

Climate, Conflict, and Development Assistance

Estimates and Policy Recommendations

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Executive Summary

Overview

Global climate change is predicted to increase the number and severity of natural disasters and other severe weather events. Concern about how this change will affect the livelihoods, resources, and security of people, particularly those in developing and unstable nations, has led to a debate over the relationship between climate and the risk of conflict.

To date, a clear link between climatic events and conflict has not been found. Results have been highly sensitive to issues of data selection and model specifications. In this paper I estimate two new models in an attempt to clarify any climate conflict relationship that may exist

Data and Methods

First, I test a global climate-conflict-aid relationship using country-year observations of violent civil conflict, natural disasters, official development assistance, and humanitarian assistance. This model is similar to much of the existing literature, but includes additional controls for international aid and aid's interactive effects with disasters.

Second, using geocoded conflict, rainfall, and development project data from East Africa I examine local, rather than national, conflict behaviors. I test if proximity to aid projects is a contributing factor to conflict frequency in Ethiopia, Kenya, and Uganda. This approach complements the cross country analysis because rainfall variation is the primary factor in most natural disasters reported in East Africa.

Findings

Using a cross county dataset including country-year observations in both the presence and absence of conflict or disaster incidence, I found no evidence that the incidence of natural disasters is a significant predictor of the risk of violent civil conflict. This finding of its self was not necessarily surprising since both disasters and conflicts are rare events. Interestingly, I do find that post-disaster humanitarian assistance appears to reduce the probability of conflict. While the erogeneity of the humanitarian assistance data in this model is suspect, this link deserves further study.

Using a geocoded conflict dataset from East Africa comprised of subnational monthly observations of conflict incidence I found that extreme rainfall fluctuations lead to an increase in the number of conflict events in a given location. Extreme rainfall fluctuations are the primary cause of the most common natural disasters in East Africa, suggesting that country-year aggregation, using civil war incidence as a dependent variable, or the inclusion criteria from disasters may be hiding the link between climate and conflict.

Conclusion

I find that a link between climate and conflict is plausible and deserving of additional study. It appears that foreign aid influences this relationship, at least when delivered as humanitarian assistance, and may also instigate rent-seeking behavior on in the absence of climate variability. Policy makers should carefully consider these implications when planning future projects.

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Introduction

Concern about climate change has led many to speculate that changing weather patterns may contribute to an increase in violent conflict. Research testing this hypothesis generally uses historical data on either natural disasters or rainfall variation to test for the influence of climate on the onset of conflict. Floods and droughts are the most common natural disasters in regions that are vulnerable to conflict, so both methods are in essence testing different severities of rainfall shocks. To date, the results of this research have been inconclusive. Despite the inconclusive evidence, policy makers appear to have followed the popular narrative that climate change will create scarcity and scarcity will lead to an increase in conflict.

Policy in the United States has clearly been influenced by the assumption that natural disasters precipitate violent behavior. In the aftermath of hurricane Katrina armed military personnel patrolled New Orleans and media attention was focused on looting and crime committed by evacuees from the devastation. The reality is much more complex. While disasters may precipitate conflict, disasters often bring people together out of a shared necessity for survival. Anti-social behaviors may be greatly reduced, civic society is strengthened, and a “paradise built in hell” is often observed.

While disasters may bring citizens together, a reinvigorated civil society may use its strength to start or escalate conflicts when governance is not seen as legitimate. In Nicaragua, an earthquake led directly to a violent overthrow of the longest running dynastic dictatorship in the Americas. Disasters may also lead to peace. In Indonesia the 2004 Tsunami encouraged peace talks that led to the end of 30 years of violent conflict.

A notable omission from the existing literature is the influence of development assistance on the relationship between climate and conflict. The additional resources development projects bring to a community may have a significant influence on both the costs and benefits on organized violence. Aid dollars may be seen as a lucrative prize for combatants to capture, or they may lessen the resource scarcity that underlies most hypotheses about the relationship between climate and conflict.

How climatic shocks will affect a society will be highly dependent on the local context. Economic and social factors will likely play a much larger role in how and when conflict occurs. Yet, if climate change does increase the number of climatic shocks then improving our knowledge of what, if any, effect these shocks will have on conflict is necessary so that governments and aid organizations can respond appropriately.

In this paper, I examine the relationship between climate, conflict, and development assistance in two ways. First, I estimate a cross country regression model using the annual incidence of conflict, a count of declared natural disasters, and the amount of official development assistance a country received. Next, I use monthly data with geocoded rainfall variation, conflict locations,

and aid project locations in Ethiopia, Kenya, and Uganda to more precisely estimate the relationship.

Natural Disasters

The natural disaster data used in this paper comes from the Centre for Research on the Epidemiology of Disasters (CRED) Emergency Events Database (EM-DAT). The EM-DAT defines a disaster as a natural event where at least one of the following occurs: ten or more people are killed, one hundred people are affected, a state of emergency is declared, or calls for international assistance are made. Natural disasters can be biological, including epidemics and infestations; meteorological, including floods, storms, droughts, landslides, and avalanches; and geophysical, including earthquakes, tsunamis, and volcanic events.

Natural disasters as defined occur frequently, and their reported incidence has increased over time as shown in figure 1. Population growth and migration are responsible for the majority of the increased frequency; however it is likely that measurement error does influence the trend (CRED 2010). When disasters are restricted to large events, defined in relation to the world average of recorded damage, the trend is reduced as shown in figure 2 (Cavallo and Noy 2009).

Droughts, floods, and storms all will be observed through rainfall variation. While the disasters are the result of extreme variation, rainfall data is available at the community level while disaster data is only available at the country level. Therefore, in the sample from East Africa I use rainfall rather than disasters in the analysis.

