Over-fishing, Conflict, and the South China Sea

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In this paper, we determine whether scarcity of a resource that is high in demand can induce international conflict. Specifically, we test whether the combination of fishery depletion and high fishing activity causes an increase conflict in the South China Sea using an instrumental variable approach. This relationship between scarcity and conflict in the South China Sea has been predicted by the resource conflict literature, but this is the first instance it has been confirmed empirically. To operationalize conflict we utilized an original data set of confrontations involving claimants to territory in the South China Sea. Through the use of an instrumental variable, we find support for our hypothesis.

1 Introduction

In recent years, there are few maritime regions that have received as much attention from academics and policy makers as the South China Sea (SCS). This is due in part to its role as a transit point for much of global trade, as well as the fact that it has been the setting for at times violent conflict. Conflicting claims over territory between China, Taiwan, the Philippines, Vietnam, Malaysia, and Brunei have been accentuated by sometimes violent conflict - such as the 1988 battle between China and Vietnam over the Paracel Islands (Petty, 2016).

However, little is actually known about why conflict occurs in the region. Competition over territory is one of the most commonly cited reasons for conflict (Kaplan, 2010; Segal, 1996; Costlow, 2012). In 2016, 21% of the value of global trade was transported through the South China Sea . However, few researchers suggest that countries in the region are seeking territory exclusively for geopolitical reasons; they expect that access to the oil, gas, and fishing resources may play an important role as well (Gallagher, 1994; Klare, 2001; Fravel, 2011). These resource-oriented explanations of conflict have been examined in the political economy literature (Acemoglu et al., 2012; Wu and de Mesquita, 1994), though these predictions have for the most part not been empirically tested.

This paper represents the first empirical effort to understand the South China Sea conflict using historical data and quasi-experimental techniques. We put several existing theories of resource competition to the test using an instrumental variable to isolate the role of fishing activity and fishing resource scarcity in causing conflict between countries using a new data set of confrontations between the nations bordering the SCS. This paper utilizes new data on conflict in the South China Sea to test the hypothesis that the combination of high levels of fishing activity and environmental degradation leads to increases in conflict. Through the use of an instrumental variable model, we find significant support for a relationship between fishing activity, fishery health, and conflict. This relationship has thus far remained significant after applying different operationalizations of both independent and dependent variables, and the inclusion of additional control variables and fixed effects.

1.1 Motivation

Why might countries fight over resources and over what resources might they fight? There is a strong political economy literature on the causes of resource-related conflict. Maxwell and Reuveny (2000) examined the emergence of conflict within the context of a dynamic game with two players competing over a renewable resource. They find that conflict appears most often when the resources themselves are depleted and when the quantity demanded by the actors is high. Reuveny and Maxwell (2001) come to a similar conclusion using simulations. Acemoglu et al. (2012) developed a game theoretic model that examined the role that markets could play in the emergence of conflict over resources. They found that if an actor faced high domestic demand over a scarce resource controlled by another actor that inelasticity in the demand of that resource led to conflict between them. Additionally, they found that competitiveness in the market of the resource extracting actor led to the production of a "conflict externality": the harvesters would deplete the resource below sustainable levels, pushing up prices and increasing the likelihood of the external actor would initiate a conflict over the control of those resources.

The relationship between resource scarcity and conflict has also been explored empirically. Koubi et al. (2013) performed a literature review of empirical analysis of the relationship between resources and conflict and found that there is a large degree of disagreement about what resources matter and under what conditions. The vast majority of the empirical literature on resource conflict has focused on oil and mineral resources (Lujala, 2009; Thies, 2010). On the other hand, the relationship between renewable resources and conflict has been less thouroughly examined. Of the work that has been done, most has examined the relationship between water scarcity and conflict Theisen (2008); Gleditsch (2012); Theisen et al. (2013); Gizelis and Wooden (2010). Little empirical work has been done to examine the role of fishing resources on conflict.

The absence of empirical examinations of the relationship between conflict and fishing resources is notable, because area and conflict studies scholars have frequently described the territorial dispute in the South China Sea between China, the Philippines, Vietnam, Brunei, and Malaysia as being driven by competition over scarce oil and fish resources. Giordano et al. (2005) observe that the lack of a regional consensus on property rights to territory in the South China Sea, combined with the discovery of oil near the contested Spratly Islands could be a factor in their perceived increase in conflict in the region. Klare (2001) agrees that mutual claims to oil resources, combined with rising energy demand makes the South China Sea a region ripe for conflict. Wu and de Mesquita (1994) describe the territorial conflict as being partially driven by interest in oil reserves under the South China Sea.

More recently, scholars and experts have begun to speculate that fishing resources may also play an important role in driving conflict in the South China Sea. The International Crisis Group argues that a combination of declining fish stocks and government subsidies is pushing fishermen further into contested waters in the South China Sea. Furthermore, they point out that disagreements over policies, such as China's fishing ban lead to "deliberate sinking of boats, shooting, ramming, arrests, confiscation of radio and navigation equipment, and the detention of crews for ransom" (International Crisis Group, 2012b). Moreover, they find that many countries in the region, including China, use government resources to both protect their own fishermen and arrest the fishermen from other countries who are active in areas they claim.

(Insert Figure 1 Here)

In their review of the empirical literature on the relationship between resources and conflict, Koubi et al. (2013) identifies six limitations in the extant literature: first, the mechanisms between conflict and resources are mostly under-specified; second, the state rather than sub-state entities is the focus of much of the literature; third, resources may be endogenous to armed conflict; fourth, much of the literature depends on only a few data sets - UCDP/PRIO Armed Conflict Dataset or the Correlates of War - which may miss important smaller-scale events; fifth, they suggest exploring interactive effects between natural resources and grievances; finally, most resource-oriented studies have focused on intrastate conflict, leaving the question open as to how they affect relationships between states.

Our study addresses several of the gaps in the extant resource conflict literature identified by Koubi et al. while also expanding on the limited empirical literature on the relationship between renewable fishing resources and conflict. It also is the first empirical study to assess the role of fishing activity and environmental health on conflict in the South China Sea.

2 Hypothesis

Essentially, we predict that over-fishing along the coastlines of the South China Sea pushes fishermen deeper into contested territories in the South China Sea, where they more frequently engage in confrontations with one another and patrol boats from other claimant countries. This hypothesis has a foundation in the political economy literature.

While competition over increasingly scarce fishing resources is not a commonly cited explanation for conflict in the South China Sea, we expect it to play an important role for several reasons. First, countries along the South China Sea have overlapping claims, thus lacking the institutional means to resolve conflicts. Essentially, since each actor has no explicit property rights to the region's fishing resources, each has an incentive to appropriate as much of the common resource as is possible. This situation is commonly know as the "tragedy of the commons" (Hardin, 1968).

As illustrated by Reuveny and Maxwell, competition over a scarce renewable resource can drive violent conflict between pairs of countries. While they only modeled the behavior of primitive societies, as Giordano et al argued, it is reasonable to expect nation states to behave in a similar manner where no strong institutions exist to manage conflicts of interest (Giordano, 2005). Also, there have been several studies that have previously identified resource competition as a corollary of civil and international conflict (Lei and Michaels, 2011; Hendrix and Salehyan, 2012; Toset et al., 2000).

The relationship we are attempting to identify should exist between pairs of countries. If a pair contains a country with little or no fish catch, we predict that there to be virtually no conflict between those countries over fishing resources irrespective of ecosystem health. Alternatively, if both countries engage in high levels of fishing activity, but the ecosystem is able to easily sustain that fishing level, we expect that conflict over fishing resources will likewise be rare or nonexistent. It is only when both countries have high levels of fishing activity and ecosystem health is low that confrontations should occur more frequently. We should note that our predictions are most consistent with those made by Reuveny and Maxwell.

Because our hypotheses involves the interplay of two variables - ecosystem health and fishing activity - the appropriate operationalization of our hypothesis necessitates an interaction in our model. Put another way, we expect the following relationships between fishing activity, ecosystem health and conflict:

(Include Table 1 here)

Since this hypothesis is an empirical prediction of substate and interstate behavior, we employ econometric analysis on retrospective data to test its validity.

