Maritime Piracy Dataset (Coggins, 2012). We use the variation in phytoplankton abundance off the individual countries' coasts, measured with satellite data, as a source of economic shocks to the fishery industry. The approach is based on the well-documented fact that local phytoplankton abundance represents the constraining factor for fish abundance and, consequently, fish catches (e.g., Chassot et al. (2010) or Ware and Thomson (2005)). Because the variation in local plankton abundance is determined by a complex interaction of biological and physical processes, it can be regarded as an exogenous input factor—i.e., outside the control of the economic agents—in the fish capture production. Variation in plankton abundance therefore constitutes an idiosyncratic productivity shock to the fishery industry.

[1] Own calculations, based on the Maritime Piracy Data of Coggins (2012).

[2] See Besley et al. (2012) and Bensassi and Martínez-Zarzoso (2012).

[3] United Nations (2012, p. 44)

[4] Due to the lack of data, we cannot include Somalia in our empirical analysis. Since our main goal is to assess the general relationship between negative shocks in the fisheries sector and increased pirate activity, this omission constitutes only a minor restriction.

Figure 1 depicts the yearly variation in phytoplankton abundance for three countries, where the values are normalized at the countries' respective means. The shaded areas indicate the years in which piracy incidents occurred. The figure suggests the existence of a negative association between plankton abundance and piracy attacks. In years with low phytoplankton abundance, piracy attacks are more likely. In fact, our regression results

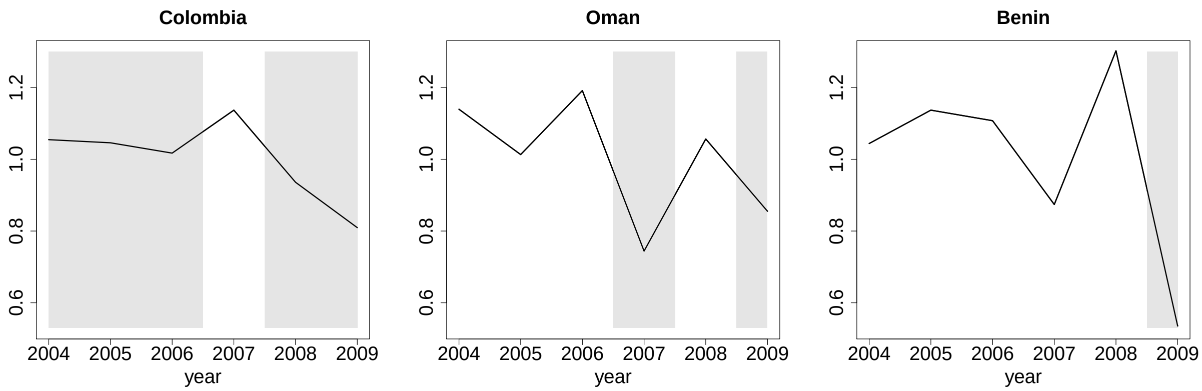

Figure 1: Time series plots of the variation in phytoplankton abundance. The shaded areas indicate the years with at least one reported incident of maritime piracy. The y-axes depict the value of the phytoplankton abundance (normalized by the country-specific mean).

document a statistically significant and negative relationship between contemporaneous plankton abundance and the incidence of piracy. A one percent decrease in local plankton abundance increases the probability of observing at least one piracy incident by 0.37 percentage points.

Using the abundance of phytoplankton off each country's coast as an instrument for the country-year level of fish catches, we can quantify the effect that economic shocks in the fisheries sector have on the piracy activity. Our results indicate that the probability of the incidence of piracy increases by 1 percentage point when the fish capture production drops by one percent. Similarly, a reduction in fish catches is associated with an increase in the probability of onset of pirate activity as well as a rise in the absolute number of piracy incidents. We do, however, not detect any persistence with respect to the incidence of pirate activity. A possible interpretation for these findings is that piracy is driven—at least partly—by opportunity cost effects in the fisheries sector. People do not turn into hardened criminals permanently, but rather try to compensate for forgone income from legal sources.

We conduct various robustness checks to substantiate the validity of our results. For example, we show that our results also hold when controlling for international anti-piracy actions or when including control variables for local weather conditions.

Our work relates to multiple areas of the economic literature. The study most closely related to our paper is that by Daxecker and Prins (2012). Using country-level information on the annual number of piracy attacks, they show that these are negatively correlated with the growth rate of fish capture production. However, their regression analysis does not account for the potential endogeneity between pirate attacks and fish catches. The study by Jablonski and Oliver (2012) analyzes the effect of variation in commodity prices on the number of pirate attacks. Based on their results, the authors argue that lower opportunity costs in the agricultural sector, induced by reduced prices for agricultural products, increases maritime piracy activity. Additional research directed at identifying factors contributing to the existence of maritime piracy has been restricted to the special case of Somalia. The results of these studies suggest that negative economic shocks in the fisheries sector—driven mainly by illegal fishing activity—were a contributing factor to the present-day piracy problems (see, e.g., Bueger et al. (2011), Bawumia and Sumaila (2010) or Menkhaus (2009)).

More broadly, our paper relates to the branch of literature that analyzes the association between economic shocks and illegal activities and conflict. For example, Miguel et al. (2004) demonstrate that negative income shocks increase the probability of civil conflict in Sub-Saharan countries. Similarly, Dube and Vargas (2013) show that a drop in prices of labor-intensive commodities increases the extent of civil conflict in Colombia. Dube et al. (2013) find that a reduction in the maize price—resulting in a drop in income for maize farmers—leads to an increased cultivation of marijuana and opium poppies. Finally, Bignon et al. (2011) as well as Cortés et al. (2013) show that negative income shocks are associated with a rise in nonviolent crimes. This last result indicates that people who find themselves in dire economic circumstances engage in criminal activity in order to substitute their forgone legal income rather than being motivated by the prospect of a career as hardened criminal.

Our study is also linked to the field of biology that analyzes the connection between plankton abundance and fish capture production. The results indicate that primary production represents the constraining factor for fish catches (e.g., Chassot et al. (2010) or Chassot et al. (2007)). Iverson (1990) as well as Sommer et al. (2002) document that the relationship between plankton abundance and fish capture production is approximately linear. Finally, there is also a close link between our paper and the literature that uses satellite data to measure phytoplankton abundance (e.g., Shang et al. (2011) or Chassot et al. (2011)).

Overall, the literature review suggests that concluding evidence with respect to the identification of driving forces of maritime piracy is scarce. This study contributes to filling this gap. The paper is organized as follows: In Section 2, we describe our empirical approach before presenting the data in Section 3. In the subsequent section, we document and discuss our regression results. Finally, Section 5 concludes.

2 Empirical Strategy

Our main interest lies in analyzing the association between negative economic shocks in the fisheries sector and the occurrence of piracy incidents. We use the variation in phytoplankton abundance off each country's coast as the source of such country-specific shocks. We argue that plankton abundance constitutes an exogenous input factor in fish capture production. Consequently, greater phytoplankton plankton abundance implies increased fish capture production. This in turn suggests an improvement in the economic opportunities in the fisheries sector which raises the opportunity cost of engaging in illegal activity. We therefore expect that a rise in plankton abundance has a negative impact on piracy activity.

The validity of our empirical approach relies on the following identifying assumptions: (a) the factors determining the abundance of phytoplankton are exogenous to other factors influencing piracy activity, (b) phytoplankton abundance influences the amount of fish caught, and (c) changes in phytoplankton only affect piracy incidents through the variation induced in the fish catches. The plausibility of these assumptions is discussed in the following.

2.1 Plankton Abundance and Fish Capture Production

Phytoplankton constitute the basis of the oceans' food web. Through photosynthesis they convert carbon dioxide into organic matter, i.e., food. Phytoplankton account for approximately 90 percent of the overall primary production (Duarte and Cebrián, 1996) and are therefore of critical importance to all living organisms in the oceans. There are two main factors controlling the productivity and, consequently, the abundance of phytoplankton: sunlight intensity and the availability of nutrients (Castro and Huber, 2013, p. 350). The first component depends, among other things, on geographical latitude, the clarity of the water and weather conditions. On cloudy days, for example, exposure to sunlight is lower than on clear days which reduces the productivity of phytoplankton. The density of nutrients varies by location and by season. Because the nutrients sink towards the bottom of the oceans, deeper waters are typically nutrient-rich, whereas the upper stratas of the water column are relatively nutrient-scarce. Since sunlight is an essential ingredient for photosynthesis, nutrient-rich deep water generally has to ascend to the surface in order to enable a high primary production by phytoplankton.