Figure 1: Number of disasters is increasing

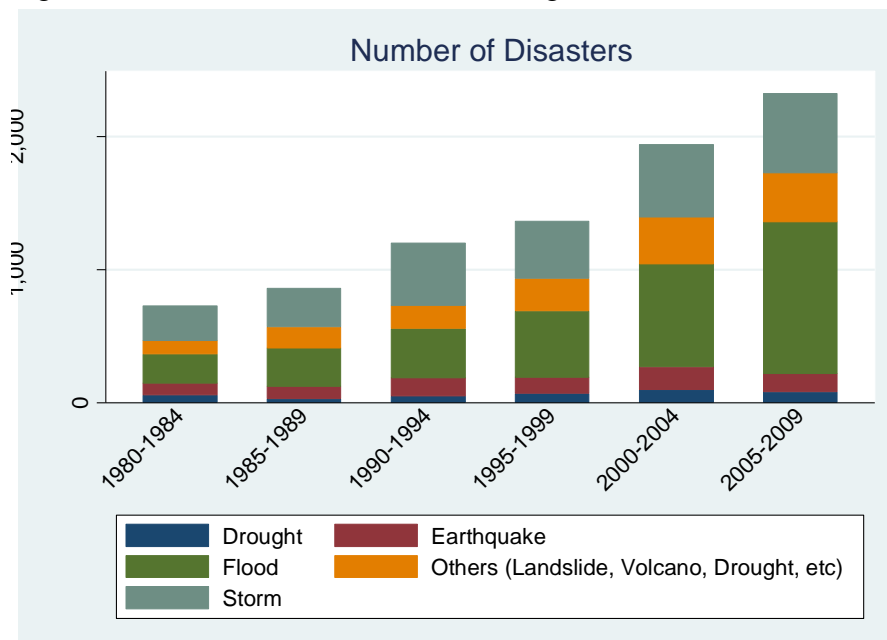


Figure 2: High death toll disasters are also increasing

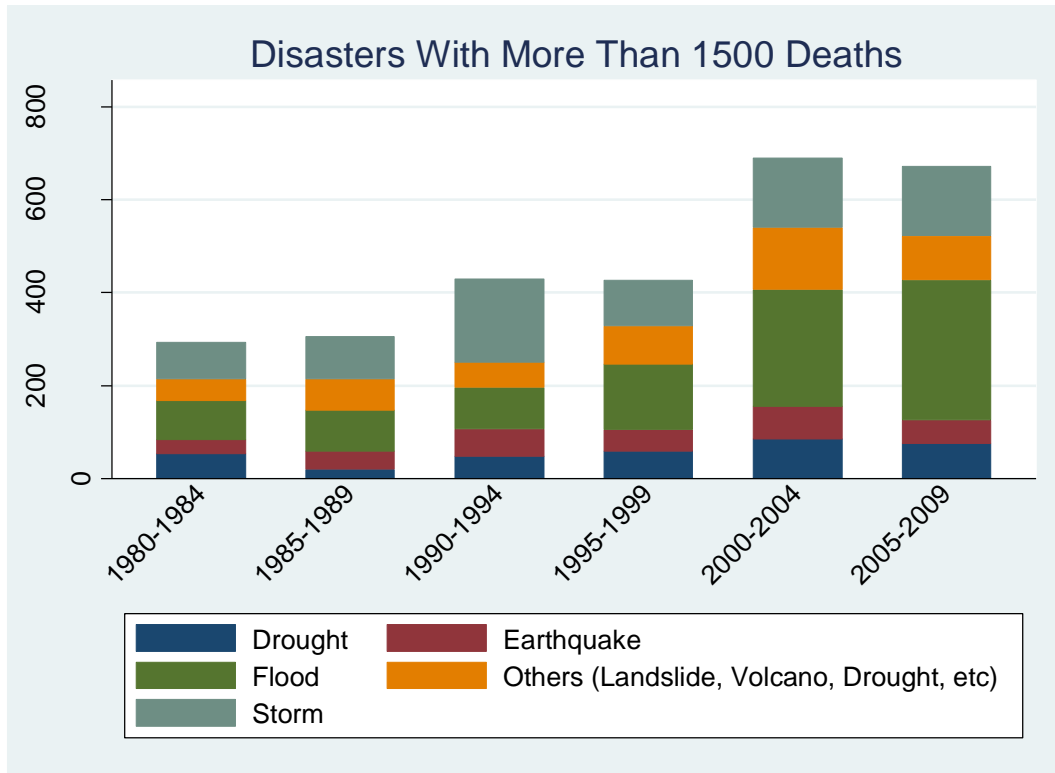
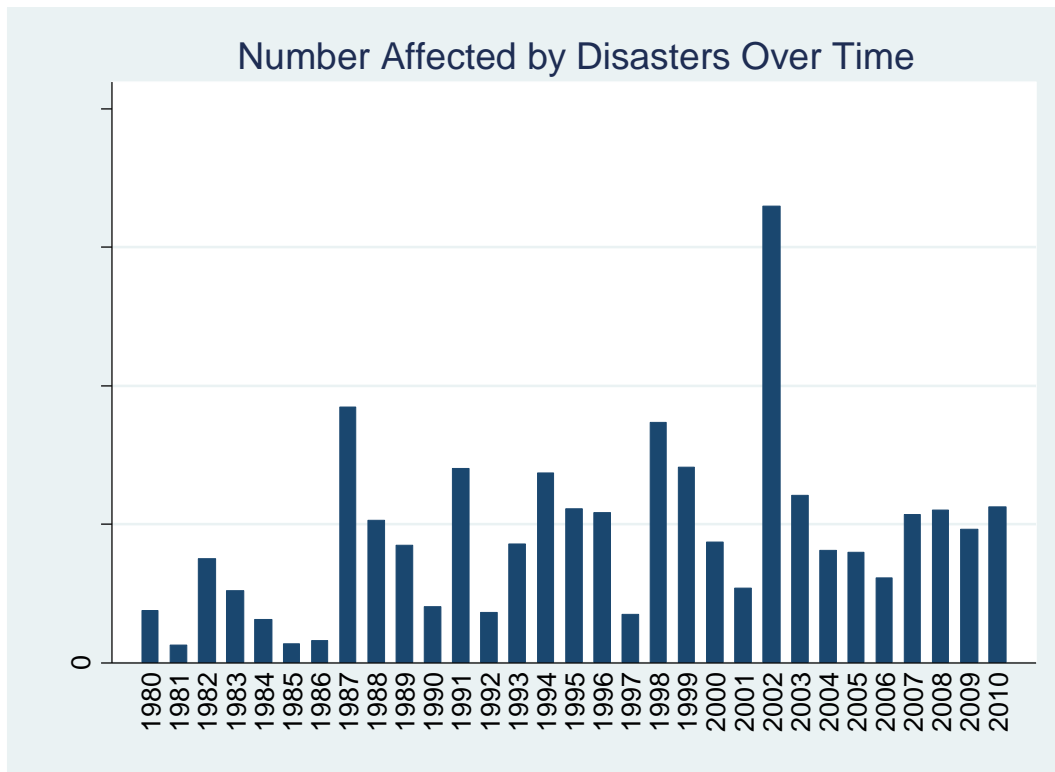