3 Data

A key objective of this project was to gather a comprehensive and current compilation of confrontations in the South China Sea. Other conflict data sets, such as the Militarized Interstate Dispute (MID) data base from the Correlates of War Project and the Uppsala Conflict Data Program (UCDP) armed conflict data set, are of limited utility to us, because the conflicts they measure typically have a minimum number of causualties required before an event is considered a conflict; moreover, Correlates of War and the UCDP ignore low-level disputes, such as clashes between fishing boats and the coast guard of other nations (Jones et al., 1996; Themnér and Wallensteen, 2011). To address our research question we need a more comprehensive data set that includes low-level oceanic conflicts as there have been multiple instances where the arrest or killing of fishermen has resulted in protests and harmed inter-state relationships (International Crisis Group, 2012b). Thus, we worked to create a new data set to capture these important events.

This new South China Sea confrontation data set was coded from news articles accessed from news archives by several research assistants. In this instance, the Lexis Nexis news data base was the primary resource employed to identify and code events ranging from the years 1980 to

2013. Those dates were determined first by the fact that the international Lexis Nexis news article database only extends as far back as 1980 and second by the amount of funding we had available. A wide variety of search terms and three research assistants participated in discovering and validating events data.[1] The database will continue to be expanded upon as more confrontation events occur and as more historical events are discovered.

The confrontation as it is defined in this paper denotes a specific type of event. Namely, a confrontation means a zero-sum interaction between two actors that, respectively, are either operating on behalf of a state or are engaged in an economic activity that is not explicitly prohibited by their state of origin. This definition excludes police actions made against non-state actors engaging in explicitly illegal activities, such as pirates or smugglers, while including arrests of fishermen.[2] This definition was developed to include smaller events, such as fishermen arrests or sabotage of oil refineries, that have been frequently cited by experts as evidence of aggression or conflict in the region (Klare, 2001). For more on the methods used to collect this data and its relevance to the study of conflict, see Appendix 8.3.

3.1 Dependent variable

Using this data, we generated a variable that we believe to be the most parsimonious means of quantifying conflict intensity in the South China Sea. It is a simple count of the number of confrontations that occurred between any pair of states in a given year for all claimants to South China Sea: China, Taiwan, Vietnam, the Philippines, Malaysia, and Brunei. Once quantified, it is clear that this variable - *Confrontations* - is skewed with the majority of dyad-years showing no confrontation (see Figure 2). Additionally, some dyads are far more active than others, with the dyad pairs of China-Philippines and China-Vietnam accounting for over 80 percent of all confrontations. As mentioned in the data collection section, this data was gathered from news reports that we assume represent what we assume to be a representative sample of the true population of confrontation events that had the potential to impact interstate relations in the South China

[1]For examples of search terms please see Appendix 8.1.

[2]The illegality of fishing activity in contested waters, is - for lack of a better word - contested.

Sea. All things considered, we believe that this variable represents the best available means to approximate conflict between countries in the South China Sea.

(Insert Figure 2 here)

3.2 Independent Variables

To operationalize the hypothesis, we required measures of fishing activity and the health of the fish stocks in the South China Sea. To quantify the former, we used the fish catch data from the Food and Agriculture Organization of the United Nations (FAO); the latter was measured using the Marine Trophic Index (MTI) as calculated by the Sea Around Us Project.

In an ideal world we would utilize a geospatial measure of fishing activity to test our hypothesis; however, fishing vessels in the South China Sea are usually small boats that do not carry GPS equipment common in the ships from wealthier countries. Thus, a direct geospatial measure of fishing activities is not an option.[3] However, each littoral country reports total annual fish catches by region in which they were caught to the FAO, thus giving an approximate measure of the total mass of fish that was caught by each country in a year. We defined *Fish catch* for an individual country ($Fish\ catch_{i,t}$) as the total number of tonnes of fish caught by that country in the FAO region that includes the South China Sea (region 71).[4]

We argue that since there is a limit to how much fish can be caught on a given ship in a unit of time total fish catch is strongly correlated with the amount of fishing activity in that year (FAO, 2014a). We approximate this effect by geometric mean of *Fish catch* for each pair of countries. In other words, for each country pair and each year, our variable *Fish catch* will be calculated in the following manner:

[3] We also attempted to utilize light at night data from the National Oceanic and Atmospheric Administration to quantify fishing activity. However, inconsistency in satellite coverage and quality made such an inter-temporal comparison unreliable.

[4] We limited the fish catch to this region to reduce measurement error, as we do not expect fish caught elsewhere to impact conflict between countries that have territorial claims in the South China Sea.

$$Fish\ catch_{g,t} = \sqrt{Fish\ catch_{i,t} \times Fish\ catch_{j,t}} \tag{1}$$

Where $Fish\ catch_i$ and $Fish\ catch_j$ are the respective fish catches for individual countries in our data set and the subscript g represents the dyad of which countries i and j are members.

We use the geometric mean of the pair - as opposed to the mean or the minimum, because while we expect that both country's fishing activities contribute to conflict, we also expect that zeros will be meaningful. For instance, if country i has no fishing industry, and country j has an active fishing industry, then we would expect an ideal measure of joint fish catch to be zero. This is because we anticipate that no matter how large j's fishing industry is, the fact that i has none would lead us to expect that there would be no conflict between the two due to competition over fishing resources.

As mentioned in our hypothesis section, we expect the effect of *Fish catch* to have an effect on conflict that is contingent upon the health of SCS fisheries. Gauging the health of marine ecosystems is a daunting task, particularly in regions where large-scale oceanographic studies are rare. One measure of ecosystem health available to researchers is the Marine Trophic Index (MTI), also known as the Mean Trophic Level. In our model we refer to this variable as *Trophic level*.

Trophic Level measures the average hierarchy in the food chain of a given set of species caught by commercial fishermen over a certain period of time. Essentially, higher values of the scale indicate that predatory fish were a larger proportion of the total fish catch; lower values indicate that prey species of fish make up a larger ratio of fish caught. Because large predatory fish - such as high demand salmon and tuna - are essential to maintaining ecological balance between fish species lower MTI values are presumed to indicate poor ecosystem health. Conversely, high MTI values are associated with a more vibrant marine ecosystem.

The Sea Around us Project calculated the MTI for the South China Sea for the years 1950-

2014 (Pauly, 2007). It is a metric that is well established as a measure of ecosystem health in the environmental science and oceanographic literature [5] and is well suited to the purpose of measuring the abundance or scarcity of fish in the South China Sea.

3.3 Control Variables

To minimize the potential for omitted variable bias, we include several control variables in our model. Among them is a set of political variables: *Cold War end*, *Democracies*, and *ASEAN*. The first was included to control for the possibility that the end of the Cold War in 1991 resulted in a change in both economic and conflict behavior among the countries along the South China Sea. The second variable, *Democracies*, is a binary indicator for dyad pairs that are both democratic in a given year. A pair is considered to both be democracies if for both countries the difference between their respective democratic and authoritarian Polity IV scores was greater or equal to three.[6] *Democracies* was included, because there is a substantial literature indicating that joint democracy reduces conflict between countries (Ray, 1998). Since it is possible that international agreements of international governmental organization impact both fishing activity and the propensity for countries to enter conflict we created an ASEAN variable that is equal to one if both countries of a dyad pair are members of the Association of Southeast Asian Nations. Finally, in our robustness check section we have included the difference in military spending between countries as a control variable.[7]

To control for possibly confounding economic variables, we include several measures of relative economic strength and development. The first, *Logged GDP difference*, represents the logged difference in GDP between the two countries in the dyad pair. This variable measures the rel-

[5] For applied examples of the MTI in the marine ecology literature, see Branch et al. (2010), Giovanardi and Vollenweider (2004), and Naylor and Burke (2005).