There are different mechanisms which enable deep waters to ascend. An example of such a mechanism are coastal upwellings. These occur when prevailing wind patterns carry the surface water levels away from the shore. This allows deep, nutrient-rich water to move up the water column at the break of the continental shelves, thereby increasing primary production. Upwellings are generally locally and seasonally confined phenomena. In regions with marked seasonal differences in temperatures and sunlight exposure, an additional mechanism exists that allows deep water to ascend: the overturn. When the surface water cools off, it becomes denser and sinks. Consequently, the deeper, nutrient-rich water reaches the surface. Finally, in the relatively shallow waters over the continental shelves, wind and waves may be sufficiently strong to mix the water column all the way down to the bottom. This makes these areas of the oceans—especially when combined with the presence of upwellings—particularly productive. In fact, primary production over the continental shelves supports over 90 percent of world fish catches (Pauly et al., 2002). In addition to the rate of production, local phytoplankton abundance is also influenced by currents and winds which determine the direction in which the plankton is transported.

The description above shows that the geographical occurrence and abundance of phytoplankton is the result of a complex interaction of many factors such as biological processes, wind patterns and local geographical characteristics. Therefore, the regional and temporal abundance in phytoplankton can be regarded as exogenous. In the empirical analysis, we will conduct robustness checks in order to validate this assumption.

Our identification strategy further relies on the assumption that spatio-temporal variation in phytoplankton causes variation in the abundance of fish, and consequently variation in the volume of fish caught within a given region and year. This assumption presupposes the presence of a bottom-up control regime. That is, the abundance of fish is determined by the availability of plankton and not vice versa. The bulk of the literature supports this assumption. For example, Chassot et al. (2010), Sherman et al. (2011), Chassot et al. (2007) and Ware and Thomson (2005) document the presence of a bottom-up regime and show, that fish catches are constrained by primary production.[5]

Finally, changes in the abundance of phytoplankton should only influence the decision to engage in piracy activity via the variation induced in fish catches in order for our 2SLS instrumental variable regression results to yield unbiased estimates. It is indeed difficult to imagine an alternative mechanism through which phytoplankton could influence piracy activity. However, it is conceivable that one of the factors influencing the abundance of plankton also affects economic opportunities through other channels. For example, variation in rainfall could induce variation in phytoplankton as well as changes in the agricultural sector, which in turn could induce variation in pirate activity (Jablonski and Oliver, 2012). However, variation in local phytoplankton abundance is the result of a complex interaction of various parameters, including changes in factors independent of local conditions. We therefore expect that phytoplankton abundance is largely uncorrelated with such individual local factors. We will conduct robustness checks in the empirical analysis—by including local weather conditions as control variables—to substantiate this assumption.

Overall, the exposition above suggests that variation in the local abundance of phytoplankton causes variation in the volume of fish catches and therefore can be used in an instrumental variable estimation approach. The methodology used is outlined next.

2.2 Methodology

We first examine the effect of plankton abundance shocks on fish capture production and maritime piracy activity. We then quantify the effect of economic shocks to the fisheries sector—induced by the fluctuations in plankton abundance—on piracy activity by using a 2SLS instrumental variable approach. In particular, we employ plankton abundance as an instrument for the quantity of fish caught. In the following, we will discuss the regression setups.

We investigate the relationship between phytoplankton abundance and fish catches using

[5] A concern with our identification strategy is the possible existence of a top-down effect. In this case, an increase in fish stock would result in a decrease in phytoplankton abundance. The studies that analyze the presence of such a top-down regime in marine waters do not deliver any conclusive results (see e.g., Sommer and Sommer (2006)). The literature review of Baum and Worm (2009) additionally reveals that in each case where a top-down effect was detected, it did not reach down to the phytoplankton level. Note additionally, that the presence of the top-down effect would bias our estimates towards zero.

the following regression:

$$\ln(f_{i,t}) = \theta\, py_{i,t} + \mu_i^A + \gamma_t^A + \delta_c^A\, t + \boldsymbol{\beta}'_A\, \mathbf{X}_{i,t} + \xi_{i,t}, \tag{1}$$

where $f_{i,t}$ are the (log) tonnes of fish caught in year t by country i; $py_{i,t}$ represents the measure of phytoplankton abundance off the coast of country i at time t. The country-fixed effects are given as μ_i^A. Their inclusion implies that we will only rely on within-country variation over time for the identification of the effect. We additionally include year dummies (γ_t^A), continent-specific time trends (t) as well as a set of control variables ($\mathbf{X}_{i,t}$) in our regression setup.[6] Finally, $\xi_{i,t}$ represents the error term. The standard errors are clustered at the country level. As explained in Section 2.1, we expect that a greater abundance of phytoplankton is reflected in a higher volume of fish capture production ($\theta > 0$).

To analyze the impact of phytoplankton shocks on maritime piracy activity, we use a similar setup. It is represented by:

$$y_{i,t} = \psi\, py_{i,t} + \mu_i^B + \gamma_t^B + \delta_c^B\, t + \boldsymbol{\beta}'_B\, \mathbf{X}_{i,t} + \zeta_{i,t}, \tag{2}$$

where $y_{i,t}$ are the the different measures for the activity of maritime piracy in country i and year t. Specifically, we will use the incidence, the onset, as well as the (log) number of piracy attacks as dependent variables. The explanatory variables are identical to the ones included in Eq.(1); $\zeta_{i,t}$ constitutes the error term. Because phytoplankton abundance represents an input factor in fish capture production, we expect plankton to be negatively associated with the piracy activity variables ($\psi < 0$).

To quantify the effect of phytoplankton shocks on piracy activity in economic terms, we employ a 2SLS instrumental variable approach, where we use plankton abundance as an instrument for fish capture production. The first stage is given by Eq.(1), the second stage by:

$$y_{i,t} = \phi\, \ln(f_{i,t}) + \mu_i^C + \gamma_t^C + \delta_c^C\, t + \boldsymbol{\beta}'_C\, \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $y_{i,t}$ are again the different measures for the activity of maritime piracy in country i in year t. The (log) tonnes of fish caught by a given country and year is represented by $f_{i,t}$. Analogously to Eq.(1) and Eq.(2), we include country-specific fixed effects, time dummies, continent-specific time trends and a set of control variables in our regression setup. $\epsilon_{i,t}$

[6] We include the time trends to account for possible climate changes. Our results, however, do not rely on the inclusion of these trends (see, e.g., Table 2).

represents the error term. We expect that an increase in fish catches, constituting better economic opportunities in the fisheries sector, has a negative effect on maritime piracy activity ($\phi < 0$).

Since the number of piracy attacks constitutes a count, we additionally conduct a robustness check by employing a Poisson instrumental variable approach in Appendix C.1. The results obtained are comparable to our 2SLS estimates.

Before presenting our results in Section 4, we next describe the data.

3 Data and Descripive Analysis

In this section, we describe the sources as well as the construction of the data used in the empirical analysis. Further, we present descriptive statistics of the key variables.

3.1 Data

Piracy Attacks

The number of annual piracy incidents aggregated at country level are extracted from the Maritime Piracy Dataset (Version 1.0) developed in Coggins (2012). This source contains harmonized data originally published by the International Maritime Bureau (IMB) for the years 2000-2009 (ICC International Maritime Bureau, 2000-2009). A piracy incident is specified according to the IMB's definition as "an act of boarding or attempting to board any ship with the apparent intent to commit theft or any other crime and with the apparent intent or capability to use force in the furtherance of that act". This definition differs from the general piracy definition (UNCLOS III, §101) in that incidents are also classified as piracy acts when they occur in territorial waters and do not involve violence.

We exclude all the attacks which target fishing vessels from our analysis, since a rise in the number of attacks on fishing vessels could be due to an increase in the number of fishing boats scouring the local waters, which in turn could be caused by an upsurge in fish abundance. The presence of such an effect would bias our results towards zero. Overall, we exclude 4 percent of the incidents reported in our sample. Information on the type of vessels is available from the event-level dataset accompanying the country-level dataset of Coggins (2012).

A general concern with the data on piracy incidents is the considerable degree of underreporting (Hastings, 2009). This is partly attributable to the fact that filing a report about an attack can entail substantial costs for the ship owners, for example, increased insurance premiums or delays. However, in the absence of any systematic reporting errors in the dependent variable and under the usual OLS assumptions, our estimates will not be biased (Wooldridge, 2001, p. 72).

Phytoplankton Abundance

We derive information on local phytoplankton abundance from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua satellite data.[7] More specifically, we use the annually aggregated observed phytoplankton absorption coefficient at 443 nm (Aph) as the basis for our measure. The coefficient is available at a spatial resolution of 4 km by 4 km for the years 2003-2012 and has been shown to precisely characterize the true amount of phytoplankton abundance (Shang et al., 2011). The Aph-coefficient takes a non-negative value, where a higher coefficient represents a higher degree of primary production by phytoplankton.