Figure 3: Number of people affected by disasters



Natural Disasters and Conflict

Large natural disasters undeniably cause widespread destruction and human suffering. A disaster can cause resource scarcity, weaken the state's ability to enforce the rule of law, and can make it difficult or impossible for large segments of the affected population to meet their basic needs for food, shelter, and sanitation. Both popular perception and several quantitative studies suggest that these conditions will lead to societal breakdown, making both anti-social behavior and outcomes such as violent civil conflict more likely in the aftermath of the disaster (Homer-Dixon 1999; Miguel, Satyanath et al. 2004; Nel and Righarts 2008).

Sociological research on natural disasters has found the opposite. Early research in this field, including Durkheim (1897) and Prince (1920) found that disturbances such as disasters and war found that traumatic events increase social integration. As a result anti-social behaviors are less likely due to the strong social structure in the affected communities. During the Cold War, the United States funded further research into the effect of disasters on populations in search of new military techniques that could be applied to nuclear warfare. The problem was two-fold, how would the American population react after a nuclear strike and how could the American military best destabilize an enemy population. Fritz (1961) expected that the events he was able to study, natural disasters and World War II bombing campaigns, would cause panic and the breakdown of society. Instead, after thousands of interviews it was apparent that in the United States, Germany, and Japan that people are concerned for the wellbeing of others and social cohesion increases (Disaster Research Group 1961).

Recent examples continue this trend, at least within developed western countries. Hurricane Katrina struck the Gulf Coast of the United States in 2005. The destruction wrought by the storm would make it one of the deadliest hurricanes to strike the United States and the costliest natural disaster in the country's history (Knabb, Rhome et al. 2005). As a result of the storm large numbers of New Orleans residents were displaced to other cities. Despite widespread claims in the popular media that the New Orleans diaspora was responsible for large increases in crime in communities such as Houston, San Antonio, and Phoenix time series analysis shows only modest changes in crime rates in these communities (Varano, Schafer et al. 2010; Settles and Lindsay 2011). Surveys of the New Orleans population most affected by the storm confirm that violence was not a major part of their experience either in New Orleans or once they had relocated (Brezina and Kaufman 2008).

Case Examples

Naturally, disasters are only one of many factors that can lead to conflict. Economic, political, and social factors all likely play a much larger role in determining when and where conflict events happen. Two widely cited examples of how disasters can lead to conflict are the 1972 earthquake in Nicaragua and the 1985 earthquake in Mexico.

1972 Managua Earthquake

In 1972 an earthquake in Managua Nicaragua devastated the capital city largely because the city had no effective building codes. Fires following the earthquake destroyed a much of the remaining infrastructure in the city. All told, it is estimated that the GDP of Nicaragua fell by 40% as a result of the event (Olson and Gawronski 2003).

Managua was previously devastated by an earthquake in 1931. When the dynastic dictatorship of the Somoza family came to power in 1937, they chose to concentrate their power in the capital city. Due to their influence Managua grew rapidly at the expense of other Nicaraguan cities (Woodward Jr and Worcester 1976). The Somozas built Nicaragua's economy around the export of agricultural goods. Large farms bought up fertile farmlands and the poor crowded in slums around the capital. Incomes were low, and infant mortality and illiteracy were high despite and constant influx of development aid pouring into the country due to the Somozas pro US stance (Woodward Jr and Worcester 1976; Walker 2000).

In the late 1960's the regime's power was based on their direct control of the National Guard and the cooperation of the domestic elite. The domestic elite were willing to live with the regime as long as it stayed out of the private sector (Cruz 2005). The late 1960s also marked what was thought to be the end of a protracted fight with the Sandinista Front for National Liberation (FSLN) whose numbers were greatly diminished.

After the Managua earthquake in December of 1972 Somoza lost the support of the elite and it became clear the regime would not last much longer. Over \$100 million dollars in relief funds flowed into the country, but the rubble from the city center was never removed until after the Somoza regime fell in 1979 (Anderson 1988). Rather than spend the money on actually rebuilding, Somoza forced his way into the construction industry. Debris removal and construction contracts were used to enrich himself and his cronies (Walker 2000). Somoza's behavior lost him the support of the elites and the dissident press immediately began to criticize his behavior.

Opposition to the regime grew rapidly throughout 1973. Opposition parties and labor unions appeared, but were barred from participating in formal politics (Woodward Jr and Worcester 1976). The FSLN capitalized on this time to reorganize and in a coalition with other community groups successfully carried out a violent campaign to oust the regime.

Several factors were in place in Nicaragua in 1972 that allowed the earthquake to serve as a tipping point for the start of a conflict. Oppressive politics, a history of conflict, misappropriation of relief funds, and massive suffering all spurred the rejection of Somoza. Many of these conditions had existed for years, but there is widespread agreement among historians that the mismanagement of the disaster led to the regimes ultimate demise (Woodward Jr and Worcester 1976; Anderson 1988; Walker 2000; Olson and Gawronski 2003).

Anastasio Somoza used the earthquake as an excuse to tighten political controls and to funnel aid money to his associates through government involvement in the demolition, concrete, and construction industries (Woodward Jr and Worcester 1976). Hundreds of millions of dollars flowed into the country and then were moved back out into overseas accounts. Almost no rebuilding occurred in the devastated city center, with the Somoza and his cronies developing land outside of the city center. This alienated powerful forces within Nicaragua including the Catholic Church, the domestic elite who were shut out of lucrative rebuilding contracts, and the middle classes whose businesses were not rebuilt (Olson and Gawronski 2003). As these groups moved away from supporting the regime they began to ally with the Sandinistas, the only viable opposition group.