[6] Brunei's levels of authoritarianism or democracy were not calculated by the Polity IV project. However, since Brunei has never held direct elections, we assumed that it had a Polity IV score of less than 3 for all years in the data set (Golder, 2005).

[7] This variable was not included in our main regression results, because the military spending data from SPIRI only covers the years 1989-2013.

ative economic capacity of each country, whereby larger countries have more economic resources to commit to protecting their fishermen, and probably more demand for fish in the first place. Similarly, we included the logged difference in per capita GDP - *Logged GDPPC difference* - which is intended to control for the relative levels of development between the dyad members. Finally, we control for the price of oil, *Oil*, which could both be correlated with fishing activity - the cost of fuel is an important consideration for a fishermen planning a fishing expedition - and with conflict, since it could be the value of oil resources, rather than competition over fishing resources that is driving conflict.

4 Methodology

In this section, review the methods that we employed to analyze our data and test our hypothesis. First, we describe the data generating process with which we hope to describe the underlying causes of conflict in the South China Sea. Second, we evaluate some of the identification challenges inherent in this data generating process. Third, we describe our rationale behind our decision to use an instrumental variable to identify the relationship between our dependent and independent variables. Fourth, we describe the instrumental variable and its use in our model. We conclude by reviewing several robustness checks that we employ to ensure our results are not spurious.

Based on our understanding of the region and our hypothesis, we expect the data generation process of conflict in the South China Sea to resemble the linear equation below:

$$Y_{g,t} = \alpha + \beta_1 D_{g,t} * S_t + \beta_2 D_{g,t} + \beta_3 S_t + \beta_k X_{k,g,t} + \alpha_g + \theta_t + \gamma_{g,t} + e_{g,t} \tag{2}$$

In the function above, the variables D and S indicate fishing activity and the health of the South China Sea's fisheries, respectively. The subscripts g and t, indicate the dyad and the time period, respectively. The dependent variable, Y, is the the number of confrontations in a given year between a dyad pair. The matrix $X_{k,g,t}$ is a set of observable control variables, such as the difference in GDP per capita between country pairs. The variables α_g, θ_t and $\gamma_{g,t}$ represent dyad and time fixed effects and dyad time trends, respectively. Finally, e represents variation in Y that is unexplained by D, S, or X_k.

Our hypotheses would indicate that $\beta_1 < 0$ and that $\beta_2 > 0$. The former would suggest that increasing the global fish supply would mitigate the effect of fishing activity on conflict due to a higher supply of fish in less conflict prone areas. The latter would indicate that increases in fishing activity would increase the propensity of conflict between a dyad pair. We have no strong prior for β_3 as we do not anticipate that changes in the global fish supply will have any direct effect on conflict except through its impact on fishing behavior.

We are skeptical that it would be possible to causally identify β_1 and β_2 through the use of traditional OLS. First, it is likely that there exist omitted variables. In other words, $e_{g,t} = \gamma_k U_{g,t} + v_{g,t}$ where U is a matrix of unobserved variables that are both correlated with *Confrontations* and *Fish catch*. One example could be the use of government naval or coast guard vessels to encourage fishermen to encroach on the territory of their rivals. China, in particular, is prone to using such policies to protect its fishing fleet as was observed by the Indonesian coastguard when they attempted to arrest Chinese fishermen in 2016 (Arshad, 2016). Second, there is a strong possibility of an endogenous relationship between *Confrontations* and *Fish catch*. While I anticipate that higher levels of fishing activity increase the likelihood of conflict occurring between countries, it is also likely that the occurrence of conflict dissuades subsequent fishermen from venturing into high risk areas. Thus, any observed relationship between *Confrontations* and *Fish catch* in a simple OLS regression would likely underestimate the true effect of *Confrontations* on *Fish catch*.

The instrumental variable identification strategy is an attractive option to address these identification problems. First, so long as the instrument has a valid first stage and satisfies the exclusion restriction, then the coefficient on *Fish catch* obtained through a Two Stage Least Squares (2SLS) regression can be interpreted as causal. Second, a good instrumental variable solves the problems of omitted variable bias and endogeneity in independent variables, such as what we described with *Fish catch*.

To avoid these problems of omitted variable bias and endogeneity, we make use aquacultural output (*Aquaculture*) as an instrument for to identify the joint effect of high demand and resource scarcity on conflict. This variable is defined as the geometric mean between the total aquacultural output of each dyad pair in each time period, where aquacultural output for a single country is the total number of tons (in units of 10,000) of non-plant biomass that was produced in marine, brackish, and freshwater farms in that country. This data was obtained from the Food and Agriculture Organization of the United Nations and is measured in thousands of tonnes (FAO, 2014b).

For a variable to be considered a valid instrument, it must first be a strong predictor of the endogenous independent variable; it must also not be directly correlated with the dependent variable, nor can there be variables that are correlated with both the instrument and the dependent variable (the exclusion restriction assumption) (Angrist and Pischke, 2008). To the first requirement, as you can see in Figure 3 there exists a strong positive correlation between fish production and aquacultural output are responsive to consumer demand for fish.

(Insert Figure 3 here)

This strong correlation between fish catch and aquaculture may be surprising to some, as one might think of aquaculture and deep sea fishing as being industries that produce similar products that compete with one another in the price markets. However, the literature on the relationship between aquaculture and fisheries suggests that aquaculture and deep sea fishing can instead be considered to be complementary industries: bycatch, or the low value fish that are unintentionally caught by fishermen, is a valuable resource to the aquaculture industry which processes it into feed pellets for fish raised in aquaculture farms (Naylor et al., 2000).[8] Moreover, provided that the

[8]This practice of fishermen selling bycatch to the aquaculture industry is particularly prevalent in China (Peng, 2004).

fishing and aquaculture industries are largely composed of price-taking firms, then their output can be seen as a function of market forces of demand and supply. While there are state-owned fishing aquacultural firms in China and Vietnam, most fishermen and aquaculturalists are small in scale and are responsive to market incentives (Luttrell, 2006; Peng, 2004; Mallory, 2013; Naylor and Burke, 2005; Ha and Bush, 2010) This makes aquaculture a valuable instrument, because it is likely to be exogenous to unobserved government economic and military policies designed to protect their fishing fleets and deter foreign actors.

Regarding the exclusion restriction requirement, we must beware any alternative pathways by which aquaculture may influence conflict other than through its impact on fishing activity; otherwise, our estimates will be biased (Stock and Yogo, 2005). One of the most plausible pathways by which the exclusion restriction would be violated is that aquacultural and fishing output are the products of military activity designed to gain control over new swaths of territory in the South China Sea. Control over this territory would in effect increase the fish population available to the fishermen and decrease the risks they face from the navies and cost guard from other countries. At the same time, the presence of navies protecting their fishermen could increase the likelihood of armed conflict between armed vessels. This behavior could also increase the productivity of the aquacultural industry, as the increased bycatch obtained by fishermen would provide a more affordable and nutritious feed for fish and crustaceans raised in fish farms. To account for this possible violation of the exclusion restriction, I evaluate a model that controls for the simple average military spending for each dyad pair in a given year. The data we use for this control was obtained from the Stockholm International Peace Institute and covers years 1988-2014 (Stockholm International Peace Research Institute, 2014). This story is most plausible with China, given the size of its fishing fleet, aquacultural industry, and its claim to the nine-dashed line (an area that encompasses virtually the entire South China Sea). Since the data obtained from SIPRI does not cover the entirety of our data set, the results of controlling for this potential omitted variable are included in our robustness check section.

One challenge presented by the data generating process is that since we expect fishing activity to be endogenous with conflict, then both β_1 and β_2 (from Equation 2) will be affected by that endogeneity. Subsequently, it is necessary for us to use two instruments to identify unbiased estimates of both β_1 and β_2.