To construct a country-specific measure for the abundance of plankton, we have to define the specific area of the ocean to be included in our analysis. A straightforward choice is to use the countries' exclusive economic zones (EEZ). Within these zones that generally stretch 200 nautical miles into the ocean from the nations' shorelines, the countries have special rights with respect to the exploitation of marine resources (UNCLOS III). However, as described in Section 2.1, the most productive areas of primary production and, consequently, the most important fishing grounds are located over the continental shelves. These shelves are, on average, only 68 km wide (Karleskint et al., 2012, p. 56). By including all the APH-coefficients that lie within the EEZ boundaries, we would therefore—on average—include large sections of the ocean that are not very relevant, either for primary production or for the fisheries sector. Doing so would, consequently, introduce a lot of noise into our measure. Therefore, we compute the country-specific abundance of phytoplankton as the sum of all the Aph-coefficients that lie within 68km of a countries coast and lie within the EEZ boundary. We define the logarithm of this sum as our phytoplankton abundance measure. In Appendix C, we demonstrate that we obtain very similar regression results when using the information of all the Aph-coefficients within a given EEZ. The precision of these estimates, however, is reduced. The shapefiles for the individual EEZ are available from `www.marineregions.org`. The country-specific offshore projections with a width of

[7]The data is available at `http://oceancolor.gsfc.nasa.gov/`.

68km were constructed using the shapefiles contained in the GADM database of Global Administrative Areas (`http://www.gadm.org/`).

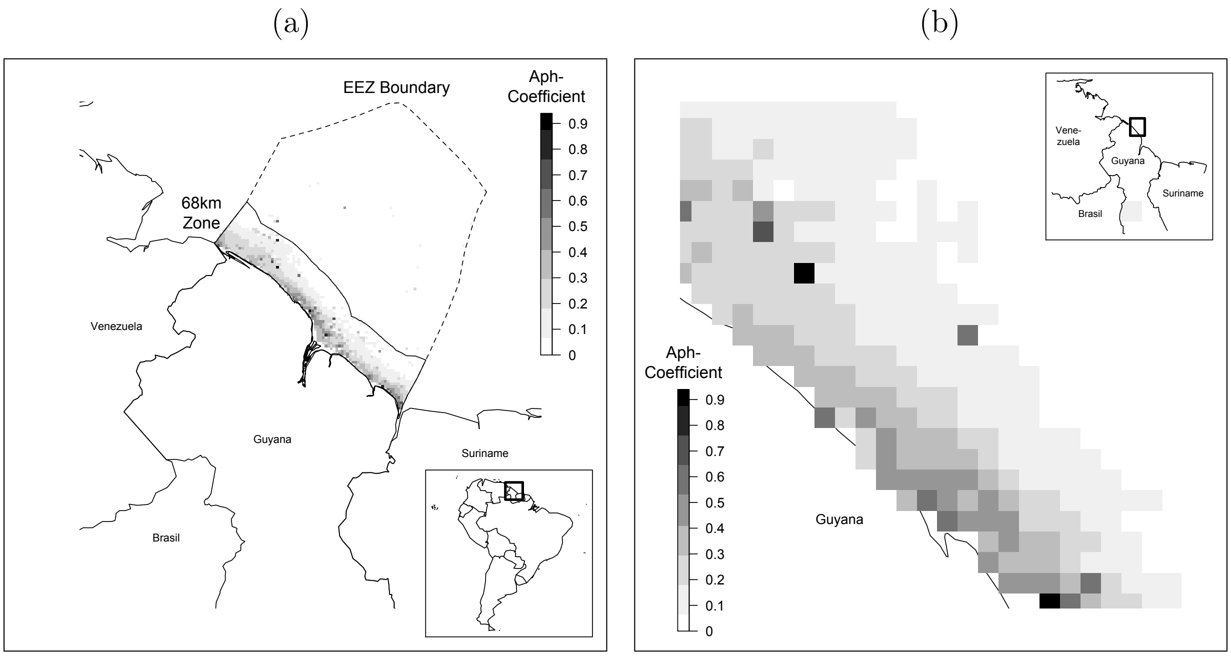

Figure 2: Panel (a) depicts the EEZ boundary as well as the 68km offshore projection for Guyana. The differently shaded areas represent different values of the annually aggregated observed phytoplankton absorption coefficient at 443 nm in 2006 (provided by NASA's MODIS Aqua satellite). Panel (b) zooms in on a small section of Guyana's coastline.

In Figure 2, panel (a) we depict the country-specific ocean area of Guyana included in the analysis. It is clearly visible that most of the variation—as for all countries—in the Aph-coefficients stems from regions near the coastline, i.e., the 68km zone. Panel (b) depicts a small section of Guyana's coastline. Each pixel represents the value of the Aph-coefficient for the respective 4km by 4km square. The darker the pixel, the higher the plankton abundance. Note that because we apply a fixed effects approach, our estimates will only rely on the variation in phytoplankton abundance within a predefined, time-invariant area. Therefore, differences in the time-invariant size of the country-specific polygon do not drive our results.

Fish Capture

The fish capture data is extracted from the FAO's Fishery Statistical Collections. This database contains country-year-specific information on the volume of fish caught (measured in tonnes) in marine regions stratified according to the fish species for the years 1950-2011.

The catches are assigned to the individual countries according to the flag of the vessel conducting the capture (FAO, 2011). Therefore, the volume reported in the database for a given country may—in addition to the fish caught in its territorial waters—also comprise fish caught off the coasts of foreign countries. This in turn implies that when a large proportion of a nation's catches is realized in foreign waters, the link between biological changes in local waters and the overall volume of fish caught is weak. In such a case, our instrument—the local abundance of phytoplankton—would be unsuitable. This issue is particularly marked for the tuna fish family, where up to 90 percent is caught by vessels operating in foreign waters (Petersen, 2006, p. 16). Therefore, we compute the country-year-specific volume of fish capture by summing all the fish catches reported in the FAO database, with the exception of tuna catches. The association between this measure of fish catches and the local plankton abundance is statistically significant, albeit weakly so (see Appendix C). This is partly attributable to the fact that the total catches also includes species that do not directly feed on plankton, but, for example, on other fish. Even though the link between plankton and fish abundance is still existent, it is weakened the further one moves up the food chain.[8] For the regressions shown in the results section of this paper, we will therefore construct a measure of fish catches by only including the fish species that feed mainly on phyto- and/or zooplankton. The species belonging within this category are identified by matching the species-specific diet information from `www.fishbase.org` with the FAO data. The details of this procedure are outlined in Appendix A.2. Including only the plankton-feeding fish in our capture measure is less restrictive than it might appear at first sight. Many commercially important species belong to the group of plankton feeders, including three of the four most important species.[9]

In Appendix C we show that the results obtained when using total catch data and the catches restricted to plankton-feeders are very similar. Due to the stronger association between capture of the latter group of fishes and the local phytoplankton abundance, our estimates gain precision when using the measure of fish catches restricted to the plankton feeders.

As is the case with the reporting of piracy attacks, the fish catch data are susceptible to measurement errors. This is mainly due to inadequate reporting (Garibaldi, 2012) as well

[8]For example, Murawski (1993) and Perry et al. (2005) show that small prey fish are generally more mobile than larger fish.

[9]The species that were caught in greatest quantity in 2009 are: the Anchoveta, the Skipjack Tuna, the Atlantic Herring and the Alaskan Pollack (FAO Fishery Statistical Collections). Only the Skipjack Tuna does not primarily feed on plankton.

as unreported or illegal fishing activity (Pauly et al., Forthcoming). Since we instrument the catch volume with the local phytoplankton abundance, we do not expect any bias to result from these issues. The covariation between phytoplankton and the catch data only stems from local variation (shocks) in phytoplankton abundance.

For some countries, the reporting of the fish data is poor and does not allow for the partition of the total fish catches into plankton and non-plankton-feeding categories. Table A.2 in Appendix A lists the countries, for which sufficiently disaggregated fish data are available and which can consequently be included in our analysis.

Control Variables

In our regressions, we control for (log) GDP per capita (in US dollars) and (log) population. This information is drawn from the UN statistics database. As a control variable for trade activity, we include the volume of total merchandise trade. This variable is extracted from the WTO database and is measured in USD millions. We also include the average value of the freedom house democracy index and the imputed polity 4 revised combined Polity score (Polity2) of the Polity IV data base (Marshall and Jaggers, 2007), the incidence of civil conflict (UCDP/PRIO Armed Conflict Dataset), as well as the index for agricultural productivity (World Development Indicators) into our set of control variables. In robustness checks, we also control for country-specific variation in rainfall. The rainfall variation at the $1^{\circ}\times 1^{\circ}$grid level is from the 1948-2010 "PRECipitation REConstruction over Land" (PREC/L) dataset (Chen et al., 2002), which in our case has the best coverage.[10] Finally, we also make use of an ad hoc fish price (constructed from the information regarding fish export quantity and value), as well as the number of country-specific fishermen to support our arguments. This information can be retrieved from the FAO Fishery Statistical Collections for the years 2000-2009.