1985 Mexico City Earthquake

The aftermath of the Mexico City earthquake in 1985 is a great example of sociologists' view that disasters lead to stronger communities. The ruling Institutional Revolutionary Party (PRI) had been in power since 1929 and had overseen four decades of growth but was widely considered to be corrupt (Crandall 2004). After the 1968 massacre of student protestors in Tlaltelolco plaza the PRI lost much of their legitimacy. Resentments lingered under the surface until the earthquake in 1985 which led to the reshaping of Mexican politics (Solnit 2009).

Much of the damage from the quake occurred on the South side of Zocalo, a poor section of the city. In other parts of Mexico City large apartment buildings, the central telephone exchange, and several government ministries collapsed. In the aftermath of the quake the government assisted only minimally in rescue and reconstruction efforts. The collapse of the buildings revealed the shortcomings of the party, corruption, lax enforcement of building codes, and tortured bodies in the basement of a government ministry. The public trust in the PRI was lost.

Throughout the recovery President de la Madrid focused on macroeconomic issues rather the relief efforts. At the same time aid money was being siphoned off and lost to corruption. Citizens organized, unionized, and fought for improved housing rights as hundreds of thousands camped in front of their damaged homes.

By 1986 it was clear that political change was inevitable. Cuauhtémoc Cardenas, the son of a popular former president, broke from the party and ran as an opposition candidate in the 1988 Presidential election. Evidence suggests that he won the election, but the PRI claimed the vote counting system had crashed and announced their candidate had won a few days later. The PRI continued to lose popular support and in 1994 the first non-party candidate to win the Presidency was elected.

Lessons from Cases

Managua and Mexico City both illustrate the political nature of nature disasters. In Managua the outcome was a civil war that unseated a dictator. In Mexico City the earthquake helped create an organized opposition and led to the election of opposition president in 1994. In both cases

underlying social and political factors for change already existed, but the disasters created a political opportunity to expose the extent of corruption of the incumbent regime and to galvanize the population to organize and take action. Common factors in both cases included: political structures, corruption, misuse of aid money, and economic reforms. Clearly any model attempting to causally link disasters with conflict must account for their influences.

Empirical Literature Review

A growing literature has established an empirical link between large natural disasters and the initiation of violent civil conflict. It is generally assumed that one of two causal stories underlies this relationship. In the first story, the disaster shocks the system awakening public dissatisfaction with the government and makes conflict preferable to living under the current regime. This usually supposes an inadequate response to the populations' needs and a government that either lacks the resources to respond appropriately or misallocates the resources. In the second story, conflict arises because rebel groups recognize the potential the capture income from the recovery efforts. If the groups are not adequately paid off then they may initiate violent conflict to try to capture these resources.

Disasters and Conflict

Drury and Olson (1998) were some of the first to empirically study the relationship between natural disasters and the risk of conflict. Using a sample of 12 countries that experienced at least one disaster that killed 1,500 or more people they find that natural disasters increase the risk of political unrest. Their model presumes that prior political unrest, Gross Domestic Product (GDP) per capita, income inequality, and aid contribute to the relationship between disasters and conflict. Their outcome measure of political unrest aggregates the annual number of demonstrations, riots, armed attacks, and strikes each year.

The Drury and Olson (1998) paper paved the way for several works on disasters and conflict. However their findings are questionable for both their limited sample, a lack of important controls, and their method of modeling the decay rate of the number killed by a disaster (Slettebak 2012).

Brancati (2007) argues that earthquakes are more likely than other types of disasters to lead to conflict because they occur rapidly and unpredictably. She finds that earthquakes are related to an increase in the risk of violent conflict. While Brancati only tests earthquakes; the mechanism linking earthquakes to conflict should work similarly for climatic disasters that occur rapidly such as tsunamis. She argues that earthquakes stimulate conflict by creating scarcity for basic resources in low income countries. While this method is plausible, the cases above demonstrate that a multitude of factors can contribute to linkage between disasters and conflict. Another potential weakness of Brancati's treatment is that she uses the incidence of conflict as her dependent variable rather the outbreak of conflict. In my opinion and that of Slettebak (2012) the outbreak of conflict seems to be the better choice because it eliminates the possible that pre-

existing conflict would continue regardless of the disaster. Slettebak's replication of the study shows that Brancati's findings do not hold for the onset of conflict.

Nel and Righarts (2008) find a positive relationship between natural disasters and the onset of violent conflict. This finding holds when conflicts are divided into major (more than 1,000 killed) and minor (fewer than 1,000) killed. Their study differs from Drury and Olson (1998) in several ways. First, their sample includes 183 political units between 1950 and 2000. Second, they use the number of disasters per capita for each country-year rather than the number of people killed by disasters. The problem with this approach is that disasters affecting large populations should not have their weight reduced and that larger countries are more likely to experience more disasters and more conflicts (Slettebak 2012).

Slettebak (2012) focuses exclusively on climate related natural disasters – storms, floods and droughts – and their effect on civil war. This finding is based on an expansion of the conflict model developed by Fearon and Laitin (2003) to include climate related disasters and their interaction with population size. Interestingly, using this more robust model Slettebak finds that experiencing at least one climate related disaster is reduces the risk of violent civil conflict. Counts of disasters were not significant in her models, and she elected to not use the number of people affected or killed due to concerns that missing data may have been non-random.

Finally, Berrebi and Ostwald (2011) find a strong relationship between deaths caused by natural disasters and subsequent deaths in terrorist attacks, further establishing the link between disasters and political instability.

Aid and Conflict

Depending on how it is allocated, foreign aid may increase or decrease the expected cost-benefit ratio of conflict. Several works have examined the relationship between foreign aid and civil war (Uvin 1999; de Ree and Nillesen 2009; Polman 2010; Nielsen, Findley et al. 2011). These works operate under one of two common hypotheses. One side believes that foreign aid increases the benefits of rebellion (Grossman 1991; Azam 1995). While governments may be able to pay off potential combatants using a portion of the aid, war offers rebel groups the ability to control all of the aid. Others believe that aid can prevent civil war by increasing government capacity (Collier, Hoeffler et al. 2009; de Ree and Nillesen 2009).

Uvin (1999) argues that development aid contributes to social inequality which can fuel conflict. Using a case study of Rwanda in the 1990s he finds that development aid was focused solely on economic aspects of development. Human rights violations, income inequality, and discrimination were overlooked by the aid system. Ignoring these issues allowed for elites to capture the benefits of aid fueling the inequalities that led to the conflict.

