The Jaws Effect: An Analysis of Marine Fish Catches and Foreign Conflicts

By
Pierre Leduc
(4460050)

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Supervisor, Professor Louis Hotte
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1. *The Abstract*

We have developed a model to help predict marine fish catch, which includes an index that captures the effects of conflicts abroad. The index is meant to measure the opportunistic behaviour of fishers, in reaction to news of foreign conflict. Contrary to our hypothesis the coefficient associated with our index is negative and its significance varies with the country under study.

2. *Introduction*

Marine fisheries are an inherently complex ecosystem. Many have tried to predict some of its key features with mixed results. This paper is looking at how conflict affects marine fisheries, more specifically how foreign conflict affects domestic marine fish catches. In order to carry out the analysis, we built an index which increases with the number of foreign conflicts and decreases with the average distance of conflict.

This paper builds on previous articles such as the research by Hendrix and Glaser (2011) who analyzed the effect of domestic conflict on domestic marine fish catches. They found a strong negative correlation between these two variables, and contrary to their hypothesis they failed to find a statistically significant post conflict growth on the marine fish stock. They mentioned that a possible explanation for the lack of post-conflict increase in marine fish catches could be the presence of Illegal Unreported and Unregulated (IUU) fishing. According to Hendrix and Glaser (2011) when a country is experiencing a civil conflict it loses monitoring capacity over its sovereign water which allows for foreign fishing vessels to illegally fish in their waters. This becomes a serious issue since it can affect food security of post-conflicted society.

With the help of our index, we want to see if IUU fishing operates in conflicted waters. We therefore formulate the following hypothesis: an increase in the value of the index will bring an increase in the reported marine fish catch for a given country, ceteris paribus. The general idea is that fishermen might have predatory instincts and take advantage of conflict abroad, which is why we name the paper "The Jaws Effect".

3. Literature Review

To our knowledge, this paper is the first attempt in analysing the relationship between domestic marine fish catch and foreign conflict. In order to properly conduct this analysis, we considered studies that look at the relation between conflict and economic activity. We also got inspired from studies which discuss marine fish catch in particular marine fish catch modeling. Where the literature was not complete we fill the gap with reports of fishing activities. We needed to gain an understanding of fisheries, of conflicts and the link between foreign conflict and domestic fisheries.

The first part of this literature review explores past economic articles which discuss marine fish catch and its explanatory variables. The second section summarizes three economics articles that discuss the effect of conflicts on key explanatory variables. The last section explores the link between foreign conflicts and domestic fisheries, which we identify as the Illegal, Unregulated and Unreported (IUU) fishing phenomenon, also known as pirate fishing. No economic article could be found which analyzes the effect of IUU fishing; therefore, for this section, we will refer to reports from world organizations. The paper by Hendrix and Glaser (2011), which analyzes the effect of conflict on domestic fish catch, is the most relevant for our paper and will serve as an introduction to this literature review.

Many biological articles exist on marine ecosystems but the economic literature on marine fisheries is less common. In the writing of this paper particular attention was given to the prior work done by Hendrix and Glaser (2011), Jacquet et al. (2010), the Food and Agriculture Organization (FAO), and the OECD in contribution with the FAO. Together, these authors give a comprehension of marine fisheries models and allowed for the creation of the regression model presented in this paper.

1. Conflict and Domestic Fisheries

Hendrix and Glaser (2011) give the most salient perspective of the relationship we wish to explore and is therefore a good starting point to this literature review. The authors wanted to know if conflicts had sector specific effects which could affect domestic food security. In order to answer their question, they looked at the relationship between domestic conflict and marine fish catch.

With the use of panel data, they conducted their analysis on 123 countries from 1952 to 2004, using country fixed effect regressions with robust standard errors and a time trend. They tested six different types of models, and considered 3 different measures for their dependent variables, total catch growth, marine fish catch growth and inland fish catch growth. All models use the first difference of the log of the dependent variable.

These six models are further differentiated with the measure of conflict. Hendrix and Glaser (2011) created two different measures of conflict: civil conflicts, which takes a value of 1 when the country is experiencing at least 25 to 999 annual battle deaths, 0 otherwise, and civil war which takes a value of 1 if the country experienced at least 1000 annual battle death, 0 otherwise. The authors tested in each of these six models the significance of the conflict onset dummy variable and the conflict termination dummy variables.

An additional six models were estimated to test the significance of other conflict measures. Two of these six models included the log of battle deaths, which was added to the regressions on total catch growth. Another two models included the log of displaced person. Finally, two models were created to analyse the effect of the distance between the center point of the conflict and the coast on marine catch growth.

The data used to create the dependent variable were taken from the FAO Fisheries and Aquaculture Statistics Collection Global Production Tables. The FAO collects data from their national offices from UN-FAO member countries, government official trade statistics, regional fisheries management organizations and trade associations. Some, such as Jacquet and al. (2010), criticized these data on the ground that they might underreport catches from small independent vessel, which combined can represent a significant amount for countries that lack bureaucratic capacity. That being said, the FAO takes extra steps and relies on FAO expert analysis and regional fisheries for countries that lack proper accounting measures.

The Data on conflicts comes from Strand's (2006) update and transformation of the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002). Hendrix and Glaser (2011) use two dummy variables as indicators of conflict. The first dummy variable gets the value of one if there are at least 25 battle deaths in a year within a country and 0 otherwise. The second dummy variable gets the value of 1 if there are at least 1000 battle deaths in a year within a country and 0 otherwise. From these two dummy variables, they constructed the dummy variable conflict onset, which takes the value of 1 for the first year of recorded conflict and 0 otherwise. They also created the dummy variable conflict termination, which take the value of 1 for the last year of a conflict and 0 otherwise. All three variables were included in the regression. Hendrix and Glaser (2011) acknowledge that not all conflict types would have a marine component. Consequently, to bring some insight to the relationship of marine fish catch and conflict, they created two models which included the distance between the center point of the conflict and the coast.

They controlled for other economic variables which are thought to be associated with fish catches: GDP per capita, population and GDP growth and the Oceanic Nino Index (ONI). The ONI is a three-month rolling average which is used to represent the El Nino-Southern Oscillation (ENSO) events. They use lags of all control variables to reduce concerns of endogeneity.

Interesting results came out of the regressions. First they found that domestic conflict has a strong and negative impact on domestic fisheries. The results are stronger when the conflict dummy variables were associated with one thousand battle death. The decline in the marine fish catch is estimated to be equal to7% on average for the first two years of conflict. Secondly, the distance between the center point of the conflict and the coast doesn't have a statistically significant impact on the reported marine catches. Lastly they failed to find robust evidence of a so-called phoenix effect, i.e., a rebound in growth following the end of a conflict shock.

The lack of a robust phoenix effect can be worrisome since it means that food security of post-conflicted countries can be in jeopardy. They found that it took on average 9 years for the fish catch to be back at pre-war levels. Hendrix and Glaser (2011) explain that conflict can destabilize the state hegemony allowing illegal unregulated and unreported fishing to flourish. IUU fishing prevents the fish stock of regenerating and uses harmful fishing practices which can have prolonged environmental effect. In conclusion, they suggest that the international community should help protect domestic waters of conflict afflicted countries in order to preserve those countries future food securities.

2. The Food and Agricultural Organisation (FAO)

Hendrix and Glaser (2011) offer a good starting point in the analysis of fisheries and marine fish catch modeling. The FAO is recognized as a leading expert in the food and related industries and provides valuable insight on marine fisheries, including marine catch modeling. In their most recent report (2016), the FAO reported a new high in fish production which is attributed to the rapid growth in aquaculture. Aquaculture has now outpaced marine fisheries in fish caught.