Our main data set spans the years 2004-2009 and contains information on the number of piracy attacks for 109 countries, totalling 636 observations.

[10] The PREC/L precipitation data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA on their Web site `http://www.esrl.noaa.gov/psd`.

3.2 Descriptive Statistics

In Table 1, we depict the descriptive statistics of the key variables.[11] The yearly proportion of countries experiencing at least one piracy incident lies at 22.5 percent, the proportion observing the onset of piracy lies at 7.7 percent. The average number of piracy attacks is

Table 1: Descriptive Statistics Key Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
	Piracy Activity				
Incidence	0.225	0.418	0	1	636
Onset	0.077	0.266	0	1	482
Log Numbers of Attacks	0.346	0.769	0	4.754	636
	Fish Catches				
Log PFF Catch	10.124	2.695	0	16.022	636
	Plankton Abundance				
Log Plankton 68km	5.316	1.629	-1.032	10.385	636

1.4 incidents per year. As Figure 3 shows, the distribution of annual attacks is quite stable over our sample period: no time trends are discernible.

Conditional on the occurrence of piracy attacks (i.e., incidence equal to one), the mean number of incidents is 7.2, and the corresponding median is 3. In more than 95 percent of the observations, the number of annual attacks is lower than 10. In general, piracy incidents can therefore be regarded as relatively isolated events. For a few countries, however, this is not true. For example, Indonesia or Malaysia report, on average, more than 25 attacks per year. These large numbers of incidents indicate the existence of organized piracy (e.g., Ke (2007)) which can be partly explained by the fact that these countries are located along major sea lanes, where the density of ships is very high. Generally speaking, however, the piracy attacks can be viewed as low-tech endeavors carried out by unorganized groups (Rosenberg, 2009).

Even though our analysis takes place at the country level, it is insightful to look at the characteristics of the individual piracy incidents. As mentioned earlier, this information is available in the event dataset accompanying the country-level dataset of Coggins (2012). The vast majority of the piracy incidents reported is directed at cargo vessels (54 percent)

[11] A table containing descriptive statistics of the control variables as well as the variables used in the robustness checks is depicted in Appendix A.1.

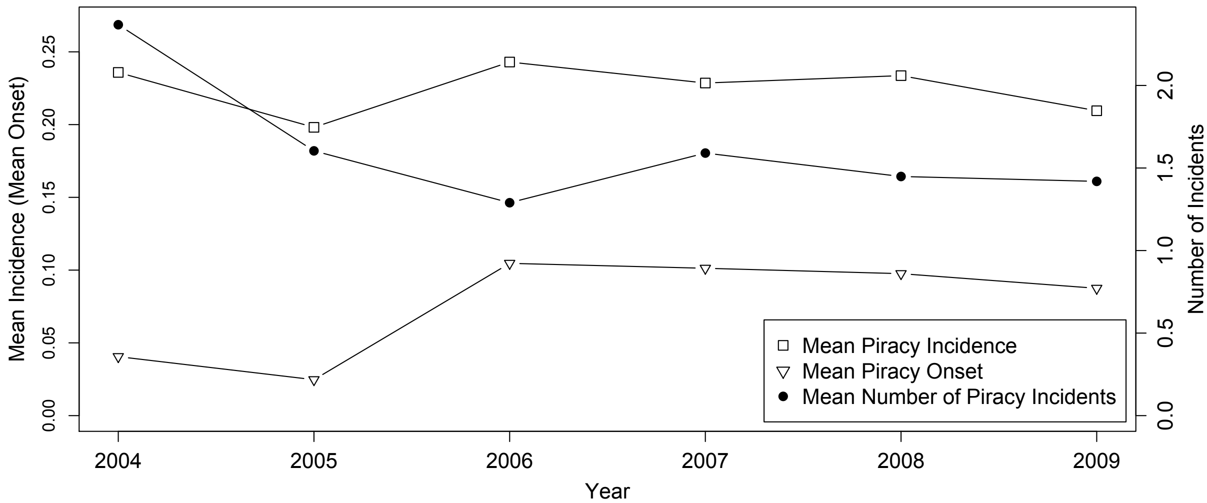

Figure 3: Time series plot of the mean of piracy incidence, piracy onset and the number of piracy incidents, respectively. The y-axis corresponding to the first two means is depicted on the left-hand side; the y-axis on the right-hand side refers to the number of incidents.

and tankers (31 percent). The incidents generally occurred near the shore, implying that the attacks could be carried out using simple boats. For the most part, the piracy incidents consisted in the theft of the ships' stores. In more than 70 percent of the incidents, no physical violence was reported.[12]

In the next step of our descriptive analysis, we look at the link between fish catches and plankton abundance. Figure 4 depicts the unconditional correlation between our phytoplankton abundance measure and the (log) tonnes of fish caught. The clearly positive and approximately linear relationship is consistent with the results reported in the marine-biology literature that documents a linear association between primary production and fish production (e.g., Sommer et al. (2002) or Iverson (1990)).

Overall, the descriptive analysis has shown that incidents of maritime piracy are relatively scarce, usually involve no violence and generally occur near shore. These facts indicate that the transition in and out of piracy activity is not associated with high costs for fishermen who have access to a boat. Together with the observation that plankton abundance is strongly related to fish capture production, this suggests that a drop in phytoplankton abundance reduces the volume of fish caught and consequently lowers the opportunity cost of engaging in piracy activity. Beginning with the next section, we empirically test the

[12]For comparison: Somali piracy, which is characterized by well-organized gangs (Hastings, 2009) involved physical violence in almost 70 percent of the attacks .

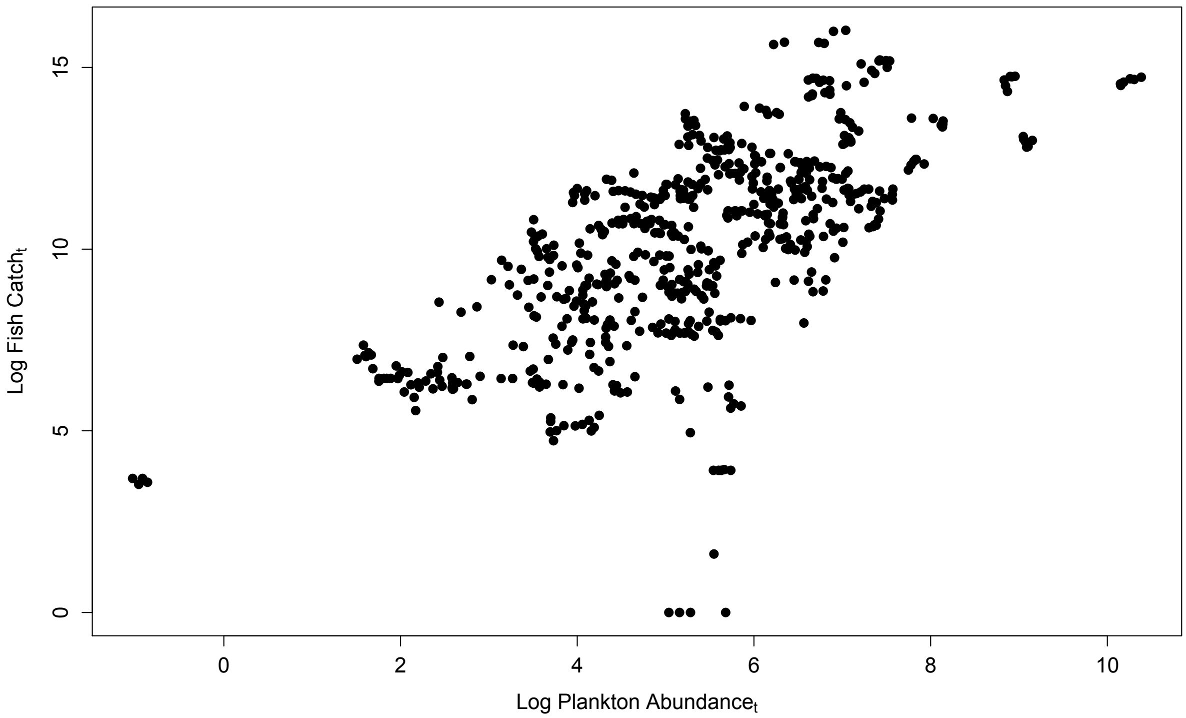

Figure 4: Unconditional contemporaneous correlation of our phytoplankton abundance measure and the (log) tonnes of plankton-feeding fish caught.

existence of this effect.