De Ree and Nillesen (2009) examine the effect of aid flows on violent civil conflict in Sub-Saharan Africa using an instrumental variables approach. Using GDP levels of donor countries as an instrument for aid, they find that foreign aid flows decrease the probability that a civil conflict will continue and that increasing aid flows tends to decrease the duration of conflict. However, they do not find a relationship between aid flows and the start of conflict.

Aid inflows are generally more volatile as a percentage of GDP than sources of domestic revenue (Eifert and Gelb 2005; Bulir and Hamann 2008). The volatility of aid is of particular concern because sudden decreases in aid have been shown to increase the risk of violent civil conflict (Nielsen, Findley et al. 2011). These negative aid shocks may increase the chance of conflict by decreasing the ability of the government to pay of rebels or resulting in cuts to military spending.

Empirical Overview

I use two datasets to test the relationship between conflict, climate, and development assistance. My first dataset is assembled from several sources and contains country-year observations from 1980 through 2010 on the incidence of violent civil conflict, the incidence of natural disasters, the number of people killed by each disaster, total foreign aid pledges, measures of political stability, and GDP per capita for all UN member states where data is available. This results in a total of approximately 5480 country-month observations, 5,109 natural disasters of varying severity, and the onset of 144 new violent civil conflicts.

My second data set contains 3447 observations of conflict locations, development project locations, and rainfall variation for Ethiopia, Kenya, and Uganda for the years 1998 to 2009.

Cross Country Analysis

Using the cross country dataset, I attempt to identify whether an exogenous inflow of aid after a natural disaster mitigates the association of natural disasters with violent civil conflict. I model the mitigating effects of aid on conflict similarly to how Collier and Goderis (2009) estimate the mitigating effects of aid on GDP growth after and export price shock. The first equation I will estimate is:

$$Y_{it} = \beta_0 + \beta_1 A_{it} + \beta_2 D_{it} + \beta_3 A_{it} D_{it} + \beta_4 C_{it} + T + e_{it} \quad (1)$$

where Y_{it} is a dummy variable equal to one if a civil conflict occurs in country i and time t . A_{it} is the value of international aid for county i in time t , D_{it} is the number of natural disasters which occurred in country i in time t , C_{it} is a vector of country characteristics containing political indicators and GDP per capita, T is a linear time trend, and e_{it} is an error term that is clustered by country

The equation is estimated by ordinary least squares (OLS) regression and the interaction coefficient (β_3) estimates the effect of the amount of aid a country receives on the incidence of conflict in the same period as a disaster. For equation (1) to produce an accurate estimate the amount of aid a country receives must be exogenous to conflict. While there is little evidence that donors can accurately predict conflicts, they still may react to unobserved factors that contribute to conflicts which would bias the OLS estimate (Jenkins and Bond 2001).

Ideally, I would be able to randomize the amount of aid received by disaster affected communities to test the null hypothesis that violent civil conflict does not respond to the level of aid after a disaster. A rejection of this hypothesis would establish proof that aid mitigates the relationship between disasters and violent civil conflict. Conducting such an experiment is not feasible and would raise significant legal and practical concerns.

A second best option would be to use an instrumental variable (IV) which is correlated with the level of aid, only affects the incidence of violent civil conflict through its effect on aid, and will be uncorrelated with the error term in equation (1). IVs for aid are commonly used in the literature on the effect of aid on GDP growth (Bahar 2009; Collier, Hoeffler et al. 2009; Nielsen, Findley et al. 2011). A sample of commonly used instruments in this literature includes: natural disasters in neighboring countries, aid recipient membership in the United Nations (UN) Security Council, fluctuations in the GDPs of aid donors, and voting similarity in the UN.

As my analysis seeks to identify the interactive effects of aid on conflict, multiple instruments would be necessary. I tested several potential instruments, based on the assumption that donor countries have a relatively fixed budget constraint for humanitarian aid. Therefore, the total number of natural disasters each year should predict the amount of humanitarian assistance available to recipients.

Ultimately, I was unable to identify enough suitable instruments for this analysis. Therefore, I rely on simply OLS models to estimate the cross country analyses. Because aid flows are unlikely to be fully endogenous, I can observe correlations of disasters, aid, and conflict but I am unable to make causal claims.

Delayed Effects

A delay of several months may exist between the shock of a disaster and the beginning of a violent civil conflict. A disaster affected population needs time to move into refugee camps, organize, and revolt before a conflict would be observed (Bueno de Mesquita 2011).

The delayed effects of disasters may pose a problem for equation (1). The model assumes that the impacts of natural disasters and the potential mitigating effects of aid would happen in the same year as the disaster. Because only annual data is available, I compensated for the possibility of a disaster in December causing a conflict in the following year by using lagged variables in some estimates of the relationship.

My previous equations use the total amount of aid received by the country in the period in which a disaster occurs. However, the more salient effect may be the change in aid that represents the international community's response to the disaster. Increases in aid may change the incentives to go war for both the government and potential combatants.

To account for the change in aid I add two additional regressors to equation 1:

$$Y_{it*} = \beta_0 + \beta_1 A_{it} + \beta_3 \Delta A_{it} + \beta_4 D_{it} + \beta_5 A_{it} D_{it} + \beta_7 \Delta A_{it} D_{it} + \beta_8 C_{it} + T + e_{it} \quad (2)$$

where ΔA_{it} is the first difference of aid and $\Delta A_{it} D_{it}$ is the interaction of this term with natural disaster incidence. The coefficients on the interaction terms are the effects of the level of aid in a country that experiences a disaster on conflict and the effect of a change in aid during the month a country experiences a disaster on conflict.

Data Sources

Dependent Variable

I use data on civil conflict from the UCDP/PRIO Armed Conflict Dataset (GLEDITSCH, WALLENSTEEN et al. 2002). A civil conflict is coded as active if 25 or more battle deaths occur in politically motivated fighting between the state and another party. The original data contains yearly observations while the conflict is active, and all of these observations contain the approximate start date of the conflict. In my primary model I do not include ensuing years of ongoing conflict and I have coded resumption of conflicts after two or more years of peace as a new conflict. I will check the robustness of assuming a gap of two years indicates a new conflict by also running regressions where I consider conflicts independent after six months, one year, and five years.