To obtain an instrument to identify β_1, we interact *Aquaculture* with *Trophic level* to obtain a variable we will call Z. We then identify β_1 by taking the quotient of the covariance of *Confrontation* and Z over the coveriance between *Fish catch* $\times$ *Trophic level* and Z (Angrist and Pischke, 2008). Thus, we estimate β_1 using the following equation which reuses the set of symbols used in Equation 2:

$$\hat{\beta_1} = \frac{Cov[Y, \tilde{Z}]}{Cov[D * S, \tilde{Z}]} \tag{3}$$

Where $\tilde{Z}$ is the set of residuals obtained by regressing the interaction between fish catch and the marine trophic level on the set of covariates X_k. We estimate β_2 similarly:

$$\hat{\beta_2} = \frac{Cov[Y, \tilde{A}]}{Cov[D, \tilde{A}]} \tag{4}$$

In addition to using an instrument, we include dyad fixed effects, time fixed effects, and dyad time trends in the 2SLS and OLS models we focus on in our analysis. We do so because we believe that it is plausible that our control variables are incomplete and that there may be unobserved bias introduced by time invariant characteristics of pairs of countries - such as whether or not they share a border; one off events that affect all countries - such as the 2008 financial crisis; and time varying dyad-level effects - such as international trade or bilateral communications between high ranking officials. Moreover, we wish to be conservative in our analysis to avoid making a Type 1 error.

Identifying accurate standard errors is another potential area of concern. The standard errors estimated by a simple OLS will be biased due to a variety of factors, including heteroskedasticity originating from dyads being observed across years and the presence of individual countries in multiple dyads. While clustered standard errors might appear to be an intuitive fix for this problem, the number of clusters - pairs of countries - used in our study is limited to 15, which is far fewer than the number that are required to asymptotically estimate the heterogeneity introduced by groups (Angrist and Pischke, 2008). Additionally, with dyadic data it would be ideal to use standard errors clustered in two ways - such as by each individual member of the dyad - but this option faces the same as clustering on one dimension: our study is limited to 6 countries, a number far too few for the clustering algorithm to asymptotically estimate the true standard errors. Faced with these concerns, we estimate heteroskedasticity robust standard errors - White errors - in our main results and use one way clustering as a robustness check.

We also employ two other robustness checks to ensure that our results are not spurious. First, we use an alternative measure of conflict where the number of confrontations in our sample are restricted to those where the interaction between the two actors involved violence. Second, we derive an autoregressive model where the lagged *Confrontations* variable is included to obviate the possibility that our results are driven by auto-correlation.

In addition to the 2SLS model, we evaluate our results with OLS fixed effects regression. This model is specified with fixed effects and covariate specifications identical to our 2SLS model. This model is included as a baseline with which we can compare our results from 2SLS.

In summary, to identify a robust correlation between fishing activity, ecosystem health, and conflict, we apply an instrumental variable while also controlling for economic and political variables. We also include results from OLS fixed effects to allow us to compare our results with baseline estimates.

(Include Table 2 here)

5 Results

In this section, we review the results of our 2SLS and OLS models. We then evaluate the reliability of these results in light of the degree to which the 2SLS model has a valid first stage and lacks any violations of the exclusion restriction assumption. Finally, we evaluate the reliability of our findings in light of the several robustness checks.

Recall that the hypothesis tested in our model was that when the health of the marine ecosystem was low and fishing activity for a South China Sea claimant pair was high, that conflict would occur more frequently. The results of the 2SLS regression models displayed in Table 3 are consistent with this hypothesis. The positive coefficient of *Fish catch* and the negative coefficient of *Fish catch * Trophic* are consistent with our predictions that fishing activity tends to increase conflict when ecosystem health is poor, but has less of an impact on conflict when the reverse is true. In the 2SLS Models 3-6, the endogenous independent variables *Fish catch* and *Fish catch * Trophic* are significant at a 0.01 level when fixed effects, control variables, and time trends are included and when they are not.

It is worth noting that the relationship between *Fish catch* and *Conflict* is reasonably consistent across models 1-6. There is an apparent slight increase in the effects associated with out independent variables when fixed effects are included; additionally, the inclusion of control variables does not appear to consistently decrease or increase the magnitude of our independent variables' coefficients. From these observations, we can infer that *Fish catch* is relatively exogenous to observed political and economic covariates. Moreover, to the extent that fixed characteristics of country pairs, time shocks, or trends within dyad pairs biased the relationship between *Fish catch* and *Conflict*, it largely biased the effect towards zero.

(Include Table 3 here)

In light of the fact that there is an interactive relationship between fishing activity, ecosystem health, and conflict, we assess the effect of *Fish catch* on *Conflict* by first taking the first order derivative with respect to *Trophic level*. In Figure 4 we present the marginal effect of fishing activity (in units of 1000 of ton of fish) on conflict over various levels of *Trophic level*. We can see that the Average Marginal Effect (AME) of fishing activity on conflict decreases as Trophic level increases from its minimum value, 3.5, to its maximum value, 3.59. In fact, after *Trophic level* reaches its median value, 3.545, we can no longer say that fishing activity increases levels of conflict with a 95% level of confidence. This tells us fishing activity causes conflict in the South China Sea when the region's fisheries were depleted, but this relationship is diminished or disappears entirely in periods when the ecosystem was healthy.

(Insert Figure 4 here)

The joint effect of *Trophic level* and *Fish catch* on conflict can be more clearly seen in Figure 5. This table shows the predicted number of *Confrontations* for a pair of countries in a given year at various levels of the independent variables using the estimates obtained from Model 6 while holding other variables at their medians. We see that the overall level of conflict is highest when *Trophic Level* is low and *Fish Catch* is high. Conversely, we see few to no conflicts when either *Fish catch* is low or *Trophic level* is high. In other words, we see the most conflict when the ecosystem is unhealthy and fishing activity is high, and little conflict if the ecosystem health is high or fishing activity is low. This pattern is precisely what we predicted in Table 1.

(Insert Figure 5 here)

Moreover, the coefficient estimates of the independent variables are larger in magnitude in the 2SLS regressions (Models 3-6) than they are in the OLS regressions (Models 1-2). The coefficient of *Fish catch* in Model 2 indicates that there is an increase of 0.08 confrontations per 1000 tonnes of fish caught by the dyad pair; in comparison, the 2SLS Model 6 shows an effect that is over twice as large. This finding is consistent with our prior that the endogenous relationship between *Fish catch* and *Confrontation* would bias our OLS estimates downward; in other words, this finding is consistent with the theory that fishermen are to some extent deterred from future fishing if they observe that their compatriots are harassed by the coast guard of foreign governments. However, it is also possible that omitted variables biased the estimated relationship between fishing activity and conflict downwards.

It is worth noting that *Trophic level* is significantly greater than zero in Models 3 and 4, but is dropped due to high multicollinearity with year fixed effects and dyad time trends in Models 1, 2, 5, and 6. In Models 3 and 4, we have a counter-intuitive finding that higher levels of fishery health are positively correlated with conflict. However, after examining the magnitude of the constant estimated in Models 3 and 4 it is clear to us that the net effect of the *Trophic level* coefficient is to counterbalance the constant term of the model such that the final predicted values follow a similar pattern to what is shown in Figure 5.

The validity of our 2SLS results depend on a valid first stage regression and no violations of the exclusion restriction. For each of Models 3-6, we ran two first stage regressions: first, *Fish catch* was regressed on our instrumental variables; second, the interaction between *Fish catch* and *Trophic* was regressed on our instruments. Our results for the first stages of our 2SLS instrumental variable regressions appear in Table 3. In all models, our instruments explain at least 63% of the variation in *Fish catch* and the interaction between *Fish catch* and *Trophic level*. The minimum value of the F-tests estimated for Models 3-6 is 70, well over the minimum of 10 described by Angrist and Pishke as the minimum level of predictive power that instruments must have for an endogenous variable to avoid being classified as weak instruments (Angrist and Pischke, 2008). These results lead us to conclude that we have a strong first stage, without which our 2SLS estimates would be biased (Staiger and Stock, 1997).