4 Results

In this section, we present our estimation results regarding the effects of shocks in the fisheries sector on maritime piracy activity. In Appendix C, Tables C.1 and C.2, we show that our results are robust to alternative specifications of the fish catch and the plankton abundance measure, respectively.

4.1 Phytoplankton Abundance, Fish Capture Production and Maritime Piracy

Table 2, columns (1)-(4) depict our estimates for the effect of plankton abundance shocks on fish capture production. The standard errors, given in parentheses, are clustered at the country level. Column (1) documents a positive and statistically significant relationship between contemporaneous plankton abundance and fish catches. According to our

Table 2: Piracy, Fish Catch and Plankton Abundance (OLS)

Dependent Variable:	Log Plankton-Feeding Fish Catch$_t$				Piracy Incidence$_t$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log plankton 68km$_{t+1}$	0.139			0.125	-0.146			-0.163
	(0.112)			(0.115)	(0.112)			(0.114)
Log plankton 68km$_t$	0.382**	0.392**	0.397***	0.382**	-0.371***	-0.379***	-0.336***	-0.373***
	(0.155)	(0.159)	(0.150)	(0.146)	(0.121)	(0.114)	(0.112)	(0.122)
Log plankton 68km$_{t-1}$	0.171			0.153	-0.073			-0.083
	(0.118)			(0.124)	(0.108)			(0.112)
Log plankton 68km$_{t-2}$	0.138			0.165	-0.114			-0.097
	(0.100)			(0.103)	(0.100)			(0.105)
Log rain$_t$				-0.074				0.007
				(0.109)				(0.072)
Log GDP per capita$_t$				0.276				0.114
				(0.194)				(0.160)
Log population$_t$				-0.964*				-0.058
				(0.508)				(0.225)
Democracy index$_t$				0.035				-0.035
				(0.040)				(0.036)
Log total trade$_t$				0.056				0.177
				(0.216)				(0.138)
Civil conflict incidence$_t$				0.083				0.012
				(0.097)				(0.083)
Continent-specific time trends	yes	yes	no	yes	yes	yes	no	yes
Obs.	636	636	636	636	636	636	636	636
F-Statistic	1.829	6.036	7.001	1.505	2.773	11.112	8.947	1.684
RMSE	0.323	0.324	0.323	0.320	0.274	0.275	0.275	0.274

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. FE estimator regressions in all columns with country dummies, time dummies and robust standard errors clustered at country level in parentheses. RMSE is the root mean square error.

point estimate, a one percent increment in plankton abundance increases the volume of fish caught by 0.38 percent, conditional on time-fixed effects, country-fixed effects and continent-specific time trends. Past indicators of plankton abundance are not significantly related to current fish catches. Additionally, the relationship between future plankton abundance and present fisheries production is also non-significant. This result—the positive and contemporaneous association between phytoplankton abundance and fish catches—is consistent with the bottom-up regime documented in the marine-biology literature (Ware and Thomson (2005); Chassot et al. (2010)).

In column (2), only the contemporaneous plankton abundance is included in the regression.

The size of the coefficient remains stable compared to column (1). This indicates that any potential cross-correlation of contemporaneous plankton abundance with its leads and lags does not affect our estimates.

To illustrate that our linear estimation method is appropriate, Figure 5 (a) depicts the nonparametric local polynomial estimates of the phytoplankton abundance on fish catches using an Epanechnikov Kernel.[13] The relationship is approximately linear and monotonically increasing, indicating that no important nonlinear relationships are neglected in our linear estimation model.

Column (3) depicts the estimates of the regression equation Eq.(1) without the continent-specific time trends; in column (4) we include additional covariates. As in the previous setups, the effect of plankton abundance remains quantitatively and qualitatively stable: plankton abundance is strongly positively related to the fish capture production. It is worthwhile to note that country-specific average rainfall is not statistically significantly associated with fish catches.

In columns (5)-(8) of Table 2, we present the estimation results of Eq.(2), i.e., the effect of plankton abundance on the likelihood of piracy incidents. As shown in column (5), only the contemporaneous plankton abundance affects the likelihood of piracy incidents. A one percent increase in our plankton abundance measure reduces the probability of observing a piracy incident by roughly -0.4 percentage points. Neither the lagged nor the forwarded phytoplankton abundance coefficient enters significantly. The non-significance of lagged plankton abundance indicates that the incidence of piracy is not persistent. If any persistent effects were present, we should observe a significant coefficient of past plankton abundance. The size of the isolated contemporaneous plankton coefficient remains stable irrespective of the inclusion of the continent-specific time trends (columns (6)-(7)). Including the set of control variables (column (8)) does not affect our estimate. None of the control variables are significantly associated with the incidence of piracy attacks. This is also true for the country-specific rainfall which the literature has, for example, associated with civil conflict and democratic transition, due to agricultural income shocks (Miguel et al., 2004; Brückner and Ciccone, 2011). Rainfall therefore neither affects fish catches nor the incidence of piracy. Additionally, rainfall is not significantly related to plankton abundance (Table A.3). This is important with regard to the 2SLS estimates presented in the next section, as it indicates that our exclusion restriction is not compromised by any

[13] We derive the incidence of piracy, fish catches and plankton residuals by partialling out the country and time fixed effects as well as the continent-specific time trends.

cross-correlation with rainfall.

Figure 5 (b) depicts the nonparametric local polynomial estimates of plankton abundance on the incidence of piracy. The relationship is approximately linear and monotonically decreasing, except at the lower-right end of the graph, which, however, is very imprecisely estimated.

(a) (b)

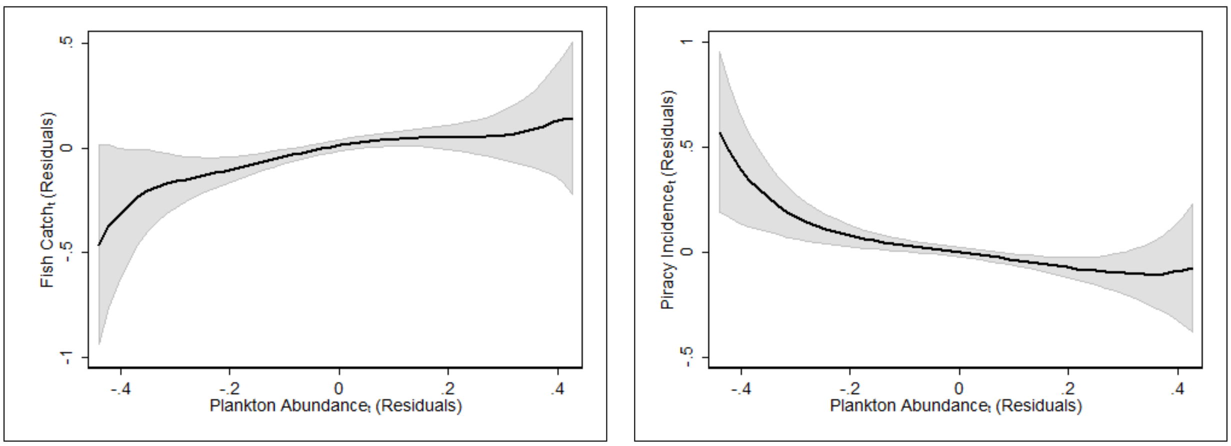

Figure 5: Panel (a): Plankton abundance measure and (log) tonnes of plankton-feeding fish caught. Panel (b): Plankton abundance measure and incidence of piracy. Second degree nonparametric local polynomial estimates are computed using an Epanechnikov kernel. The bandwidth in (a) is 0.15; in (b) 0.16. The shaded areas represent the confidence bands.

Overall, the results presented above indicate that an increase in plankton abundance induces both an increase in fish catches and a decline in the likelihood of piracy incidents. We argue that higher plankton abundance leads to an increase in the abundance of fish and, hence, to a higher productivity in the fisheries sector. This signifies an improvement in the economic conditions in this sector and therefore increases the opportunity cost of a fishermen engaging in piracy activity.

However, due to the lack of data, we do not observe the income levels in the fisheries sector directly, but have to rely on the volume of fish catches as a proxy. In order for our results to be interpretable along the lines of the opportunity cost argument, positive plankton shocks—implying an increased volume of fish catches—have to be proportional to the fishermen's income. To support this argument, we define an ad hoc country-specific price of fish by dividing the value of fish exports by the volume of fish exported (tonnes) for a given country and year. As shown in Table B.1 of Appendix B, the relationship between the plankton abundance measure and the fish price is not statistically significant.