Variables of interest

International aid data comes from the OECD. This dataset includes all commitments by OECD countries and breaks total foreign aid down into several categories. In my analysis I use total foreign assistance, which includes all types of foreign aid, and humanitarian assistance, which is defined much more narrowly as a short term response to disasters.

Natural disaster incidence data comes from the Centre for Research on the Epidemiology of Disasters (CRED) Emergency Events Database (EM-DAT). An event is reported as a disaster if any of the following occur: ten or more people are killed, one hundred people are affected, a state of emergency is declared, or calls for international assistance are made. CRED further separates disasters into the following categories: natural, biological, climatological, complex, geophysical, hydrological, meteorological, and technological. Data from CRED is collapsed to the country-year level to create an indicator variable equal to '1' if a disaster was experienced by a country in a given year and a count of the total number of disasters the country experienced

that year. Data on estimated damages is also available and has been used extensively in previous research. I believe relying on estimated death tolls and economic damages introduces too much measurement error to be useful. However, these measures could be useful to segregate disasters into categories based on their severity.

Controls

My controls are inspired by Fearon and Laitin (2003) and include per capita GDP, measures of political stability, democratization, and population size.

Results

Table 1 contains summary statistics from the cross country data for the years 1995 to 2007. Reliable data on most variables is available from the 1980s to the present, but separate records for humanitarian aid were not kept until 1995. A total of 61 new conflicts, defined as the resumption of violence after at least one year of peace, are observed during the 13 year period. A minimum of two new conflicts were observed each year and a maximum of eight new conflicts were observed in 1997. The sample mean is 4.7 new conflicts per year. Approximately 3% of the country year observations mark the start of a new conflict.

Natural disasters were much more common than conflict in the sample. A total of 3016 disasters were observed that met the standards for inclusion in the EM-DAT database, for an average of 232 per year. I considered restricting these results based on the number of people killed or affected by each disaster, but these figures are subject to significant measurement error and are biased by the level of development and government responsiveness in the affected country.

Both official development assistance (ODA) and humanitarian aid increased sharply during the sample period. ODA averaged \$33.2 billion to the recipient countries included in the sample. The total amount of ODA in the sample doubled from \$25.2 billion in 1995 to \$51.8 billion in 2007. Humanitarian aid nearly tripled during the same time period from \$1.6 billion in 1995 to \$4.5 billion in 2007.

The results of my cross country regression models are found in table 2. All 5 models are estimated as linear probability models (LPM), and therefore the coefficients on individual terms represent the change in the probability of the onset of violent civil conflict.¹ It is important to note that these findings are not causal, as donors' perceptions of the probability of conflict are likely to influence ODA and annual data aggregation makes separating humanitarian aid intended for disaster relief from that intended for relief of concurrent conflicts impossible. These findings should be treated as correlations, and will be used to inform the more detailed models from East Africa later in this paper.

¹ Logit models were also estimated with similar results. The LPM results are included here for ease of interpretation.

Table 1: Summary Statistics - Cross Country Sample

Year	New Conflict Onset	% Observations in Conflict	Natural Disasters	ODA (millions)	Humanitarian Aid (millions)
1995	2	0.012	183	\$25,239.38	\$1,592.23
1996	6	0.037	148	\$25,183.29	\$1,540.24
1997	8	0.049	200	\$20,284.54	\$1,149.01
1998	4	0.024	165	\$21,033.86	\$1,130.83
1999	4	0.024	210	\$21,076.77	\$1,719.12
2000	5	0.030	272	\$20,379.04	\$1,066.48
2001	4	0.024	246	\$22,329.88	\$1,652.61
2002	3	0.018	290	\$26,075.51	\$2,198.08
2003	3	0.018	212	\$36,311.27	\$3,623.68
2004	6	0.037	245	\$39,725.03	\$3,982.67
2005	6	0.037	307	\$63,602.91	\$5,556.28
2006	4	0.024	247	\$58,310.47	\$4,686.20
2007	6	0.037	291	\$51,812.16	\$4,505.76

In model 1 there is a marginally significant correlation between natural disaster incidence and the outbreak of violent conflict. Each natural disaster is associated with a 0.5% increase in the probability of conflict onset. This finding is not robust to the addition of country fixed effects and a linear time trend in model 2. In both models the lagged number of natural disasters is not significant predictor of conflict.

Model 3 adds annual amount of ODA and humanitarian aid received each year. While neither is significant, ODA has a negative coefficient indicating that this type of aid may be directed to more stable regimes. In contrast, humanitarian assistance has a positive coefficient as expected due to the inability to separate conflict assistance from disaster assistance using this data.

Model 4 introduces interactions between both assistance types and the number of natural disasters. All coefficients in the model, with the exception for the humanitarian aid interaction term, remain insignificant and of the same direction and magnitude as in model 3. The interaction of humanitarian assistance with natural disaster incidence is negative and significant at the 5% level. Contrasted with the positive, but insignificant, coefficient on humanitarian aid this may indicate that disaster relief is associated with a reduced risk of conflict. Model 5 adds additional controls for population, gdp per capita, regime type, and previous instability. The additional controls add little explanatory power to the model ($R^2=0.152$ v $R^2=0.142$) and result in the loss of 194 observations where data were not available. In model 5, the interaction of humanitarian aid and disaster incidence is again significant, with the same direction and magnitude as in model 4.