The FAO also provides the breakdown of total fishing vessels between continents; Asia is leading with 3.5 million vessels while Europe and North America reports only a fraction of that number with a recorded number of fishing vessels of 0.1 million for each of these regions. Lastly the FAO estimates that IUU fishing accounts for 15% of annual fish catch.

In 2012, in their report 'The State of World Fisheries and Aquaculture', the FAO started to make projections on fish catch using models on short term and long term outlooks. These models help predict supply and demand using endogenous price and exogenous variables such as the El Nino events. To make their projections they make simplifying assumptions such as an unchanging macroeconomic environment, constant trade rules, absence of fish related diseases, fishery quota and the non-appearance of market shocks.

3. Modeling Conflict

Contrary to economic articles on marine fish catch, the effect of conflict on economic variables has received additional attention. In this section we will discuss three articles that bring interesting insight into this relationship. Cerra and Saxena (2008) analyze economic recovery following a shock such as a civil conflict. Abadie & Gardeazabal (2003) analyses the effect of conflict on a province of Spain. Their paper is particularly interesting since they use matching techniques to perform their analysis. The last paper reviewed is the paper by

Buhang and Gates (2002), who analyze the scope of conflict on specific conflict characteristics.

1. *Conflict and Economic Recovery*

Cerra and Saxena (2008) address the question of whether countries recoup the output lost during shocks and crisis once the negative event has passed. In order to analyse the relationship between economic growth (the dependent variable) and various indicators of shock, the authors use annual panel data for 190 countries for the years ranging from 1960 to 2001. They divided the countries into seven geographical regions for one set of models, while separating the countries depending on their relative income for another set of models. The different shock indicators that the authors used for their regression are banking, currency, civil war and a measure of political constraint.

According to their regression a banking crisis has the most negative impact on economic output, with a long and persistent effect. Following banking crisis there is a loss in output estimated at 7.5%, output is still 6% lower ten years after the crisis compared to the output that would have achieve if they did not experience a crisis. The output loss following a currency crisis is less severe with a recorded 4% loss in output. To analyse the effects of a currency crisis they constructed, what they call, an exchange market pressure Index (EMPI), which accounts for the percentage loss in foreign exchange reserves. The EMPI is calculated as the percentage depreciation in the exchange rate plus the percentage loss in foreign exchange reserves.

Conflict reported the lowest persistence in output loss. The authors used data from Sarkees (2000) in order to create a dummy variable for intrastate wars, which would have a value of 1 if the country is experiencing a conflict and 0 otherwise. Using this dummy variable they found that conflict causes an initial loss output of 6%. Half the output lost is recuperated after four years, although Cerra and Saxena (2008) found a three percent cumulative lost which persists after a decade.

Abadie and Gardeazabal (2003) analyze the effect of terrorist activity using matching techniques. They used the terrorist outbreak in the Basque Country in the late 1960's as their case study. In order to conduct their analysis they constructed a synthetic control region, which resembles the Basque Country, using weighted economic variables from other region of Spain. They also use the 1998 truce as a natural experiment. Their findings were that terrorist activity in the Basque region contributed to a 10% decrease in GDP compared to the synthetic region.

2. Geographic Characteristics of Conflict

Finally the last article in this literature review which analyzes conflict is the article of Buhaug and Gates (2002). The authors wanted to know if specific geographic and social characteristics influenced the location of conflict and the size of the area being affected by conflict. Their main contribution is the creation of a geographic conflict location variable which they used in order to determine the distance of the conflict from the capital and the size of the conflict zone (the scope). The scope of conflict is a measure of the conflict area, the scope area is a circular zone centered on the conflict center point and the diameter of the zone is built to include the most distant conflict.

With their new geographic data they were able to analyse geographic and social aspects of conflict on the location of the conflict and its scope. They use a dummy variable to indicate if the rebel group is from a different ethnic origin than the government. Their second explanatory variable is the incompatibility variable from PRIO/Uppsala dataset's which is a dummy variable indicating if there is incompatibility between the government and the rebel group.

For geographic variables, they constructed a dummy variable with the value of 1 if the conflict zone includes or is adjacent to a national border and the value of 0 otherwise. The second geographic variable is another dummy variable with the value of 1 if the conflict zone includes natural resources (fossil minerals, metals and/or diamonds) and 0 otherwise. They include another variable with the value of 0 to 96% which represents the land area covered by forest and a mountainous variable with the value of 0 to 94% which represents the mountainous aspect of the conflict zone.

In order to conduct their analysis they created two sets of models, one set of model regressed the explanatory variable on the location (the distance between the center point of conflict and the capital) of conflict. The other set of variables used the explanatory variables to regress the scope of conflict. They used ordinary least squares (OLS) and three-stage least squares (3SLS) estimation techniques. In order to control for the size of the country they included the total land area of a country as a control variable. All their estimations were run using logged and unlogged variables, with the logged variables producing stronger results. The logged variables also produced stronger results when looking at diagnostic tests.

Their first result is that population variables (total population, population density, and dispersion of the population), has no significance on the dependent variables. Secondly they found that mountainous and wooded area did not yield significant result as an explanatory variable for the scope of conflict. On the other hand, they found that scope is strongly influenced by proximity to a national border, the incidence of natural resources in the conflict zone, and the duration of the conflict. They also found that groups from a different ethnicity from governing elite tends to fight farther away from the capital, while groups whose objective is state control tend to fight closer to the capital. Lastly they report that the incompatibility variable plays the most significant role in determining the location of conflict.

4. Reports on Illegal, Unreported and Unregulated Fishing

Now that we have reviewed articles about marine fisheries modeling and conflicts let us discuss a possible link between domestic fisheries and foreign conflicts. We have identified this link as being the Illegal Unreported and Unregulated (IUU) fishing phenomenon, also known as pirate fishing. Work by Le Gallic and Cox (2006) and the Environmental Justice Foundation (EJF) (2015 and 2017) will be discussed below in order to bring insight to IUU fishing.

Since the 1950s, the international community has reported IUU fishing as a major contributor of the marine stock degradation and in 2001 the FAO organised the first major international initiative to deter IUU fishing. With these facts in mind, Le Gallic and Cox (2006) looked into the economic causes of IUU fishing as well as institutional and social factors. They also present some key results regarding the causes and some potential solutions to the widespread problem.

The authors identified three possible economic causes, which can explain the existence of IUU fishing. The first identified cause is overcapacity of fishing vessels. Due to quota and other restriction of fish catches many fishing vessels are operating at under capacity and it is therefore tempting for vessel operators to transgress their quota. The second economic incentive for IUU fishing is ineffective management and the existence of government subsidies. Subsidies have been recognized as a cause of IUU fishing as government would finance the construction of new fishing vessels which would bring domestic total capacity above the total issued fishing quota. The recognition of these factors led to the WTO consensus which prohibits any support for the construction of new vessel.

The authors also found institutional explanation for IUU fishing. On the institutional side, the authors identified gaps in the current international legal framework as the main contributor of IUU fishing. These gaps include loopholes where fishing vessel can operate without nationality or under the nationality of state with a lax legal framework; operating under flag of convenience (FOC). Another loophole is that currently in high seas there are no international laws which forbid IUU fishing practices. Furthermore, according to Gallic and Cox current domestic fines are not high enough to deter IUU fishing and/or countries don't have sufficient monitoring measures to regulate IUU fishing. The last institutional loophole is the presence of tax havens where organisations can hide their assets and avoid paying potential fishing fines. Analyzing the pros and cons, the authors conclude that under current legislation IUU is clearly a profitable undertaking.

The Environmental Justice Foundation (EJF) spends a lot of effort in fighting IUU fishing and one of their main channels is monitoring and reporting of IUU activities. The EJF is a non government organisation that investigates IUU fishing. The EJF petition governments, industry and consumers to help close current loopholes that facilitate IUU fishing.