On the other hand, the revenue—i.e., the price multiplied by total fish catches—increases significantly when plankton abundance rises. This indicates that quantity is proportional to income in the fisheries sector. Overall, interpreting the changes in the volume of fish catches as changes in the opportunity cost of fishermen—or more generally, the people employed in the fisheries sector—seems plausible.

A further constraint in our macro analysis is that we are not able to identify the precise nature of the adjustment mechanism. For example, we cannot determine whether fishermen engage in illegal activity because they have lost their job altogether or because their legal income is reduced. Using information on the country-specific number of fishermen, we show in Table B.1 that revenue per fishermen is also positively associated with an increased plankton abundance. This indicates that the labor supply elasticity in the fisheries sector is relatively low and hints at the presence of the second adjustment channel. In fact, we do not find a statistically significant relationship between plankton abundance and the number of fishermen employed. However, the accuracy of the labor market data is limited.[14] They do, for example, often not include small-scale and subsistence fishermen. Furthermore, the data is not available for all countries in our sample. Therefore, the results involving the number of fishermen should be interpreted with caution.

A possible concern with our interpretation is, that the correlation between phytoplankton and the incidence of piracy could arise owing to a supply effect. For example, a rise in plankton abundance could attract more fishing vessels, which in turn increases the number of potential targets of the pirates. However, since we exclude the attacks on fishing vessels from our analysis, we do not expect this effect—which would bias our results towards zero—to influence our estimates.

4.2 2SLS of Fish Capture Production and Maritime Piracy

To quantify the effect of variation in plankton abundance on the probability of the incidence of piracy in terms of fish catches, we instrument fish capture production with our plankton abundance measure. As discussed in Section 2.1 and 4.1 we argue that plankton abundance affects piracy activity only via the variation induced in fish catches. Additionally, we argue that plankton is exogenous to economic activity and piracy. Under these assumptions the exclusion restriction within our 2SLS setup is satisfied. In the following, we report the

[14] In many cases, the number of fishermen is estimated and constant over a number of years.

p-values of the Anderson-Rubin Chi-squared test statistic for the endogenous variables.[15] This test statistic is robust to weak instruments and therefore appropriate given the relatively low F-statistic for the excluded instruments in the first stage (Andrews and Stock, 2005, p. 8).

Column (1) of Table 3 depicts the naive OLS estimate. The coefficient of the (log) fish catches is negative but close to zero and non-significant. However, the effect of fish catches on the incidence of piracy becomes negative and statistically significant at the 99 percent confidence level when instrumenting the capture production with plankton abundance. As presented in column (2), a one percent reduction in fish catches leads to a 1 percentage point increase in the probability of observing a piracy incident. The substantial effect documents the importance of changes in the fisheries sector in explaining the occurrence of piracy incidents. The difference between the naive OLS and the 2SLS estimates might be due to reversed causality. For example, as a consequence of increased piracy activity, fishing effort and, consequently, the volume of fish caught could be reduced. This would bias the coefficient of fish catches upwards, i.e. towards zero.

It is important to note that the second-stage estimates rely on the within country variation of the incidence indicator. Countries in which piracy is deep-rooted and carried out partly by well-organized criminal gangs—as is the case, for example, in Indonesia or Nigeria (e.g., Ho (2006); Murphy (2007))—and which therefore experience incidents of maritime piracy on a habitual basis each year, do not contribute to our second-stage estimates. This is also true for countries for which no piracy incidents are reported during the entire time span of our sample.

The results in column (3) suggest that there is no persistence in the occurrence of piracy attacks. The estimates are obtained using two instruments: The plankton abundance measures in t and $t-1$ as instruments for the incidence of piracy in $t-1$ and fish catches in t.[16] The coefficient of past incidence enters non-significantly and therefore is not an indicator for current pirate activity. The effect of fish catches, on the other hand, remains stable and significant. This result is consistent with the observation that piracy attacks are generally low-tech, low-budget operations (e.g., Rosenberg (2009)). Transitions in and out of piracy therefore are often not associated with high costs.

[15] In the case of multiple endogenous variables, we report the subset Anderson-Rubin test statistic for each structural parameter. See, for example, Guggenberger et al. (2012) or Kleibergen (2004) for a more detailed exposition.

[16] Because we employ an instrumental variable for lagged incidence, our estimates are not subject to endogeneity issues of the type described in Arellano and Bond (1991).

Table 3: IV-2SLS Results - Fish Catch and Incidence of Piracy

Dependent Variable: Incidence of Piracy$_t$							
	Full Sample						Non-OCED/EU Sample
	OLS (1)	IV (2)	IV (3)^a	IV (4)^b	IV (5)	IV (6)^c	IV (7)^d
Piracy incidence$_{t-1}$			-0.502 [0.423]				
Log PFF catch$_t$	-0.007 (0.035)	-0.967*** [0.001]	-1.081*** [0.003]	-0.994*** [0.001]	-0.989*** [0.001]	-0.904*** [0.003]	-0.919*** [0.001]
Agriculture prod. index$_t$				-0.697 [0.641]			
Log rain$_t$					-0.065 (0.146)	-0.042 (0.141)	-0.084 (0.161)
Log GDP per capita$_t$					0.391 (0.249)	0.390 (0.270)	0.452 (0.273)
Log population$_t$					-1.010 (0.609)	-0.9251 (0.627)	-0.917 (0.576)
Democracy index$_t$					-0.001 (0.051)	0.004 (0.050)	0.001 (0.050)
Log total trade$_t$					0.220 (0.209)	0.196 (0.194)	0.260 (0.242)
Civil conflict incidence$_t$					0.088 (0.096)	0.067 (0.095)	0.091 (0.092)
Counter Piracy	no	no	no	no	no	yes	no
Obs.	636	636	636	636	636	636	456
RMSE	0.278	0.419	0.469	0.4281	0.421	0.401	0.465
F-test excl. IV		6.036	5.64/2.50	5.69/8.91	6.42	5.42	7.763

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). The values in the squared brackets [] represent the p-value of the Anderson-Rubin Chi-squared test statistic which is robust to weak instruments. The IV-2SLS regressions in columns (2)-(7) use the log plankton 68km$_t$ as an instrument for log PFF Catch$_t$. The F-test is the first-stage test statistic of the excluded instrument(s). RMSE is the root mean square error.

[a]In column (3), the IV-2SLS estimates use the log plankton 68km$_t$ and log plankton 68km$_{t-1}$ as instruments for PFF catch and lagged Piracy incidence, respectively, in the first stage. F-test excl. IV in column (3) first gives the value for the PFF catch and then the value for lagged incidence of piracy.

[b]In column (4), the IV-2SLS estimates use log plankton 68km$_t$ and log rainfall$_t$ as instruments for PFF catch and the agricultural production per capita, respectively, in the first stage. F-test excl. IV in column (4) first gives the value for the PFF catch and then the value for agricultural production per capita.

[c] In column (6), we add year-specific dummies for the group of countries bordering on the Malacca Straits and the Gulf of Aden, respectively, in order to capture any effects from coordinated counter piracy measures.

[d]In column (7), we drop all countries that are either European and/or OECD members.

Column (4) helps to distinguish between the income shocks that specifically affect the fisheries or the agricultural sector. We use contemporaneous variation in rainfall as an instrument for the changes in the agricultural productivity index. As before, contemporaneous plankton abundance is employed as an instrument for fish capture production. The first-stage estimates (not shown) exhibit a significantly positive relationship between rainfall and agricultural output with an F-test statistic of 8.91.[17] Because rainfall (plankton) is not correlated with fish catches (agricultural output), we are able to identify and distangle the two individual effects. We find no significant effect of fluctuations in agricultural productivity on the incidence of piracy. On the other hand, the size of the fish-catch coefficient remains stable and statistically significant. In agreement with the results above, this suggests that changes in agricultural productivity are unrelated to the incidence of piracy.

Column (5) demonstrates that the effect of fish catches remains unchanged when we include control variables in our estimation setup. To take into account possible effects of coordinated counter-piracy actions, we include year-specific dummies for the group of countries bordering on the Malacca Straits and the Gulf of Aden, respectively.[18] As depicted in column (6), the results remain unaltered. In the regression shown in column (7), we only include non-European and non-OECD countries in the regression. The fish-catch coefficient is of similar magnitude compared to the previous results. Thus, our results are predominantly driven by variation in non-EU/OECD countries. This is not surprising, since only three countries within the group of the EU/OECD countries contribute to the variation of the second-stage dependent variable.

In Appendix B, Table B.2 instead of using log catch volume as an explanatory (instrumented) variable, we employ log catches per fishermen, log revenue, and log revenue per fishermen as second-stage explanatory variables. Even though this constrains our sample considerably, we get very similar results to the ones depicted in Table 3.