5.1 Robustness Checks

To determine whether our results are robust and not spurious, we subjected Model 6 from Table 3 to several robustness checks. We chose this model, because it represents the strictest test of our hypothesis that can be described as causal. There were several types of checks that we performed in this section: first, we used alternative specifications of our independent, dependent, and instrumental variables; second, ran variations of our model that account for the possibility of autocorrelation in our dependent variable; finally, we check more general changes to our model, such as using alternative methods of estimating parameter standard errors, and the inclusion of additional controls. Overall these robustness checks show that our results are robust to changes in specifications of our dependent, independent, instrumental, and control variables. We also find that much the relationship between fish catch, scarcity, and conflict is driven by the presence of China.

Figure 6 shows the results of the various robustness checks. The figure shows the confidence intervals estimated for both *Fish catch* and its interaction with *Trophic* across various model and variable specifications. The smaller tick in each confidence interval represents the 95% confidence level while the larger tick shows the 90% confidence level for our coefficient estimates. The solid red line indicates a coefficient value of 0, while the dashed black line represents the coefficient estimates obtained from Model 6 in Table 3.

(Include Figure 6 here)

In Models 1 and 2, we check for two alternative specifications of our *Fish catch* independent variable. Recall, our original parameterization of this variable involved taking the geometric mean of the total fish catch of each pair of countries. We chose this method, since it allowed us to assign zeros to dyads in which one member had no fishing activity but still allowed us to consider the fishing activity of the larger of the two partners. However, it could be argued that taking the average *Fish catch* is a more parsimonious approach or using the minimum fish catch would also allow us to retain meaningful zeros. We wanted to ensure that our findings were robust to these alternative specifications, so we estimated our model with the average *Fish catch* in Model 1 and minimum *Fish catch* in Model 2.

We find that our results remain significant in both Models 1 and 2. In Model 1, *Fish catch* remains significant at a 0.05 level, albiet with a coefficient that is 83% smaller than the one we estimated in our baseline model (see Table 3 Model 4); the interaction between *Fish catch* and *Trophic level* is likewise smaller. However, in Model 2, we see that the coefficients for both *Fish catch* and its interaction are substantially increased relative to our baseline model; additionally, both are significant at less than a 0.001 level. These findings are consistent with our reasoning behind using the geometric mean. We believed that we would see less conflict as a consequence of competition over scarce fishing resources between actor pairs in which one or both actors did not have active fishing fleets in a given year. However, in the case where we average fish catch of both actors, the average fish catch does not distinguish between two important cases: in the first, one actor caught a lot of fish and the other caught little or none - here we would expect there to be no resource conflict; in the other case both actors caught a moderate quantity of fish - here we would expect more conflict as consequence of resource competition. Thus, using the average fish catch biases the observed link between fish catch and conflict towards zero.

In Models 3 and 4 we assess whether our parameterization of aquaculture led to spurious results. Recall that we defined *Aquaculture* as the geometric mean between the total aquacultural output of a dyad pair. However, we did not distinguish between marine aquaculture and terrestrial aquaculture. This could be a problem, as it is possible that there exists some variable that is both associated with marine aquacultural production and fishing activity, such as weather and climate patterns that were not captured by time fixed effects. The presence of such a variable would be a violation of the exclusion restriction and thus would invalidate our identification strategy. To address this problem, we disaggregated our aquaculture instrumental variable into marine aquaculture and freshwater aquaculture – marine aquaculture refers to aquaculture that was produced in a salt-water environment, typically in a coastal zone, whereas freshwater aquaculture is produced in non-oceanic freshwater bodies, typically located inland. We expect that if there are any unobserved policies or oceanic climate patterns that impact both marine aquaculuture and marine fishing activity that they will not affect freshwater aquacultural production in the same way.

We see in Figure 6 Model 3 that when we use freshwater aquaculture as our instrument that the coefficient of Fish catch and its interaction with trophic level remain statistically significant at a 95 % confidence level. This indicates that the relation between our instrument and independent variable is not entirely driven by any omitted variable that is common to both marine aquaculture and marine fishing activity. For instance, it is not driven by government incentives to produce/catch as specific species of fish. Instead, our results are consistent with our hypothesized relationship between aquaculture and fishing activity: that the association between both variables is driven by general consumer demand for fish. As for Model 4, it shows larger effect sizes for both of our independent variables as would be expected: the goods produced by marine aquaculture more strongly resemble those produced by marine fishermen and thus the demand for both products would be more strongly correlated.

We also wondered to what degree our results were dependent on violent vs non-violent confrontations. If we were to remove all non-violent confrontations - ie. those that did not involve the use of a weapon by either party - would we still observe the same relationship between fish scarcity and conflict? This question is important, as violent confrontations may be more likely to escalate into violent conflict between states and a more hostile diplomatic relationship than non-violent confrontations.[9] In Figure 6 Model 5, we evaluated our baseline model with violent confrontations as our dependent variable. We find that our results remain robust even when we limit confrontations to those that involved violence. This suggests that our model has important implications for not just fishery health but also peaceful relations between states along the South China Sea.

[9] This robustness check is arguably the most costly test of our hypothesis, because it directly measures the impact of over-fishing on violent confrontations, but at the cost of 76% of our confrontation events.

We were also concerned that there may exist autocorrelation in our dependent variable. Since state actors are strategic, it is possible should one actor confront the agents of another, the aggrieved party could engage in tit-for-tat retaliation, resulting in some inter-temporal correlation in our dependent variable. In addition to being a violation of the assumptions of OLS regression, this autocorrelation may lead to incorrect estimates of our coefficients if it is not properly accounted for (Nickell, 1981). We evaluated two alternative models that were designed to address autocorrelation. In Model 6, we estimate a first difference model where for all variables $\Delta x_t = x_t - x_{t-1}$. We find that the results of the first difference model are largely consistent with those of our baseline model. For Model 7 we evaluate our base model with the lagged dependent variable included as a control variable. Here, we see that controlling for the effects of previous levels of *Conflict* does not meaningfully change our coefficient estimates of either *Fish catch* or its interaction.

In Models 8 through 10, we make relatively minor changes to our baseline model to see if the results hold up to changes in our standard error estimation, choice of control variables, and sample. Recall that in our baseline model, we estimated our standard errors using White's method of adjusting for heteroskedasticity. However, one could argue that since our data is composed of dyads measured over time, that it would be appropriate to estimate standard errors at the dyad level.[10] Surprisingly, we find that clustering our standard errors at the dyad level actually decreases them relative to those estimated using the heteroskedastic robust methodology.

For Model 9, we control for the average logged military spending of both countries. This is to address potential concerns that military spending may be a potential omitted variable that biases our observed relationship between scarcity and conflict. It was not included in our original models, because we do not have military spending data for Vietnam from the years 1980-1988. However, after controlling for military spending, we see virtually no change in our coefficient estimates of *Fish catch* and its interaction with *Trophic* relative to our baseline model, indicating that military

[10] We do not do so in our baseline model, because the number of dyad pairs in our data set (15) is substantially fewer than the 30 or so needed to meet the asymptotic assumptions of the clustered standard error model (Angrist et al., 1993).

spending is not biasing our findings.

Finally, in our last model we estimate our base model on a subset of our original data set that excludes China. While we are not concerned that the inclusion of China would threaten our identification strategy, if it were the case that our results were entirely driven by observations that included China, that would limit the external validity of our findings. In other words, it could be that the relationship between resource scarcity and fishing was driven entirely by the presence of China, thus limiting the utility of our findings to understanding resource conflicts in other regions. As it turns out, while removing China does diminish the magnitude of the coefficients of our independent variables, they are still significantly different from zero at a 95% level of confidence. This suggests that even when examining conflicts between dyads that do not include China, such as Vietnam and the Philippines, our parameterization of conflict as a function of ecosystem health and fishing activity remains significant.

After running these regressions, we found that the estimates of the effect of fish production and the tertiary level on conflict are largely stable. While there are deviations in the magnitude of the coefficients and the degree of significance, they proved to be at least significant at a 95% level in all iterations of our baseline model. This leads us to conclude that the causal relationship between fishing activity, ecosystem health, and conflict are robust to alternative parameterizations of our baseline model.