According to the EJF, losses associated with IUU fishing are evaluated at $US 10 billion to 23.5 billion. They define IUU fishing as: fishing without a licence, under-reporting catch or catching prohibited species, operating with illegal fishing gears and fishing in marine protective area. The main difficulty that EJF encounters is the lack of a global tracking system for fishing vessels which makes it quite simple for IUU fishing organisation to launder illegal catch in international water, also known as high seas transshipment. These catch can then enter the international fish market as if it was legally caught.

In concluding to this literature review we would like to present a case study reported by the EJF (2015) which provides a good example of the detrimental effect of IUU fishing. The case studied is the effect of piracy fishing that lead to human exploitation and human trafficking in Thailand. IUUs and its associated poor fishing practices has depleted the marine stock of Thailand domestic fisheries and now boats can catch only 14% of what they used to catch in the mid-1960s. The depletion of the resource puts a lot of economic pressure on fishing organisations that see their cost rise while keeping a competing price on the international market for their product.

These organisations turned to human trafficking as a cheap source of labor. The lack of government control over sovereign seas and transshipment in high seas makes control over human trafficking on fishing boats near impossible. Transshipment in international waters allows for IUU fishers to launder their illegal catch by transferring their catch to seemingly legitimate boats, while limiting their forced labor any access to the inland.

4. The Data

1. Marine Fish Catch

Our dependent variables come from the Food and Agriculture Organisation of the United Nation, Fish and Aquaculture Department, Statistics and Information Branch (FIAS)[1]. It is an annual aggregate of total marine catch for all countries expressed in metric tons. Species reported by the number of fish caught (whales and seals) has been excluded from the analysis. The weight used for reporting is the live fish weight at time of catch, for aquatic

[1] The data comes from the FishStatJ software and is accessible at http://www.fao.org/fishery/statistics/software/fishstatj/en

plants the reported weight is the wet weight. Data includes all fish caught, including fish for human consumption and feed. The data does not include any fish discarded during fishing activity. The data is available from 1950 up to 2016. In order to assign a nationality to catches the FAO uses the flag of the fishing vessel.

2. The Distance Between Marine Ports

The data for the distance between marine ports comes from Bertoli, Goujon, and Santoni (2016) 'Le centre d'études et de recherche sur le dévelopment international' (CERDI). The data represents bilateral maritime distance between two countries for 227 states; it is therefore a 227 x 226 matrix. In order to conduct the calculation they decided on one main port for each country (except Canada, Russia and the U.S.A, which, due to their size, bilateral distances has been calculated using two ports). Countries that don't have access to the coast were taken off the analysis since they should not report any marine fish catch. For countries that have access to the coast, the authors chose the port with the highest number of shipping line and is connected to a major road.

3.The Index

Our explanatory variable of interest is the index. The index is constructed using the data from the marine fish catch and the bilateral distance between marine fish ports, as explained above. The index represents the sum of marine fish catch for all countries experiencing a civil conflict divided by their respective marine distance to the selected country. For this paper, the bilateral marine distance was transformed to its cubic root to give more relative weight to the size of foreign fisheries. Further explanation on the construction of the index is given in the methodology section. Due to the time constraint resulting from the specification and testing of the index, we conducted the analysis for three countries, Chile, Greece and Spain.

4. The Conflicts Variables

Data on conflict comes from the UCDP/PRIO Armed Conflict Dataset Version 4-2016. The conflict variable is a dummy variable which takes the value of 1 if the conflict is characterized by at least 1000 annual battle deaths and 0 otherwise. Gleditsch et al. reports the location of a conflict as the government side of a conflict which isn't always the same as the geographic location of where the fighting took place. Where a country reported multiple conflicts within the same year, the sum of battle deaths is calculated to see if the country experienced battle deaths over the threshold of 1000. Countries without any marine fish catch were dropped from the data.

5. Control Variables

We control for the change in demand by including the total population for the country in study and the GDP of the country. Total population can also control for an increase in labor supply. Oil price is also included as a control variable since it might affect fishing activity via operation costs. We also include a time trend which should capture trends in technology related to fishing equipment. The El-Nino effect is also included since it is reported to have tremendous effect on marine wildlife (Hendrix & Glaser (2011) and OECD/FAO 2016).

Data on total population and GDP are compiled within the World Bank database: World Development Indicator. Total population values are midyear estimates and include all residents regardless of their residency status. GDP is calculated using the value added approach and converted to current U.S. dollars using a single year official exchange rate. Oil prices come from the World Bank database: Global Economic Monitor (GEM) Commodities. The oil price used for the data is the average spot price of crude oil such as dollars per barrel at real 2010 American dollars.

Our measure of the El Nino-Southern Oscillation events, also called El-Nino or ENSO, is the Oceanic Nino Index (ONI) which comes from NOAA (2017). The Oceanic Nino Index is a three month running mean of ERSST.v4 SST anomalies in the Niño 3.4 region (5^{o}N-5^{o}S, 120^{o}-170^{o}W). It is the annual deviation of 30 year average (In order to reduce autocorrelation and unit roots issues in the data the first difference of all variable was used).

6. Chile Descriptive Tables

Table 1: Chile, Summary Statistics
Source : (World Bank 2017, FAO 2017, NOAA 2017)

Variables	Median	Mean	Std. Dev	Min	Max
Fd marine catch x 10^3	120	32	736	-2,527	1,818
Fd total pop. x 10^3	180	182	17	148	216
Fd of GDP x 10^6	2,687	4,334	11,266	-18,472	46,148
Fd of the Index	322	423	146,55	-373,282	352,560
Fd of the El-Nino effect	-0.04	0.02	0.77	-2.00	1.76
FD price of crude oil	-0.22	0.79	10.43	- 37.10	27.92

Fd is the first difference of the variable

Table 2 :Chile, Correlation Table
Source : (World Bank 2017, FAO 2017, NOAA 2017)

	Fd Marine Catch	Fd of the total population	Fd of GDP	Fd of the El-Nino effect	FD of the price of crude oil	Time Trend	Fd of the Index
Fd Marine Catch	1.00						
Fd of the total pop.	0.0684	1.00					
Fd of GDP	-0.0634	-0.0659	1.00				
Fd of the El-Nino effect	-0.1402	-0.0841	-0.2068	1.00			
FD of the price of crude oil	0.0508	-0.0542	0.5364	-0.2319	1.00		
Time Trend	-0.1903	-0.2004	0.3214	0.0500	-0.0271	1.00	
Fd of the Index	0.1847	-0.0466	-0.0678	-0.4027	0.0906	-0.0484	1.00

Fd is the first difference of the variable

7. Greece Descriptive Tables

Table 3: Greece, Summary Statistics
Source : (World Bank 2017, FAO 2017, NOAA 2017)

Variables	Median	Mean	Std. Dev	Min	Max
Fd marine catch	787	-233	10,706	- 47,048	21,532
Fd total pop. x 10^3	44	45	44	-79	141
Fd of GDP x 10^6	2,271	3,462	16,460	-42,127	48,093
Fd of the Index	-62	992	180,662	-438,425	512,874
Fd of the El-Nino effect	-0.04	0.02	0.77	-2.00	1.76
FD price of crude oil	-0.22	0.79	10.43	- 37.10	27.92

Fd is the first difference of the variable

Table 4 : Greece, Correlation Table

Source : (World Bank 2017, FAO 2017, NOAA 2017)

	Fd Marine Catch	Fd of total population	Fd of GDP	Fd of the El-Nino effect	FD of the price of crude oil	Time Trend	Fd of the Index
Fd Marine Catch	1.00						
Fd total population	0.0864	1.00					
Fd of GDP	0.0197	0.3230	1.00				
Fd of the El-Nino effect	0.2627	0.0129	-0.1544	1.00			
FD of the price of crude oil	-0.0971	0.1919	0.3465	-0.2319	1.00		
Time Trend	-0.1637	-0.5149	-0.0361	0.0500	-0.0271	1.00	
Fd of the Index	-0.1480	-0.0110	0.1033	-0.3652	0.0644	-0.0572	1.00