In Table 4, columns (1)-(2), we use the onset of piracy incidents as the dependent variable. The results accord with our findings regarding the incidence of piracy activity. A one percent drop in fish catches leads to 0.6 percentage point increase in the probability of the onset of piracy activity. The drop in the number of observations is due to the exclusion of continuous periods of piracy incidents (Collier et al., 2004).

Next, we address the question of whether variation in fish catches influences the (log) number of piracy incidents, i.e., the intensity of pirate activity.[19] The results in columns (3)-(4) show that a 1 percent increase in fish capture production decreases the number of piracy

[17] The coefficient is significant at the 99 percent confidence level with a size of 0.09.

[18] These are the regions for which coordinated, multinational counter-piracy measures are/were implemented (Jablonski and Oliver, 2012).

[19] More specifically, we use $\ln(\text{Number of incidents} + 1)$ as a dependent variable.

Table 4: IV-2SLS Results - Onset and Number of Piracy Attacks

Dependent Variable:	Onset Piracy Attacks$_t$		Log Number of Piracy Attaks$_t$	
	(1)	(2)[a]	(3)	(4)[a]
Log PFF catch$_t$	-0.620**	-0.666**	-0.868**	-0.861**
	[0.042]	[0.037]	[0.020]	[0.026]
	First stage regression: Log PFF Catch$_t$			
Log plankton 68km$_t$	0.439**	0.435**	0.392**	0.385**
	(0.209)	(0.194)	(0.159)	(0.149)
Control variables	no	yes	no	yes
Obs.	476	476	636	636
RMSE	0.303	0.313	0.441	0.436
F-test excl. IV	4.424	5.037	6.036	6.722

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). The values in the squared brackets [] represent the p-value of the Anderson-Rubin Chi-squared test statistic which is robust to weak instruments. The F-test is the first-stage test statistic of the excluded instrument. RMSE is the root mean square error.
[a]In columns (2) and (4), we control for, but do not report, log GDP per capita$_t$, log population$_t$, democracy index$_t$, log total trade$_t$, and incidence of civil conflict$_t$.

events by −0.86 percent. This indicates that better economic opportunities in the fisheries sector also reduce the scale of piracy in countries with a deep-rooted piracy industry. For example, criminal gangs find it harder to recruit fishermen (Rosenberg (2009);Ke (2007)). Because the number of incidents constitutes a count, we additionally estimate the effect of fish catches on the number of attacks using a Poisson regression procedure (see Appendix C.1). The results are comparable to the estimates presented in Table 4.

Summarizing, we find that negative shocks in plankton abundance result in a decrease in the volume of fish caught. This, in turn, increases the probability of pirate attacks occurring as well as their absolute number. We argue that the underlying mechanism driving these results are changes in the opportunity costs caused by variation in the economic conditions in the fisheries sector.

5 Conclusion

Maritime piracy activity is a worldwide phenomenon. More than 40 percent of all coastal countries experienced at least one piracy incident during the period 2004–2009. Due to the importance of maritime transport for the international trade, piracy activity is likely to affect international transport costs and trade volumes. Even though there is an emerging economic literature on maritime piracy, the underlying mechanisms that drive piracy activity are not well understood. This study contributes to filling this gap.

For a sample of 109 coastal countries, spanning the period from 2004 to 2009, we show that negative economic shocks in the fisheries sector are associated with an increase in piracy activity. By using exogenous local phytoplankton abundance as the source of these shocks, we are able to avoid potential endogeneity problems between pirate activity and fish capture production. Our estimates indicate that the effect of such negative productivity shocks is considerable, and thereby contributes towards a better understanding of modern-day piracy. We find that a one percent reduction in fish capture production increases the risk of incidence of piracy by 1 percentage point. Our analysis further documents similar results for the onset of piracy and the (log) number of attacks. These findings are consistent with the opportunity cost theory. Lower phytoplankton abundance results in a decline in fish capture production and, as a consequence, deteriorates the economic opportunities in the fisheries sector. This in turn increases the relative attractiveness of engaging in piracy activity.

Developing policy measures that effectively address the modern-day piracy problem is a complex task. Our results suggest that the implementation of fisheries management systems and the prosecution of illegal fishing activity could constitute viable ways of smoothing fishermen's incomes and thereby reduce the incentive to engage in maritime piracy.

The present study has shown that economic conditions in the fisheries sector have an important impact on modern-day piracy. This finding therefore indicates that other factors which influence fish capture production—such as climate change—are also likely to have an impact on maritime piracy. The investigation of such links is left to future research. A further issue not tackled in this study is the identification of the costs inflicted by piracy activity. Such an analysis, however, is unfortunately impeded by the lack of adequate country-level data on transport costs.

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Appendices

A Data Description

A.1 Descriptive Statistics

Table A.1: Descriptive Statistics Control Variables

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Log rain	6.595	1.059	2.448	8.173	636
Log GDP per capita	8.502	1.519	5.138	11.461	636
Log population	16.262	1.641	13.034	21.009	636
Democracy index	6.757	3.083	0.000	10.000	636
Log total trade	24.270	2.125	18.462	28.872	636
Civil conflict incidence	0.132	0.339	0.000	1.000	636
Log ad hoc fish price	0.753	0.818	-2.619	4.511	630
Log revenue	12.136	2.251	4.008	17.426	630
Number of fishermen	135970.900	409609.700	45	2346782	408

A.2 Determining Plankton-Feeding Fish Capture Production

To categorize the fish capture production reported in the FAO Fishery Statistical Collections into plankton and non-plankton-feeding catches, two requirements have to be met: First, we have to know what the fish eat. This information is contained in the FishBase database (`http://fishbase.org`). We assign the fish species to the class of plankton-feeding fish whenever phyto- and/or zooplankton is reported as the main food. In order to make use of this information, a second requirement has to be fulfilled: The fish catch data in the FAO database has to be differentiated enough, as to allow for the categorization into plankton-feeding and non-plankton-feeding fish catches. The level of detail with which the fish capture production is reported varies considerably by country. For some countries, the fish capture production is only stratified according to very broad classes that do not permit the division into plankton-feeding and non-plankton- feeding fish catches.[20] Whenever the fish capture production is stratified at the level of fish species, we can match the species name with the FishBase data and, provided the matching is successful, extract the

[20] For example, the fish catch for Somalia is categorized into three groups: Cephalopoda, Osteichthyes and Panulirus.

Table A.2: Countries Included in the Analysis

Albania	Equatorial Guinea	Latvia	Saudi Arabia
Algeria	Eritrea	Lebanon	Senegal
Angola	Estonia	Liberia	Sierra Leone
Argentina	Fiji	Libya	Singapore
Australia	Finland	Lithuania	Slovenia
Bahrain	France	Madagascar	Solomon Islands
Belgium	Gabon	Malaysia	South Africa
Benin	Gambia	Mauritania	Spain
Brazil	Georgia	Mauritius	Sri Lanka
Bulgaria	Germany	Mexico	Suriname
Cameroon	Ghana	Morocco	Sweden
Canada	Greece	Mozambique	Syria
Cape Verde	Guatemala	Namibia	Tanzania
Chile	Guinea	Netherlands	Thailand
China	Guinea-Bissau	New Zealand	Togo
Colombia	Guyana	Nicaragua	Trinidad And Tobago
Comoros	Honduras	Nigeria	Tunisia
Congo	India	Norway	Turkey
Costa Rica	Indonesia	Oman	Ukraine
Côte d'Ivoire	Iran	Pakistan	United Arab Emirates
Croatia	Ireland	Panama	United Kingdom
Cuba	Israel	Papua New Guinea	United States
Cyprus	Italy	Peru	Uruguay
Denmark	Japan	Philippines	Venezuela
Dominican Republic	Jordan	Poland	Yemen
Ecuador	Kenya	Portugal	
Egypt	Korea, North	Qatar	
El Salvador	Kuwait	Russia	

information regarding the diet. If the fish catches are only stratified according to the fish families, we manually assign these families to the plankton and non-plankton-feeding fish groups. Thereby, we draw on various sources. We primarily rely on the family-specific diet information contained in Carpenter and Niem, eds (1998) and the FishBase database. If these sources clearly identify phyto- or/and zooplankton as the main component of the diet, we add the family-specific catch volume to the plankton-feeding fish capture production.

Using the procedure above, we are able to match and classify 91 percent of the total volume of fish catches reported in the FAO database. A list of all the species and families assigned into the plankton-feeding fish category is available upon request.