6 Analysis

In summary, these findings lend credence to our hypotheses that competition over scarce fishing resources causes conflict between states in the South China Sea. These findings are also consistent with the model developed by Reuveny and Maxwell (2001) that predicted higher levels of conflict when a renewable resource became scarce.

This study also has strong implications for policymakers of countries that border or traverse through the South China Sea. These actors include not just the six countries described in this study, but also the United States, South Korea, and Japan, as these countries have trade vessels that would be adversely impacted by an outbreak of larger conflict in the region. The United States in particular has attempted to reduce tensions and conflict in the region by pressuring China and the Association of South East Asian Nations (ASEAN) into agreeing to a set of rules of the sea (Gearan, 2014).

This study implies an alternative means of reducing conflict by protecting and restoring the fisheries to a healthy and productive state. If the fisheries are exploited at sustainable levels (i.e. do not result in a drop in the trophic level of the region) then it is possible for countries to enjoy both lower levels of potentially violent and politically disruptive confrontations and more productive fishing industries.

There is reason to believe that such an agreement would be possible, though difficult to achieve. China has unilaterally imposed a fishing ban in the South China Sea from May to August since 1999 and has attempted to enforce its ban on fishermen from other countries (International Crisis Group, 2012a). Unsurprisingly, that ban has elicited a strong push back from its neighbors.

Should China's leadership choose to take a more diplomatic approach the Philippines may be amenable to some form of agreement. In the past, the Philippines has also called for a ban on fishing near coral reefs, particularly with harmful fishing techniques, such as fishing with explosives.

If the major fishing countries in the South China Sea choose to act collectively to restore the health of the region's fish population, we would expect to see a decline in confrontations between these countries and a consequent decline in regional tensions. Furthermore, were countries to reduce their fishing production sufficiently to allow predatory fish to repopulate the region's waters, there would be an increase in the region's trophic level over the long term. As is apparent in

Figure 5, increases in tropic levels and reductions in fishing activity should result in fewer confrontations occurring ceteris paribus. Since it is probable that these some of these confrontations negatively impact diplomatic relations, it follows that reductions in confrontations should lead to improved diplomatic relations around the region.

7 Conclusion

In this study, we have examined the role of competition for fishing resources in the South China Sea and impact on conflict. we have found significant evidence that a causal relationship exists between confrontations between actors in the South China Sea and fish production and environmental health. These findings have proven to be robust to several measures of robustness. We hope that these findings mark a significant contribution to the growing environmental conflict literature from which it drew inspiration.

In addition to the policy ramifications of this study, these results contribute to our understanding of conflict surrounding renewable resources. To date, few studies have confirmed a robust relationship between resource scarcity and conflict. This study suggests that under certain conditions, conflict can occur over renewable resources that are both scarce and for which there is a strong domestic demand.

However, this study has some important limitations that may be addressed in future research. First, as our analysis was exclusively on the South China Sea, it is not clear whether our results depend on the absence of property rights over fisheries. A larger study that included other fisheries, such as those of the Arctic Ocean, Mediterranean Sea, and so on, would help elucidate to what degree international agreements that manage common resources, like fisheries, mediate the scarcity-conflict relationship that we have observed.

Second, we did not explore the relationship between non-fishery resources and conflict in the

South China Sea. While we believe that any confounding effects of oil reserves were eliminated through our instrumental variable identification strategy, it is possible that time-varying valuation of those fixed resources could independently impact conflict between countries that border the SCS. Further study is warranted into the relationship between oil and conflict in the SCS.

Finally, we do not explore the ramifications of the confrontations between states. While several of the violent confrontations involved injuries or loss of life, it is possible that even non-violent confrontation events can harm bilateral diplomatic relations between nation states. Future research could use the confrontation data we have gathered to explore whether this is the case.

As humanity becomes more aware of the role scarce resources play in economic and political behavior, we may be better able to predict and avoid future conflicts. That is a vision for political science that places the field as not just relevant, but essential to navigating a future in which pollution, population growth, and global warming place pressures on the very fisheries, forests, and soil that sustain our way of life.

8 Appendix

8.1 Data Collection

The data for this study was collected from the Lexis Nexis historical archive of news articles. This data set covers events from the years 1980-2014, and we utilized events from each year except for the year 2014. Most of the data collection was done by research assistants who were tasked with identifying relevant events in news articles and recording a predetermined set of variables from that article. Each observation was independently verified by at least two research assistants and confirmed by me.

For each confrontation, several additional variables were collected. These variables included continuous measures of the number of individuals killed and the number of people wounded in the confrontation.[11] Additionally, each observation included a binary indicator showing whether or not a weapon was used in the altercation. Finally, they include classifications of the type of actor involved in the incident for each side. For instance, if an article described a confrontation between a Chinese fisherman and a patrol boat, both ”fishermen” and ”patrol boat” along with the countries of origin were recorded. Finally, if an article mentioned that the confrontation occurred near a particular geographic location, the the location was recorded.

The search within Lexis Nexis was done through the use of several different search terms, visual identification of titles suggesting relevant information, and hand coding of that information. Below is an example of one of the search terms used by the research assistants:

> ”South China Sea” or ”East Sea” and China or Vietnam or Philippines or Malaysia or Brunei or Taiwan and ”oil derrik” or ”oil platform” or fishermen or boat or ship and conflict or clash or shots or gun or injury or death or die or kill or arrest

[11] Where articles disagreed about how many people were killed or injured, we deferred to the number posted in the most recent article.

8.2 Confrontation Data

(Include Table **??** here)

8.3 Relevance of Confrontation Data

By the criteria of the Militarized Interstate Dispute data set, only conflicts involving the threat, display, or use of force by government agents against the agents of other governments would be considered an event of interest. This data set differs from the MID data set in that it includes confrontations involving non-governmental agents that are engaged in activities that would not result in sanction in their countries of origin - such as fishing, commerce, and oil exploration. One might argue that including confrontations involving actors who are not explicitly related to the government will inflate the appearance of conflict as many of the confrontations will involve events that have little bearing on diplomatic or military relations between states. While it is true that confrontations we observed involving fishermen are by far the most common form of confrontation, these are not inconsequential events.

Of all confrontations that involved the use of weapons, over 75% involved fishermen as at least one of the actors. Also, confrontations involving fishermen tend to be more likely to involve a weapon than those that only involve ships or rigs involved with the oil industry (see Table 5). In many cases, confrontations involving fishermen have resulted in protests, diplomatic standoffs, and poor regional relations. Moreover, incidents involving civilian-government confrontations have been cited by scholars as evidence of increasing tensions. All in all, it is our belief that this more inclusive definition of confrontation is appropriate to the task of gauging regional conflict levels.

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Tables and Figures

Tables

Table 1: Theoretical Model

		Fishing activity	
		Low	High
Ecosystem	Unhealthy	Low conflict	High conflict
	Healthy	Very low conflict	Low conflict

Table 2: Summary Table

Statistic	N	Mean	St. Dev.	Min	Max
Fish catch	480	341.44	577.51	0.00	3,649.84
Aquaculture	510	636.03	1,250.18	0.00	7,823.73
Trophic level	465	3.55	0.02	3.51	3.60
Cold War end	510	0.65	0.48	0	1
Democracies	510	0.14	0.35	0	1
ASEAN	510	0.30	0.46	0	1
Oil	510	37.59	29.25	12.21	109.08
Log GDP difference	485	25.81	1.77	17.26	29.85
Log GDPPC difference	485	8.49	1.41	2.68	10.58
GDP growth difference	485	4.59	4.06	0.01	27.67