Fd is the first difference of the variable

8. Spain Descriptive Tables

Table 5: Spain, Summary Statistics
Source : (World Bank 2017, FAO 2017, NOAA 2017)

Variables	Median	Mean	Std. Dev	Min	Max
Fd marine catch	14,682	1,251	74,588	-206,405	146,308
Fd total pop. x 10^3	282	290	215	-153	829
Fd of GDP x 10^6	14,080	21,740	72,917	-182,900	214,790
Fd of the Index	-4	696	155,057	-423,416	379,569
Fd of the El-Nino effect	-0.04	0.02	0.77	-2.00	1.76
FD price of crude oil	-0.22	0.79	10.43	- 37.10	27.92

Fd is the first difference of the variable

Table 6 :Spain, Correlation Table
Source (World Bank 2017, FAO 2017, NOAA 2017)

	Fd Marine Catch	Fd of the total population	Fd of GDP	Fd of the El-Nino effect	FD of the price of crude oil	Time Trend	Fd of the Index
Fd Marine Catch	1.00						
Fd total population	-0.0132	1.00					
Fd of GDP	-0.0497	0.5290	1.00				
Fd of the El-Nino effect	-0.1981	-0.0839	-0.2009	1.00			
FD of the price of crude oil	-0.0582	0.3398	0.4467	-0.2319	1.00		
Time Trend	-0.1762	-0.0709	0.0781	0.0500	-0.0271	1.00	
Fd of the Index	-0.0594	-0.0303	0.0566	-0.3528	0.1141	-0.0625	1.00

Fd is the first difference of the variable

9. Remarks

The Chile table offers some interesting insights about the behaviour of the variables under study. The first observation is that all variables have a positive mean, since the variables are in first difference a positive means that on average the value of the variable is growing. The correlation table shows that most explanatory variable have little correlation with the dependent variable. Furthermore, explanatory variables have very little correlation between each other, except for GDP which is positively correlated with the price of oil (0.53) and surprisingly negatively correlated with the El-Nino effect.

For the Greece table we can notice that all explanatory variables have a positive mean, once again since the variables are in first difference we can conclude that the variables on average are growing in value. On the other hand the dependent variables as a negative mean. From the correlation table we notice that once again there is very little correlation between the dependent variable and its explanatory variables. GDP is the variable which demonstrates the highest degree of correlation with a correlation of 0.3465 with the price of oil and a correlation of -0.1544 with the El-Nino effect.

For the Spain table we see, once again, a positive mean for all variables. The dependent variable doesn't exhibit sign of correlation with her highest correlation value of -0.19. The GDP variable shows the highest correlation with a value of -0.20 for its correlation with the El-Nino effect and a value of 0.33 for its correlation with the price of oil.

Two overall observations are interesting from the tables above. First there is an important difference in the scale of the GDP variable, representing the data in units of million would bring the scale in line with the other variables. The second interesting observation is the negative correlation between the Index and the El-Nino effect which range between -0.4027 and -0.3528. This suggests that El-Nino events affects global marine fish catch.

A potential shortcoming of the data is the use of a dummy variable for conflict. Since all conflicts don't have the same impact on marine fish catch[2], a weighting mechanism for the

[2] Hendrix and Glaser (2011), analysed the distance of the conflict to the coast, population displacement, counter-insurgy strategy, conflict duration, to see these specific effect on reported marine fish catch.

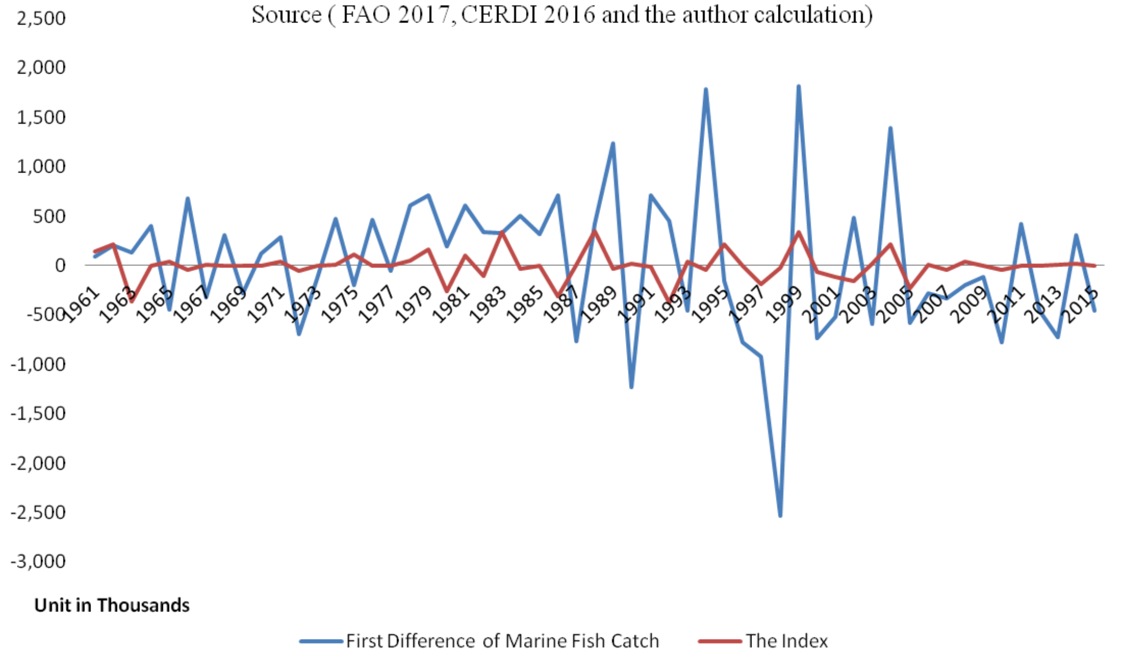
conflict variable might bring interesting results. Data on the number of battle deaths are only available after 1989; therefore for this paper precision on the conflict variable was forgone for an increase in the number of observation.

10. The Independent Variable and the Index

Below are the graphs of the dependent variable and the main explanatory variable for the three countries under study. These graphs are included so that the reader can see the co movement between these variables. The reader can see that there is very little co movement between Chile catches and the index. The Greece dependent variable demonstrates very little variation overall. For Spain we can see some co-movement between the dependent variable and the index with similar magnitude in their variation.

Figure 1: Chile, Dependent Variable and the Index

Source (FAO 2017, CERDI 2016 and the author calculation)