Table A.3: Bivariate Coefficients - Plankton

Dependent Variable:	Log Plankton 68km_{t+1} (1)	Log Plankton 68km_{t-1} (2)	Agriculture prod. index_t (3)	Log Rain_t (4)	Log GDP p. Capita_t (5)	Log Population_t (6)	Democracy Index_t (7)	Log Total Trade_t (8)	Conflict Incidence_t (9)
Log plankton 68km_t	0.075	0.033	-0.015	0.023	0.019	-0.009	-0.087	-0.002	-0.070
	(0.078)	(0.070)	(0.034)	(0.044)	(0.046)	(0.014)	(0.189)	(0.056)	(0.090)
Obs.	636	636	636	636	636	636	636	636	636

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bivariate coefficients including country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses ().

B Supporting Arguments

Table B.1: Plankton Abundance, ad hoc Fish Price and Revenue

Dependent Variable:	Ad Hoc Fish Price$_t$		Revenue$_t$		Revenue per Fishermen$_t$	
	(1)	(2)^a	(3)	(4)^a	(5)	(6)^a
Log plankton 68km$_t$	0.183	0.176	0.443**	0.434**	0.433**	0.427**
	(0.137)	(0.212)	(0.212)	(0.180)	(0.200)	(0.191)
Control Variables	no	yes	no	yes	no	yes
Obs.	630	630	630	630	397	397
RMSE	0.394	0.391	0.441	0.433	0.466	0.450
F-Statistic	1.760	1.910	4.370	5.800	4.690	4.980

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). RMSE is the root mean square error.
[a]In columns (2), (4) and (6), we control for, but do not report, log GDP per capita$_t$, log population$_t$, democracy index$_t$, log total trade$_t$, and incidence of civil conflict$_t$.

Table B.2: IV-2SLS Results - Catch per Capita and Revenue (per Capita)

Dependent variable:	Piracy Incidence$_t$					
	(1)	(2)^a	(3)	(4)^a	(5)	(6)^a
Log PFF catch per fishermen$_t$	-1.177***	-1.171***				
	[0.000]	[0.000]				
Log revenue$_t$			-0.851***	-0.877***		
			[0.001]	[0.001]		
Log revenue per fishermen$_t$					-1.331***	-1.320***
					[0.000]	[0.000]
First stage:	Log PFF Catch per Fishermen$_t$		Log Revenue$_t$		Log Revenue$_t$ per Fishermen$_t$	
Log plankton 68km$_{t-1}$	0.488***	0.478***	0.444**	0.435**	0.433**	0.427**
	(0.156)	(0.144)	(0.212)	(0.180)	(0.200)	(0.191)
Control Variables	no	yes	no	yes	no	yes
Obs.	403	403	630	630	397	397
RMSE	0.473	0.463	0.482	0.482	0.684	0.662
F-test excl. IV	9.771	11.001	4.367	5.805	4.688	4.979

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). The values in the square bracket [] represent the p-value of the Anderson-Rubin Chi-squared test statistic which is robust to weak instruments. The IV-2SLS regressions in columns (1)-(6) use log plankton 68km$_t$ as an instrument for Log PFF Catch per Capita$_t$, Log Revenue$_t$ and Log Revenue per Capita$_t$, respectively. The F-test is the first-stage test statistic of the excluded instrument. RMSE is the root mean square error.
[a]In columns (2), (4) and (6), we control for, but do not report, log GDP per capita$_t$, log population$_t$, democracy index$_t$, log total trade$_t$, and civil conflict incidence$_t$.

C Robustness Checks

Table C.1: IV-2SLS Results - Alternative Plankton Specification (EEZ)

Dependent Variable:	Piracy Incidence$_t$		Onset Piracy Attacks$_t$		Log Number of Piracy Attacks$_t$	
	(1)	(2)^a	(3)	(4)^a	(5)	(6)^a
Log PFF catch$_t$	-1.045***	-1.073***	-0.375	-0.432	-0.944**	-0.945**
	[0.004]	[0.004]	[0.134]	[0.107]	[0.031]	[0.038]
	First stage regression: Log PFF Catch$_t$					
Log plankton EEZ$_t$	0.320**	0.310**	0.473**	0.458**	0.320**	0.310**
	(0.150)	(0.144)	(0.203)	(0.195)	(0.150)	(0.144)
Obs.	636	636	476	476	636	636
RMSE	0.435	0.442	0.250	0.262	0.453	0.454
F-test excl. IV	4.546	4.637	5.419	5.508	4.546	4.637

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). The squared brackets [] represents the p-value of the Anderson-Rubin Chi-squared test statistic which is robust to weak instruments. The F-test is the first-stage test statistic of the excluded instrument. RMSE is the root mean square error.
[a]In columns (2), (4) and (6), we control for, but do not report, log GDP per capita$_t$, log population$_t$, democracy index$_t$, log total trade$_t$, and incidence of civil conflict$_t$.

Table C.2: IV-2SLS Results - Alternative Fish Catch Specification (All)

Dependent Variable:	Piracy Incidence$_t$		Onset Piracy Attacks$_t$		Log Number of Piracy Attacks$_t$	
	(1)	(2)^a	(3)	(4)^a	(5)	(6)^a
Log all fish catch$_t$	-1.409***	-1.423***	-0.819**	-0.910**	-1.265**	-1.239**
	[0.001]	[0.001]	[0.042]	[0.037]	[0.020]	[0.026]
	First stage regression: Log PFF Catch$_t$					
Log plankton 68km$_t$	0.269**	0.268**	0.332*	0.318*	0.269**	0.268**
	(0.120)	(0.111)	(0.177)	(0.163)	(0.120)	(0.111)
Obs.	636	636	476	476	636	636
RMSE	0.384	0.385	0.276	0.290	0.414	0.411
F-test excl. IV	4.985	5.874	3.540	3.788	4.985	5.874

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies, continent-specific time trends and robust standard errors clustered at country level in parentheses (). The squared brackets [] represents the p-value of the Anderson-Rubin Chi-squared test statistic which is robust to weak instruments. The F-test is the first-stage test statistic of the excluded instrument. RMSE is the root mean square error.
[a]In columns (2), (4) and (6), we control for, but do not report, log GDP per capita$_t$, log population$_t$, democracy index$_t$, log total trade$_t$, and incidence of civil conflict$_t$.

C.1 Count Data Regression

Because our dataset contains relatively few observations with a positive number of piracy incidents (see Table 1), the use of a standard 2SLS approach could result in a considerable approximation error (Winkelmann (2000), p. 160). To demonstrate that this is not the case in our analysis, we employ a Poisson model in this section which explicitly takes into account the count data structure of the dependent variable. To account for possible overdispersion—i.e., the violation of the assumption that the conditional mean and variance are equal—we cluster the standard errors at country level (see Cameron and Trivedi (2009), p. 570). In the following, we will use the two-step approach proposed by Wooldridge (2001) (p. 663 ff). The first step consists of the linear fixed effects estimation presented in Eq.(1). From this regression we obtain the predicted residuals $\widehat{\xi_{i,t}}$, which will be subsequently included in the Poisson model. In the second step, the following Poisson model is estimated:

$$\mathbb{E}\left[A_{i,t}|f_{i,t}, p_{i,t}, \mu_i\right] = \mu_i \, \exp\left(\lambda f_{i,t} + \delta\, \widehat{\xi_{i,t}} + \beta_2' \, \mathbf{X}_{i,t}\right), \tag{4}$$

where $A_{i,t}$ is the number of piracy attacks. $f_{i,t}, py_{i,t}, \mu_i$ and $\mathbf{X}_{i,t}$ represent the fish catch, plankton abundance, country-fixed effects and the control variables (including time-fixed effects), respectively. The inclusion of the error term from the first stage regression $(\widehat{\xi_{i,t}})$ purges the estimate of λ—i.e., the effect of fish landings—of the potential endogeneity issues. The standard errors will be computed using a block-bootstrap methodology where we draw randomly with replacement within each country.

Table C.3 depicts the point estimate for the direct effect as well as the second-stage estimate of Eq.(4). The coefficients can be interpreted as elasticities (Cameron and Trivedi, 2007). Both, the point estimate of the direct effect in column (1) as well as the coefficient of fish capture production are similar, although slightly higher than the results presented in Tables 2 and 3.

Table C.3: Poisson Model: Number of Piracy Incidents

Dependent Variable:	Number of Piracy Incidents$_t$	
	(1)	(2)
Log plankton 68km$_t$	-0.590*	
	⟨0.328⟩	
Log PFF Catch$_t$		-1.533*
		⟨0.793⟩
	First stage regression: Log PFF Catch$_t$	
Log plankton 68km$_t$		0.430**
		(0.169)
Obs.	273	273

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns with country dummies, time dummies and robust standard errors clustered at country level in parentheses (). The standard errors of the second-stage coefficients and the direct effect, given in brackets ⟨⟩, are computed using a block bootstrap methodology.