Table 3: OLS and 2SLS Regressions

	OLS				IV-2SLS				LIML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fish catch * Trophic	-0.347*	-0.274*	-0.526***	-0.586***	-0.706***	-0.663***	-1.046***	-1.040***	-1.040***
	(0.183)	(0.159)	(0.176)	(0.176)	(0.247)	(0.247)	(0.274)	(0.259)	(0.259)
Fish catch	0.836***	0.657***	1.604***	1.860***	1.296***	1.247***	2.189***	2.185***	2.185***
	(0.186)	(0.164)	(0.444)	(0.483)	(0.254)	(0.280)	(0.563)	(0.588)	(0.588)
Trophic level	-0.008	-0.029	-8.166	-2.368	0.074	0.067	-8.284	-2.060	-2.060
	(0.030)	(0.044)	(8.485)	(4.560)	(0.046)	(0.057)	(8.475)	(4.645)	(4.645)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Observations	510	485	510	485	510	485	510	485	485
Adjusted R-squared	0.238	0.300	0.134	0.192	0.172	0.228	0.0505	0.126	0.126
Wald F-stat					116.4	165.3	96.77	93.04	93.04

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses are all heteroskedasticity-consistent White standard errors (**?**). Fixed effects include dyad effects, time effects, and dyad time trends. The symbol "+" indicates the variable has been dropped due to multicolinearity with time variables. The Wald F test is derived from the first stage of the 2SLS regressions with Fish catch as the dependent variable. Fixed effects include year, dyad, and dyad time trends.

Table 4: First Stage and Reduced Form Regressions

	First Stage (Fish catch)				Reduced Form			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aquaculture * Trophic	-0.004	-0.015	-0.006	-0.008	-0.190***	-0.193***	-0.299***	-0.304***
	(0.011)	(0.011)	(0.006)	(0.006)	(0.057)	(0.058)	(0.065)	(0.064)
Aquaculture	0.261***	0.280***	0.341***	0.347***	0.342***	0.356***	0.830***	0.887***
	(0.012)	(0.016)	(0.029)	(0.034)	(0.057)	(0.068)	(0.187)	(0.208)
Trophic level	0.005	-0.007	2.920	-1.182	0.030	0.019	-4.304	-3.910
	(0.010)	(0.020)	(2.124)	(0.989)	(0.029)	(0.044)	(7.850)	(4.954)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	510	485	510	485	510	485	510	485
Adjusted R-squared	0.172	0.228	0.051	0.126	0.396	0.411	0.248	0.280
Wald F-stat	116.4	165.3	96.7	93.0				

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses are all heteroskedasticity-consistent White standard errors (**?**). Fixed effects include dyad effe and dyad time trends. The symbol "+" indicates the variable has been dropped due to multicolinearity with time variables.

Table 5: Violent and Non-violent Confrontations

Classes	Nonviolent	Violent	Total	Pct. Violent
Fishing	66	22	88	25%
Oil	5	1	6	17%
Patrol	3	4	7	57%
Other	7	2	9	22%
Total	81	29	110	26%

Confrontations that involved a fishing boat or fishing boats as an actor were categorized as ”Fishing.”
Any confrontation that included among its actors a boat involved in exploring for, drilling for, or transporting oil being within the ”Oil” category.
All confrontations that involved only patrol or military vessels were categorized as ”Patrol.”

Table 6: Effect of Oil Price on Conflict

	(1)	(2)	(3)	(4)
Oil	0.001	0.002	0.025	-0.010
	(0.001)	(0.002)	(0.030)	(0.053)
Observations	510	485	510	485
R-squared	0.003	0.315	0.147	0.307
Controls	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
Adjusted R-squared	0.000770	0.300	0.0293	0.192
Number of dyid			15	15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses are all heteroskedasticity-consistent White standard errors (?). Fixed effects include dyad effects, time effects, and dyad time trends. The symbol "+" indicates the variable has been dropped due to multicolinearity with time variables. The Wald F test is derived from the first stage of the 2SLS regressions with Fish catch as the dependent variable. Fixed effects include year, dyad, and dyad time trends.

Table 7: Effect of Changes in Pil Price on Conflict

	(1)	(2)	(3)	(4)
Oil price change	0.001	0.000	0.005	0.002
	(0.002)	(0.001)	(0.015)	(0.013)
Observations	495	475	495	475
R-squared	0.000	0.313	0.137	0.303
Controls	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
Adjusted R-squared	-0.00172	0.299	0.0157	0.186
Number of dyid			15	15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses are all heteroskedasticity-consistent White standard errors (**?**). Fixed effects include dyad effects, time effects, and dyad time trends. The symbol "+" indicates the variable has been dropped due to multicolinearity with time variables. The Wald F test is derived from the first stage of the 2SLS regressions with Fish catch as the dependent variable. Fixed effects include year, dyad, and dyad time trends.

Table 8: Effect of the Value of Contested Oil on Conflict

	(1)	(2)	(3)	(4)
Price * Quantity	-0.000	-0.000	-0.002*	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Price	0.002*	0.002	0.028	-0.003
	(0.001)	(0.002)	(0.030)	(0.053)
Quantity	0.106**	0.041	+	+
	(0.048)	(0.035)		
Observations	510	485	510	485
R-squared	0.020	0.316	0.152	0.326
Controls	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
Adjusted R-squared	0.0138	0.299	0.0322	0.213
Number of dyid			15	15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses are all heteroskedasticity-consistent White standard errors (**?**). Fixed effects include dyad effects, time effects, and dyad time trends. The symbol "+" indicates the variable has been dropped due to multicolinearity with time variables. The Wald F test is derived from the first stage of the 2SLS regressions with Fish catch as the dependent variable. Fixed effects include year, dyad, and dyad time trends.