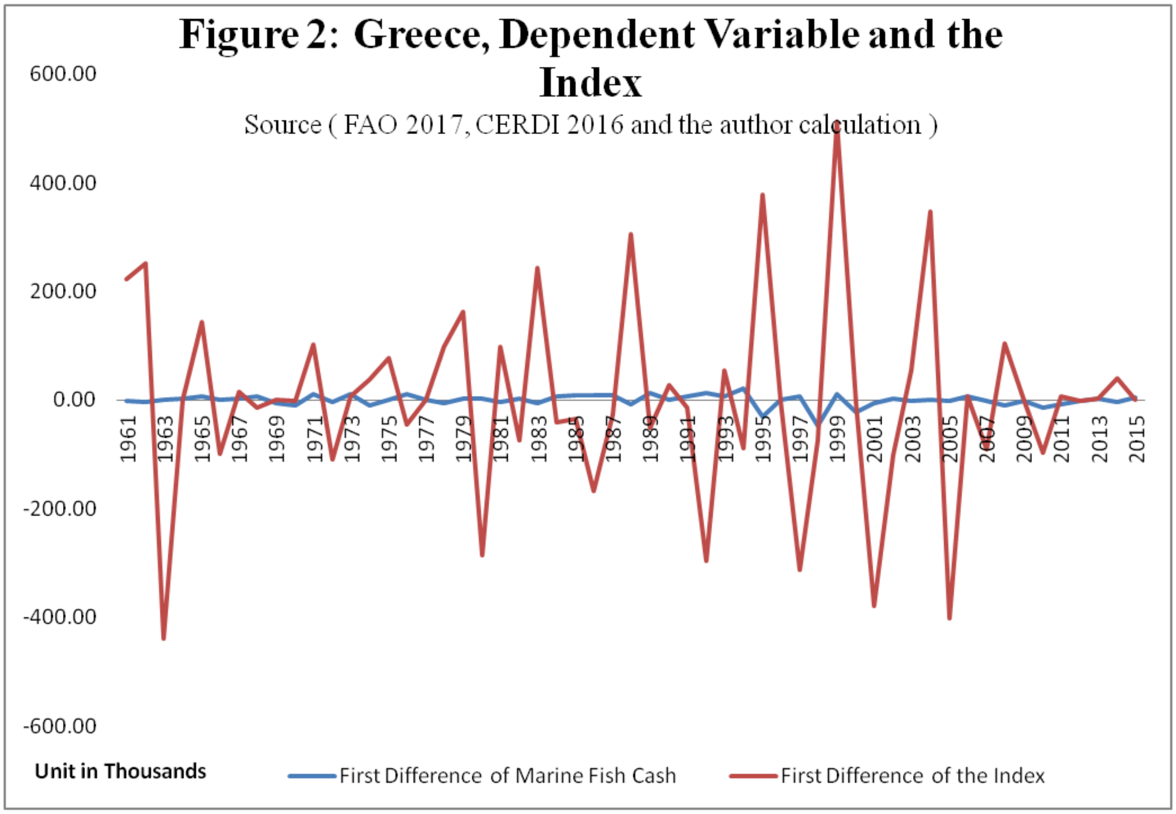


Figure 2: Greece, Dependent Variable and the Index

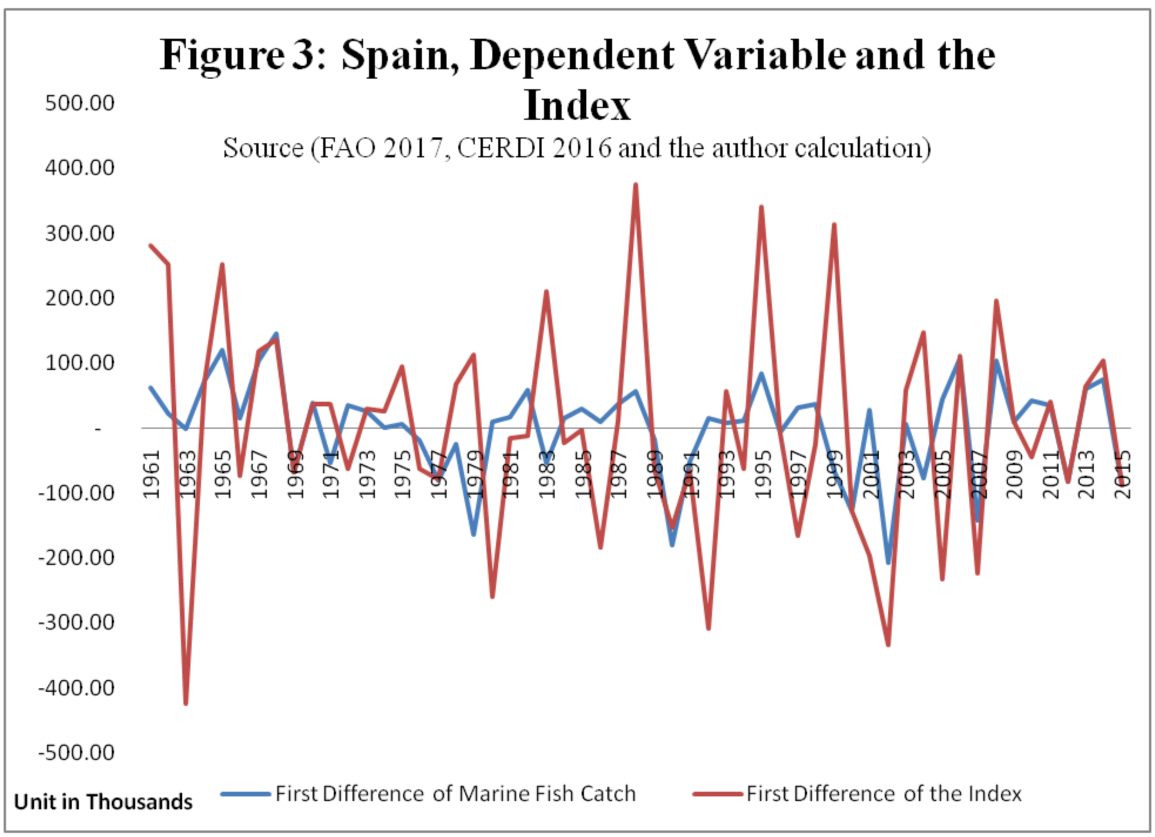


Figure 3: Spain, Dependent Variable and the Index

5. The Methodology

1. Constructing the Index

In order to conduct our analysis the first step we had to complete was the creation of an index. This index is meant to capture the opportunistic behaviour of a country's fisher given foreign conflicts. The idea is that fishers from the country under study might be tempted to illegally fish in water of conflict afflicted countries given that conflict may affect the conflicted country monitoring capacities. The index is meant to capture the fact that, all else equal, catches from country A will increase when[3]:

1. There are additional foreign countries that suffer from a civil conflict;
2. The size of the fisheries of countries under civil conflict is larger;
3. The distance from the countries under civil conflict is shorter.

The first difficulty experienced in constructing the index was the choice of the conflict variable. Many variation of the conflict variable were tested. Inspired by the work of Hendrix and Glaser (2011), who found that the effect of conflict was strongest for the first few years of conflict, we tried to include only the first few years of a conflict in the construction of the index. An index was constructed using the first year of conflict, the first two years and one with the first three years of conflict, which yield mixed results when used in a regression.

The second difficulty was the choice of the dummy conflict variable. Gleditsch and al. in their UCDP/PRIO Armed Conflict Dataset provides two dummy variables for the existence of conflict within a country. The first dummy variable takes the value of 1 if the country is experiencing at least 25 battle deaths and 0 otherwise. Their second dummy variable takes the value of 1 if the country experienced at least 1000 battle deaths and 0 otherwise. For both conflict variables an index was constructed and tested using the first year conflict to the first three years of conflict. All methods produce mixed results.

The advantage of using the conflict dummy variable with the 25 battle death threshold was that we had more conflicts in our data set. The disadvantage is that each conflict has less

[3] The index was developed by professors Louis Hotte and Maral Kichian. They suggested its use for this study.

impact on the total marine fish catch (Hendrix and Glaser, 2011). For this paper we used all years of conflict and the conflict variable which is calculated using 1000 battle deaths, although one method might be more appropriate than the other depending on the country being studied.