Table 2: Cross Country LPM Estimates

	(1)	(2)	(3)	(4)	(5)
	Conflict Onset	Conflict Onset	Conflict Onset	Conflict Onset	Conflict Onset
# Natural Disasters	0.00480*	0.00364	0.00346	0.00410	0.00222
	(0.00286)	(0.00406)	(0.00409)	(0.00367)	(0.00465)
Lagged # Natural Disasters	3.42e-05	-0.00428	-0.00434	-0.00368	-0.00358
	(0.00185)	(0.00376)	(0.00377)	(0.00378)	(0.00388)
Total ODA			-4.22e-06	-9.57e-06	-3.82e-05
			(4.31e-06)	(6.03e-06)	(2.95e-05)
Total Humanitarian Aid			0.000135	0.000300	0.000217
			(0.000141)	(0.000194)	(0.000144)
ODA x Disaster Interaction				4.56e-06	1.06e-05
				(4.68e-06)	(1.17e-05)
Humanitarian Aid x Disaster Interaction				-6.85e-05**	-7.03e-05**
				(3.47e-05)	(3.58e-05)
Log GDP per capita					0.0596
					(0.0443)
Log Population					-0.0577
					(0.101)
Previous Instability					-0.0396*
					(0.0209)
Regime Type					-0.00670
					(0.0263)
Country Fixed Effects	No	Yes	Yes	Yes	Yes
Time Trend	No	Yes	Yes	Yes	Yes
Constant	0.0232***	0.390	0.959	1.007	2.898
	(0.00453)	(2.785)	(2.747)	(2.755)	(5.998)
Observations	1,544	1,544	1,544	1,544	1,350
R-squared	0.006	0.136	0.138	0.142	0.152

Robust standard errors in parentheses

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

Discussion

The results of models 4 and 5 suggest that humanitarian assistance provided after a natural disaster may reduce the chance of violent civil conflicts. If the humanitarian assistance measured here is exogenous then these findings suggest \$1 million in humanitarian aid after a natural disaster results in a 0.01% reduction in the risk of conflict.

It is unlikely that this aid is truly exogenous, and as such we can only claim to have observed a correlation between a decreased probability of conflict and disaster relief aid. While donors are unlikely to be able to accurately predict all future conflicts, they sure have assumptions and use aid money to try and influence the results. Using annually aggregated data it is unlikely that the climate conflict relationship can be explored any further. This result adds to the existing literature by exposing that humanitarian aid may influence the hypothesized relationship between climate change, disaster incidence, and violent civil conflict.

My results are in partial agreement with the hypothesis that resource constraints lead to conflict. Post disaster humanitarian aid should provide the needed capability for the state to meet citizen needs, thus reducing the risk of conflict. ODA does not follow this relationship, but many ODA projects fund infrastructure and other large scale projects which would not be related to the post disaster needs of the average citizen. My findings also provide some evidence that the extra resources provided by aid do not provide an incentive for conflict. It has been hypothesized that development aid makes more resources available for actors to capture through conflict, and thus would be positively correlated with conflict incidence. In my three models which include ODA totals all the coefficients are negative, albeit insignificant, which does not indicate that capturing ODA is a driver of conflict.

These results provide an interesting starting point for further investigation of how any hypothesized effects of climate change on conflict could be mitigated through aid spending in the future. In the next section, I build on this result using more granular data from East Africa to examine the relationship in more detail.

East Africa Data

Using data from Ethiopia, Kenya, and Uganda I am able to examine the relationship between climate shocks, conflict, and development assistance in more detail. I use data on conflict locations, rainfall fluctuation, and aid project locations and spending to examine how climate change and development assistance affect local conflict. This analysis differs from the previous section in three key ways.

First, this analysis uses only locations where conflict has occurred. In the cross country regressions I tested if the frequency of natural disasters and international aid were associated with the onset of conflict. Here I perform a more restricted test to see if changes in rainfall patterns and development projects influence the frequency of conflict events. This sample was selected because conflict is widespread, and ample variation in conflict levels exists to accurately test environmental influences on conflict frequency. I do this for two reasons. First, associating a level of rainfall with a likelihood of conflict does not make intuitive sense. Disasters are rare events whereas rainfall fluctuations are part of daily life in East Africa. Second, precise measurements of local fluctuations in rainfall are available while data on the areas affected by natural disasters is far less precise.

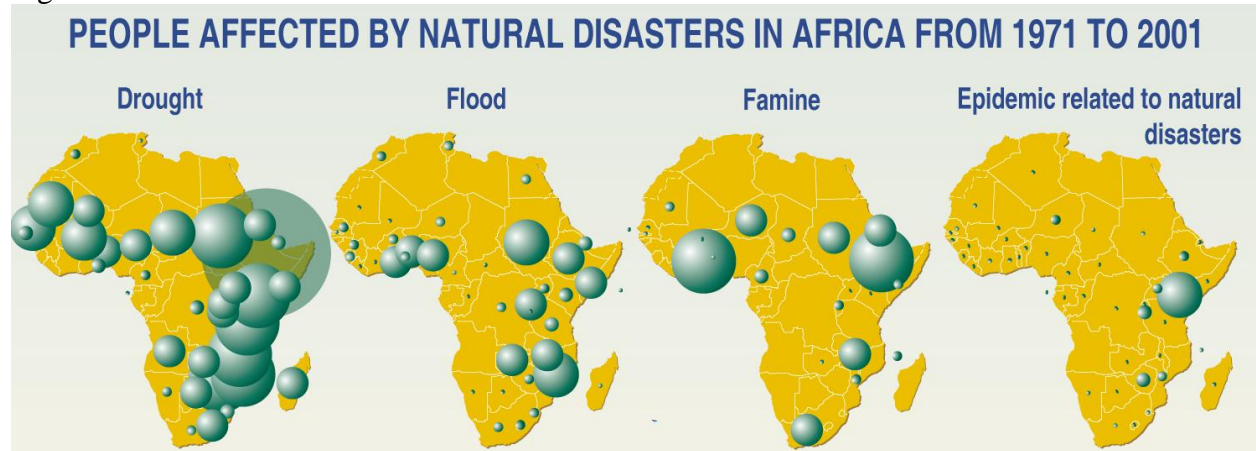
Second, this data includes smaller scale conflict events than those observed in the data used for the cross country analysis. For the previous analysis I used data on violent civil conflict, where conflict is defined as 25 or more battle deaths in fighting between rebel forces and the state. The East Africa data includes data on civil conflict by recording incidents of fighting between established rebel groups and the state. This sample also includes data on communal violence, which is likely to differ in intensity and motivating factors from rebel violence. In communal violence both combatants are civilians and the conflict is generally over local territory or

resources. Communal violence occurs frequently between different ethnic or religious groups throughout this sample.