Figures

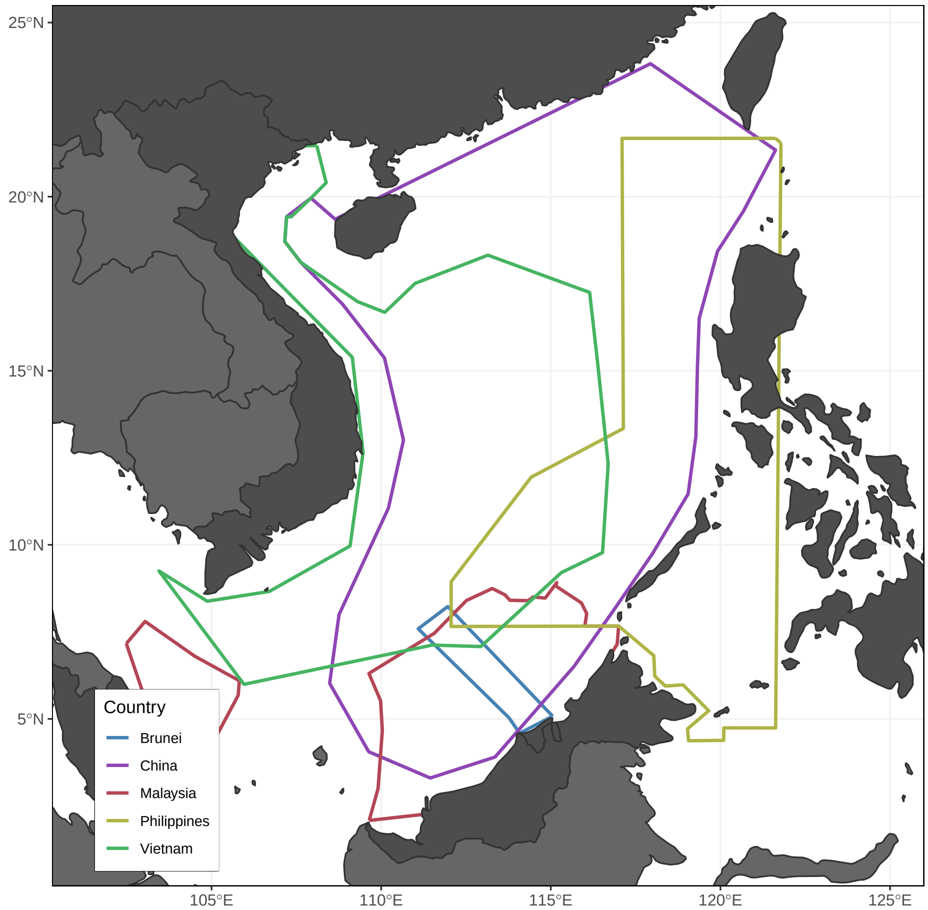


Figure 1: Geography of SCS Claims

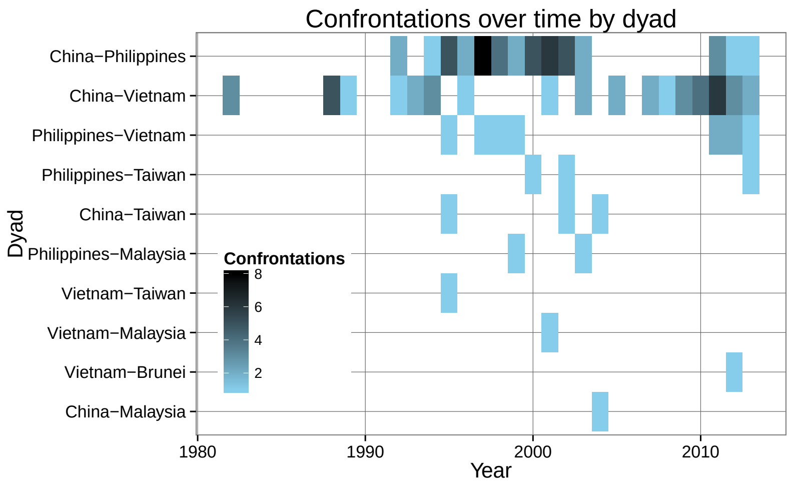
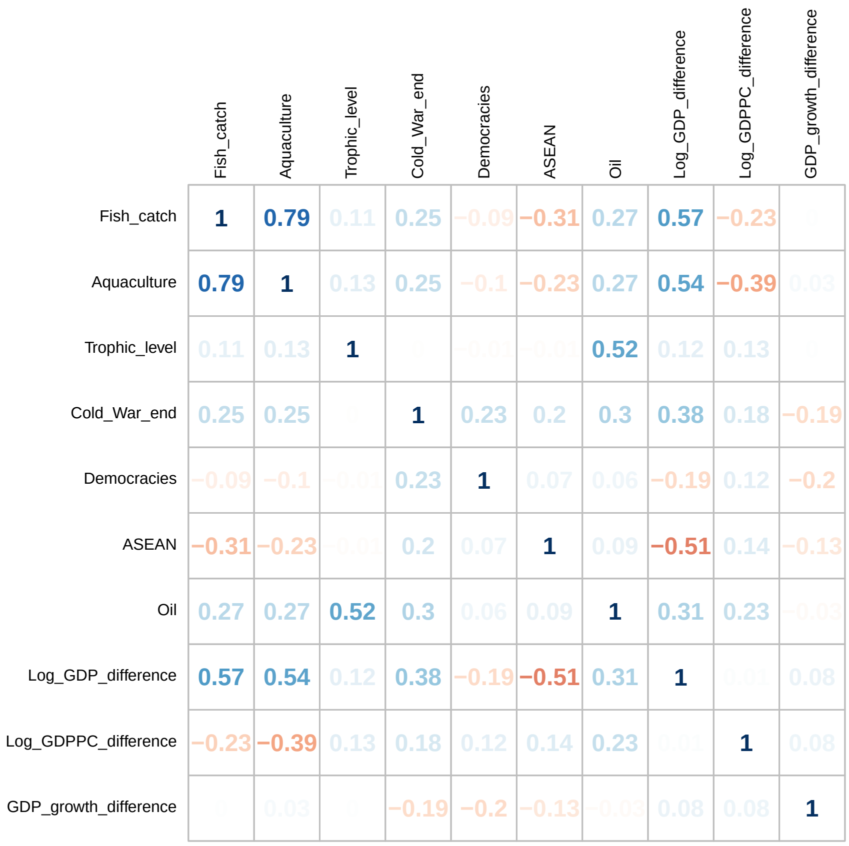


Figure 2: Confrontations over time by dyad

Figure 3: Correlation Matrix Between Covariates



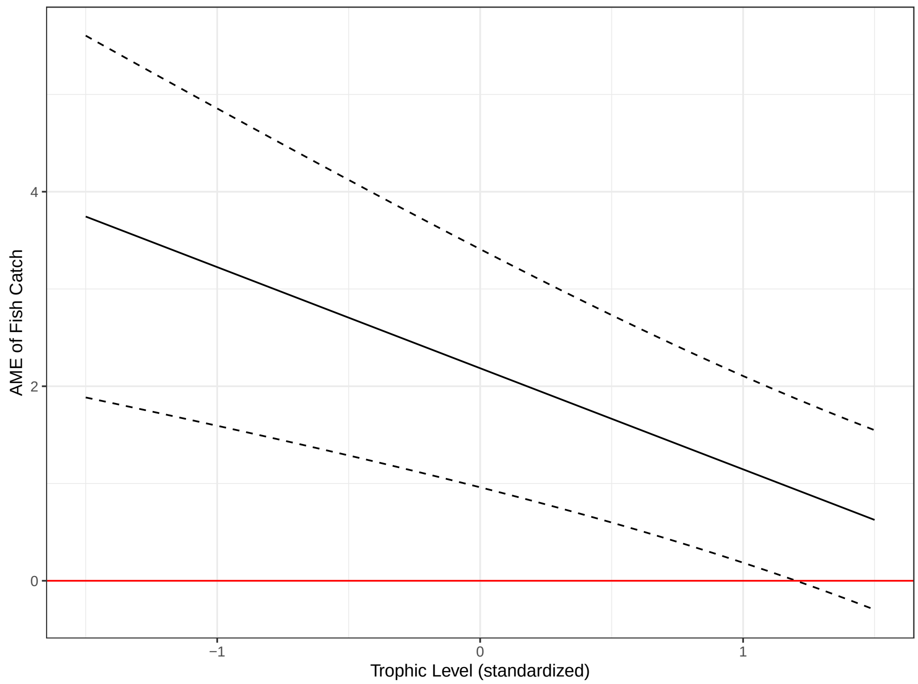


Figure 4: AME of Fish catch by Trophic Level

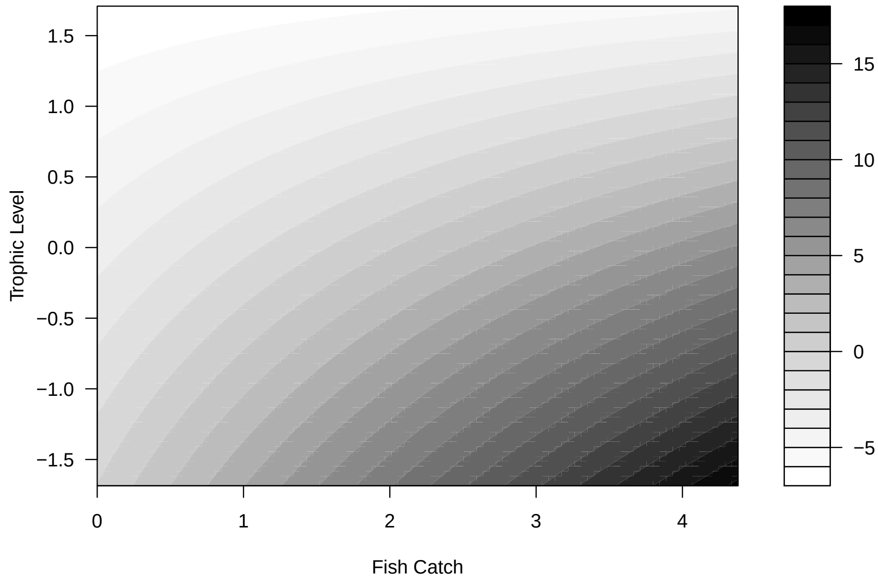


Figure 5: AME of Fish catch and Trophic level on Conflict

Figure 6: Robustness Checks