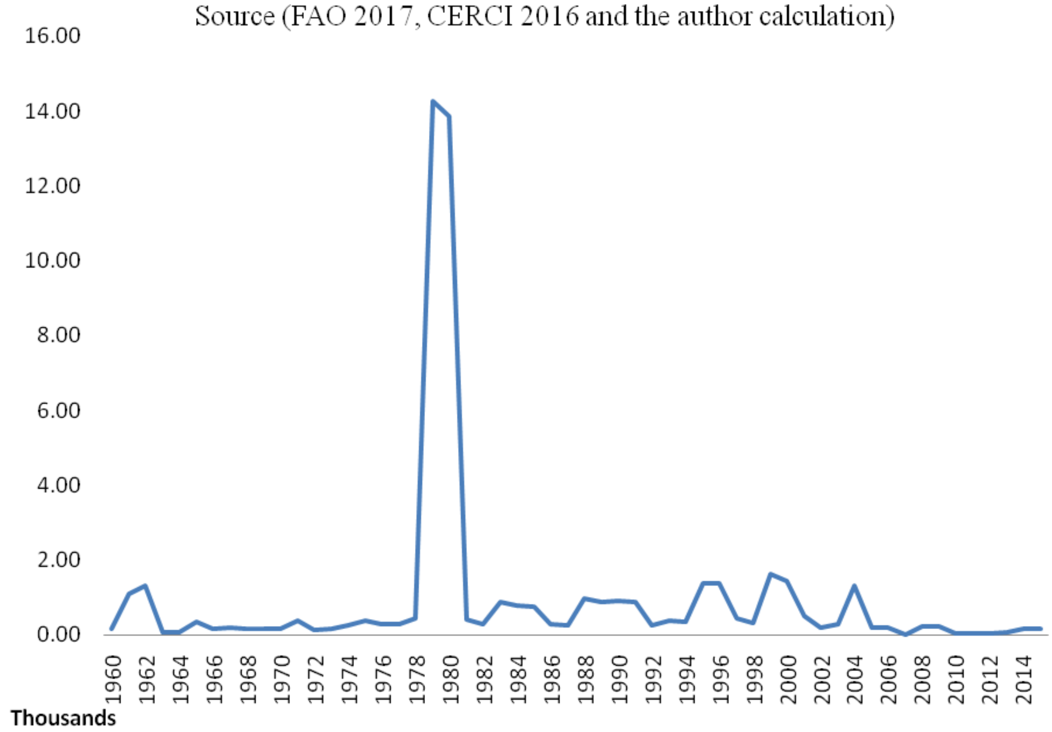
The third difficulty we encountered while constructing the index was the relative weight between the size of the conflict-afflicted fishery and its bilateral distance between the conflict-afflicted country and the country under study. While analysing our first attempt of the index we notice that the biggest variation in the index were attributed to a few conflicts, therefore we decided to explore with different weight on the distance variable.

$$\text{Index} = \sum_{i=0}^{n} \alpha i \, Y_i \,/\, d_i^{1/3}; \; i \neq j$$

α_i is a dummy variable with a value of 1 when the country is experiencing a civil conflict with over 1000 battle deaths at year t and 0 otherwise. Y_i is the normal average marine fish catch of country i. Over the sample period the average marine fish catch is calculated as the average of marine fish catch for all years excluding years where there was conflict within the country. d_i is the bilateral distance between country i and the country under study. n is the number of country and j is the country under study. Below are three expressions with graph representing three different relative weights for the Spain Index.

Figure 4: The Index Using the Distance

Source (FAO 2017, CERCI 2016 and the author calculation)



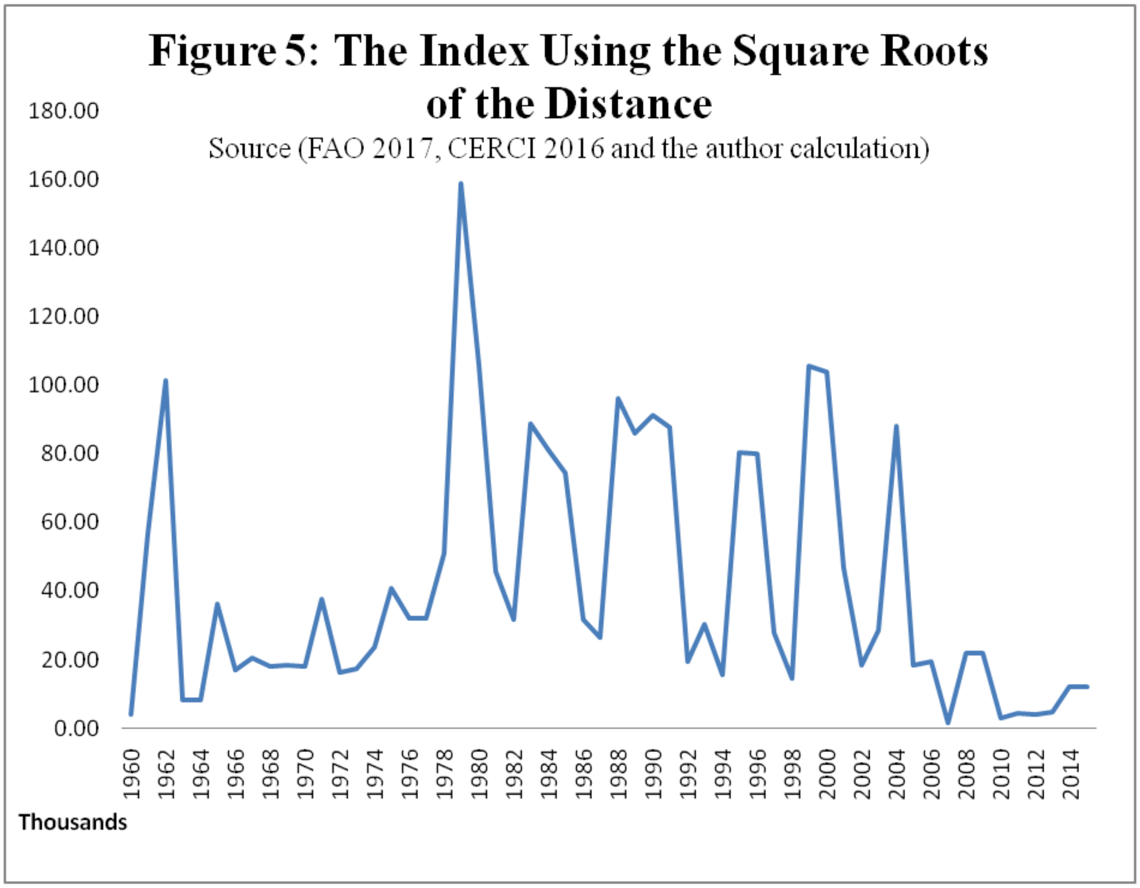
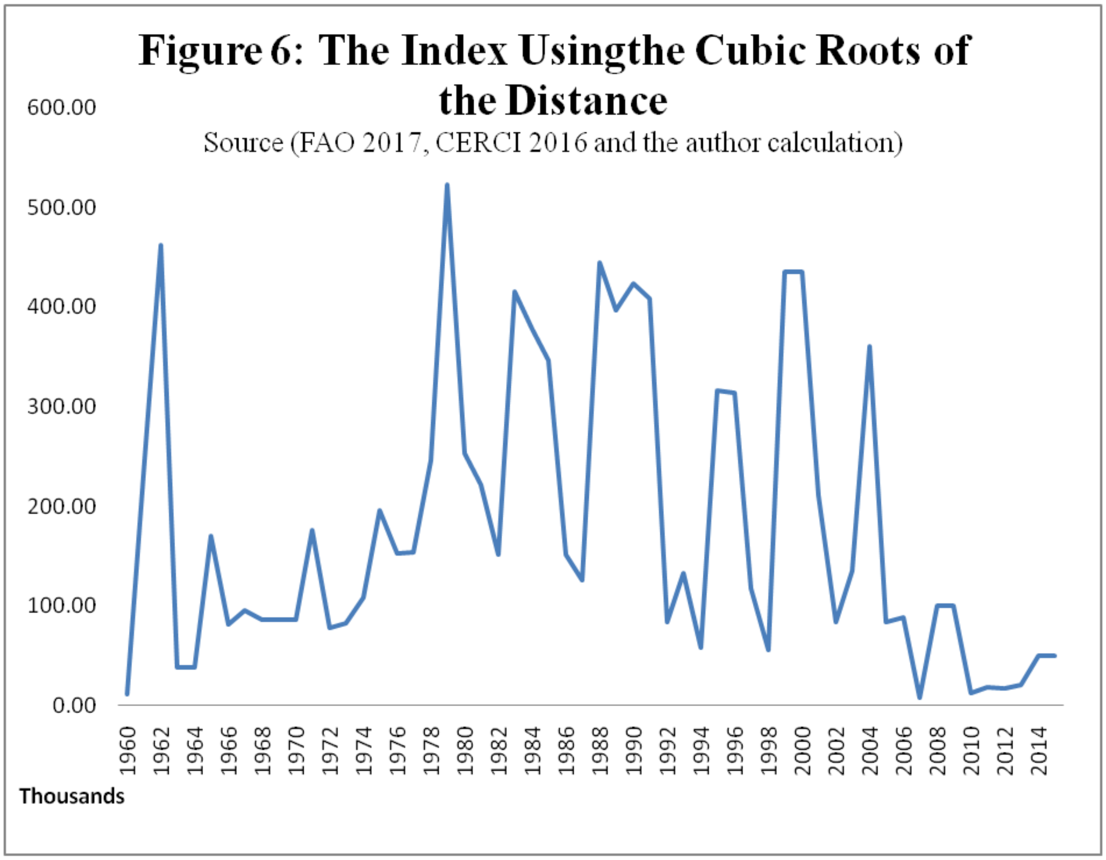


Figure 5: The Index Using the Square Roots of the Distance
Source (FAO 2017, CERCI 2016 and the author calculation)
180.00
160.00
140.00
120.00
100.00
80.00
60.00
40.00
20.00
0.00
1960
1962
1964
1966
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
Thousands



From these three graphs we can see the effect of using the cubic roots of the bilateral distance, the square roots of bilateral distance and when the bilateral distance remains untouched. In the first graph we can see a spike in the index for the years 1979 and 1980. This spike is attributed to the conflict in Morroco, since Morroco is very close to Spain (39 km), the effect of that conflict has a significant impact on the value of the index. Using the cubic of the distance, such as in the third graph, reduces the relative impact of a foreign conflict that is very close to the country of study.

In constructing the index, many model versions were tested with some using the 25 battle deaths dummy variable and others models using the 1000 battle death dummy variable. More than 15 countries were tested in our preliminary regressions, with mixed results. Finally we decided to use the cubic root of the distance and the 1000 battle deaths dummy variable for all conflict years for the construction of the index.

2. Model Specification

We have conducted a time series analysis for all countries, performing an OLS regression. We also included country specific lag values for the dependent variable and the explanatory variables in order to correct for autocorrelation. We also used the first difference for all variables in order to correct for unit roots within the data. A time trend and a time trend squared were used in order to detrend the data set.

3. Testing the Models

In order to properly specify the model many tests were conducted on the initial regression. Such test includes multicolliniarity tests, White heteroskedasticity tests and the Breusch-Godfrey serial correlation test. We also looked at the correlogram of squared residuals and the histogram of distributed error term.

Testing for multicollinearity is an important modeling step as multicollinearity[4] may pose problems for statistical inferences. When two explanatory variables are highly correlated, the regression software might attribute movement in the dependent variable to one of the explanatory variable when in fact it should be attributed to the other explanatory variable.

In order to test for multicollinearity, we looked at the Variance Inflation Factors (VIF). The VIF of variable k is calculated as follows: $VIF_k = \{1 / [1-(R^2_k)]\}$; where k refers to the explanatory variable being tested and $R^2_{k,}$ is the R^2 of the regression of explanatory variable k on the other explanatory variable. A low value for the VIF means that there is little multicollinearity, while a VIF over 10 is considered an indicator of severe multicollinearity[5].

The second test we conducted was the white test of no heteroskedasticity. It is important to test for heteroskedasticity since in its presence the coefficient of the estimator will no longer be efficient[6]; the estimator will keep its other properties such as being unbiased, consistent and asymptotically normally distributed. The null test for the white test is

[4] Greene (2012), pp 88-91
[5] Greene (2012), pp 88-91
[6] Greene (2012), pp 257-260

that the disturbance term are normally distributed[7]; H_0: $\sigma^2_i = \sigma^2$ for all i, where i is the variance of the regression error terms. The White test estimates the sample variance (s^2) and if there is no heteroskedasticity the s^2 will remain a consistent estimator of the variance, if not then there is heteroskedasticity.

The last test we conducted is the Breusch-Godfrey LM statistic test of no autocorrelation. The problems involved with autocorrelation are similar to those involved with heteroskedasticity; the estimators are unbiased, consistent and asymptotically normally distributed, although they will not be efficient. The problems are worst when a lagged dependent variable is on the right hand side of the equation, in which case the estimator will also be biased and inconsistent. The Breusch-Godfrey LM statistic test of no autocorrelation is a Lagrange multiplier tests whose null hypothesis is the absence of autocorrelation[8]. The test is ideal for our models since it remains valid when the regression model includes some lagged dependent variables and it is valid in the presence of heteroskedasticity.

Using tests discussed above, the correlogram of squared residuals and the histogram of distributed error term we corrected for multicollinearity, heteroskedasticity and autocorrelation and constructed a model for Chile, Greece and Spain. The models are presented below:

For Chile, we constructed an AR(4) model.

$$\Delta catch_t = \beta_0 + \beta_1 \Delta GDP_t + \beta_2 \Delta ElNino_t + \beta_3 \Delta ElNino_{t-1} + \beta_4 \Delta ElNino_{t-2} + \beta_5 Time + \beta_6 Time^2 + \beta_7 \Delta Index_t + \beta_8 \Delta Index_{t-1} + \beta_9 \Delta Index_{t-2} + \beta_{10} \Delta Index_{t-3} + \beta_{11} \Delta Index_{t-4} + \beta_{12} \Delta Catch_{t-1} + \beta_{13} \Delta Catch_{t-2} + \beta_{14} \Delta Catch_{t-3} + \beta_{15} \Delta Catch_{t-4}$$

For Greece, we constructed an AR(6) model.

$$\Delta catch_t = \beta_0 + \beta_1 \Delta Population_t + \beta_2 \Delta ElNino_t + \beta_3 Time + \beta_4 Time^2 + \beta_5 \Delta Index_t + \beta_6 \Delta Catch_{t-1} + \beta_7 \Delta Catch_{t-2} + \beta_8 \Delta Catch_{t-3} + \beta_9 \Delta Catch_{t-4} + \beta_{10} \Delta Catch_{t-6}$$

For Spain, we constructed an AR(1) model.

[7] Greene (2012), pp 275-280
[8] Greene (2012), pp 275-280

$$\Delta catch_t = \beta_0 + \beta_1 \Delta Population_t + \beta_2 \Delta ElNino_t + \beta_3 \Delta ElNino_{t-1} + \beta_4 Time + \beta_5 Time^2 + \beta_6 \Delta Index_t + \beta_7 \Delta Index_{t-1} + \beta_8 \Delta Index_{t-2} + \beta_9 \Delta Index_{t-3} + \beta_{10} \Delta Index_{t-4} + \beta_{11} \Delta Catch_{t-1}$$

6. The Results

Following the strategy discussed in the previous section, we present the regression output in Table 1 and Table 2 below. Table 1 holds the results of the standard OLS regression, while Table 2 holds the results of the OLS regression with White robust standard error.

1. Chile

In the first column, we see the coefficient results and their standard error for Chile's model. The model uses 51 observation (5 observation were dropped while including lags of explanatory variables) with a reported R^2 of 0.64. We fail to find a significant relationship between the index and Chile's marine fish catch, and the index coefficient changes in signs depending of the lag being used. The only significance found was with a 4 year lag, where the coefficient is significant at the 5% confidence level. This could mean that Chile fishers take four years to react to the news of foreign conflict, which seems unlikely.

Although Chile's model fails to bring conclusive results on the explanatory variable it passes the test for multicollinearity, homoskedasticity and autocorrelation. The highest reported Variance Inflation Factor (VIF) is 2.50 for the index with three lags, which is far from the severe multicollinearity threshold of 10 (the trend and trend square variable reported values of severe multicollinearity, which is normal by construction). For the White test of homoskedasticity we, obtained a p value of 0.4341, we fail to reject the null hypothesis of homoskedasticity. For the Breusch-Godfrey LM statistic test of no autocorrelation for up to five lags we obtain a p value of 0.8634, meaning that we cannot reject the null hypothesis of no serial correlation for up to five lags. All tests were conducted on the standard OLS regression.

2. Greece

The second column of the two tables presents the results for Greece's model. That model uses 49 observations after dropping 5 observations to include lags. Greece's model has a reported R^2 of 0.49. Contrary to Chile's model, the index is significant at the 5% level, although the coefficient value is negative.

Like the Chile model, particular attention has been given in order to correct the model for potential multicollinearity, heteroskedasticity and autocorrelation. The highest reported VIF for Greece is 2.95 for the first difference of total population, this exclude the VIF of the trend and the trend square which are once again quite high by construction. From the result of the White test for homoskedasticity we fail to reject the null hypothesis of no heteroskedasticity, with a p value of 0.4328. The Breusch-Godfrey LM statistic test of no autocorrelation for up to 5 lags reports a p value of 0.3678; therefore we cannot reject the null hypothesis of no serial correlation.

3. Spain

The last column of tables represents the coefficients obtained for the Spain model. The Spain model reports a R^2 of 0.51 with 50 observations. In this case model we obtain the most significant results for the index. All index variables up to the 5^{th} lag are significant to the 5% level or better. That being mentioned, the coefficients associated with the index are all negative.

Like the two other models, we failed to find the presence of multicollinearity, heteroskedasticity or autocorrelation. The highest reported VIF for Spain is 3.50 and is associated with the third lag of the index. White's test for homoskedasticity yield a p value of 0.4334, therefore we cannot reject the null hypothesis of homoskedasticity. The Breusch-Godfrey LM statistic test of no autocorrelation for up to 5 lags reports a p value of 0.7642 and once again we fail to reject the null hypothesis of no serial correlation.

4. Remarks

The negative value of the index for the case of Greece and Spain is contrary to our expectations. This could be explained by the way the FAO collects reported fish catch. Since the FAO assigns the catches to the country according to the flag of the fishing vessel, Spanish and Chile fishing could fish in foreign waters and be disrupted by a foreign conflict.

For the three models, the control variable oil and GDP were dropped since they did not provide any explanatory power. All control variables, the El-Nino variable had the most significance. For Chile and Spain the coefficient for El-Nino effects are negative while the coefficient for Greece is positive. An increase in the El-Nino index is associated with a global decline in fish catch, although it can have a positive effect on geographic specific fisheries as it alters the migration pattern of migratory fishes[9].

[9] Hendrix and Glaser (2011)

5. Table 7: OLS Regression Results

Table 7 : OLS Regression Results

	fd_catch Chile	fd_catch Greece	fd_catch Spain
Fd_pop		-0.040	-0.094
		(0.047)	(0.042)*
fd_elnino	-99,991.184	3,279.465	-26,011.427
	(146,945.159)	(1,988.458)	(13,390.304)
L.fd_elnino	-235,535.805		-18,415.197
	(139,438.382)		(13,494.613)
L2.fd_elnino	284,869.171		
	(142,740.060)		
t	34,543.699	411.159	-6,023.551
	(26,797.607)	(577.046)	(3,231.640)
t^2	-685.036	-9.856	72.528
	(445.615)	(9.967)	(50.169)
fd_index	0.219	-0.018	-0.300
	(0.745)	(0.009)*	(0.083)**
L.fd_index	0.812		-0.454
	(0.807)		(0.100)**
L2.fd_index	-0.607		-0.384
	(0.730)		(0.111)**
L3.fd_index	-0.898		-0.444
	(0.796)		(0.104)**
L4.fd_index	1.591		-0.327
	(0.752)*		(0.093)**
L5.fd_index			-0.192
			(0.076)*
L.fd_catch	-0.109	-0.244	-0.377
	(0.144)	(0.134)	(0.140)*
L2.fd_catch	0.323	0.300	
	(0.140)*	(0.146)*	
L3.fd_catch	0.027	0.393	
	(0.132)	(0.140)**	
L4.fd_catch	-0.455	-0.196	
	(0.129)**	(0.144)	
L5.fd_catch			
L6.fd_catch		-0.233	
		(0.140)	
_cons	-232,057.910	276.118	119,963.288
	(347,381.185)	(6,765.519)	(49,160.117)*
R^2	0.64	0.49	0.51
N	51	49	50

Standard errors in parentheses, * $p<0.05$; ** $p<0.01$

Fd is the first difference

Li is the i period lag of the variable

7. Conclusion

This paper only offered a brief introduction of the potential use of the index in order to analyses marine fish catches or another variable of interest. As mentioned in the methodology, changes in the construction of the index yield different level of significance when used in a regression. It can be imagined other index which would be more specific to a specific country.

1. Possible Further Work

We can imagine a country specific weighting system, where the appropriate weight between the size of the fishery and the bilateral distance would depend on the technology of the fishing vessels and the size of a country fishing fleet. A country that has a modern fishing fleet and where its fleet is of substantial size can have easier access to conflicted fisheries then a country that has a few traditional fishing vessels, and therefore distance would have a bigger impact for the smaller more traditional fishing fleet.

Another weighting system could be applied to the conflict dummy variable. The weighting system could have scale down or up the value of the conflict depending on the impact of the conflict on domestic marine fisheries. The work of Hendrix and Glaser (2011) could offer some insight on which variable that could be used in order to build that weighting system.

Possible work could be undertaken depending on method used to carry the regression. Studies such as Buhang and Gates reported that using the logs of variables yielded better statistical significance for the value of the coefficients. It was also suggest scaling down gdp and the marine fish catches by the total population of the country, this could also be performed as a robustness check for the results we presented in this paper.

2. Inherent Difficulties of the Paper

As the name suggests, trying to bring some insight on IUU fishing activities using reported marine fish catches may be more difficult than expected. Since IUU activities are in part unreported. Furthermore transshipment of illegally caught fish in international waters and the existence of multinational IUU operation may bring a different value to the index coefficient.

Another difficulty which persisted throughout this paper is the heterogeneity of relationship between countries. In building the index we did not only assumed that all conflict had the same impact on marine fisheries, we also assumed that all foreign conflict have the same relationship with the country of study. For example, we can image that Spain are currently operating illegally in a foreign fishery and a conflict in that foreign country could destabilise the existing IUU network. This kind of relationship was not taken into account in the construction of the index and it can bring unexpected values to the coefficient of the index.

Hill and al (2007) mentioned that marine fisheries are inherently complex, with spatial and temporal factors. The proper data needed for the analysis is costly to obtain, all of these factors brings uncertainty to marine modeling, and therefore having a coefficient which is contrary to our expectations should not come as a surprise.

> *Then the predators came-big tuna, four, five, six hundred pounds. Deep-sea fishing boats were catching bluefin tuna within hundred yard of the shore. In harbors sometimes. Then suddenly it stopped. The menhaden went away, and so did the other fish. I spent three weeks down there trying to figure out what was going on. I still don't know. It's all part of the ecological balance. When something tips too far one way or the other, peculiar things happen. (pp 96 Jaws.)*

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