Third, by using geocoded conflict, rainfall, and development project data inferences can be made about local, rather than national, behaviors. I use this data to determine if proximity to aid projects is a contributing factor to conflict frequency. This approach is different from the previous section both because geocoded information was not available in the cross country dataset and because information on humanitarian aid is not available here. The aid projects used for this analysis are development projects financed by the World Bank. The sample includes energy, health, public administration, transportation, and water and sanitation interventions.

This approach complements the cross country approach in the previous section because rainfall variation is the primary factor in most natural disasters reported in East Africa. As seen in figure 4, droughts and floods are the two primary natural disaster types in Africa. Both of these disasters are the direct result of extreme rainfall fluctuations.

Figure 4: Natural Disasters in Africa



Source: The Office of US Foreign Disaster Assistance (OFDA)

To identify the relationship between rainfall variation, conflict, and development assistance I estimate:

$$Y_{mlt} = \beta_0 + \beta_1 R_{ml} + \beta_2 N_{ml} + \beta_3 A_{ml} + \beta_4 X_{ml} + FE_l + e \quad (3)$$

using a negative binomial count regression. Where Y_{mlt} is the number of conflict incidents of type t in month m at location l , R_{ml} is a measure of positive (negative) rainfall variation, N_{ml} is a dummy representing no change in rainfall, A_{ml} is a vector of aid project distances and values, X_{ml} is a vector of controls including poverty measure, distance to the border, distance to urban areas, and conflict in the previous month and year, and FE are country fixed effects. The equation will also be estimated using lagged rainfall dummies for the previous 2 months.

Data Sources

Dependent Variable

Conflict data comes from the Armed Conflict Location and Event dataset (ACLED). The data codes the date, location, and type of conflict for the years 1997 to 2010. For this analysis, data from Ethiopia, Uganda, and Kenya for the years 1997 to 2009 are used. Annual summaries of the number of conflict events can be found in table 3.

Table 3: Conflict and Rainfall Variation

Year	Conflict Incidents	% Positive Rainfall	% Negative Rainfall
1998	506	0.17	0.39
1999	467	0.11	0.36
2000	555	0.10	0.31
2001	294	0.17	0.18
2002	880	0.25	0.13
2003	774	0.17	0.20
2004	169	0.18	0.08
2005	206	0.12	0.27
2006	156	0.30	0.05
2007	380	0.13	0.19
2008	480	0.22	0.32
2009	91	0.03	0.21

Variables of interest

Rainfall data from the National Oceanic Atmospheric Agency (NOAA) are used for this analysis. The merged analysis of precipitation (CMAP) data uses data from rain gauges and satellite estimates to collect global rainfall data. Rainfall averages for each month from 1997 to 2009 were calculated and matched with conflict locations from the ACLED data.

Aid project data is collected from the World Bank Mapping for Results program. Project locations, costs, sectors, start and end dates from the years 1998 to 2009 are used for this analysis. Using a geospatial add in for STATA 12 information about the closest aid project and all aid projects in a 10, 50, and 100 km radius of the conflict sites were calculated. The cost of the closest aid project, the distance of the project from the aid site, and the total number of projects and total costs of projects in a given radius were then used in the analysis. Table 4 summarizes the aid project data.

Controls

Control data was unfortunately not available at the same level of disaggregation as the conflict and rainfall data. Using replication data from Raleigh and Kniveton (2012) controls including measures of population, the percentage of children under five who are underweight (as a proxy

for poverty), and the distance to the nearest urban center were assembled for the analysis. The Gridded Population of the World version 3 was the original source of this data (CIESIN).

Results

Table 5 presents results of the positive rainfall shock model, estimated without lagged rainfall dummies. Wetter months are more likely to experience conflict events. The effect is highly significant for both rebel and communal violence, although much larger for rebel conflict events.

The distance to the closest aid project was not a significant predictor of the number of conflict events. However, the amount of aid project spending in the area had a positive and significant effect on the number of communal conflict events in the area. This effect was largest for closer projects, as shown by the decline in the coefficient as the radius of included projects increases from 10 to 100 km. The number of aid projects within the same radius was insignificant at 10km, significantly negative at 50km for communal conflicts, and significantly negative for both communal and rebel conflicts at 100km.

Of the controls poverty and conflict in the previous month were both significant predictors of communal conflict frequency. No controls were significant in the rebel models,

Interactions between the number of aid projects and rainfall shocks and the cost of aid projects and rainfall shocks were also estimated. In both cases the results were not statistically significant and are not reported here. Negative and lagged rainfall shocks were also modeled and the results are reported in the appendix. The overall pattern remained the same for negative shocks and the lagged models as it does for the positive shocks in table 5.

Table 4: Aid projects by distance from conflict site

Year	10 km radius			50 km radius			100 km radius		
	Mean \$ Closest Aid Project	Aid Projects in Radius	Mean Aid in Radius	Mean \$ Closest Aid Project	Aid Projects in Radius	Mean Aid in Radius	Mean \$ Closest Aid Project	Aid Projects in Radius	Mean Aid in Radius
1998	4.00	15	1327.00	9.59	175	5308.00	10.79	366	9156.30
1999	11.64	165	3723.70	12.07	363	4923.40	13.32	859	14347.80
2000	15.73	532	13693.20	24.92	1657	30048.50	47.65	5704	72595.30
2001	28.57	639	13897.09	45.70	1935	31218.74	65.73	5545	59860.64
2002	29.42	679	31062.97	47.52	3239	77343.41	87.56	14129	182561.30
2003	30.72	789	32792.65	58.58	3782	98056.77	84.21	15902	260155.60
2004	85.40	315	21438.04	94.22	881	49712.16	102.47	2398	113004.10
2005	94.46	325	27297.70	101.37	1185	81880.32	105.90	3548	230859.90
2006	71.43	342	25556.53	85.19	928	63594.39	88.14	2593	157028.30
2007	76.02	1264	93619.37	94.01	4775	330874.60	95.07	12581	801108.00
2008	93.77	795	60153.37	101.15	3390	238616.10	102.49	9373	603789.40
2009	116.64	199	19085.68	120.51	534	42416.85	125.15	1289	86658.72

Note: All dollar values are millions USD

Table 5: East Africa Conflict Events, Positive Rainfall Shock Current Month

	(1)	(2)	(3)	(4)	(5)	(6)
	10 km		50 km		100 km	
	Rebel	Communal	Rebel	Communal	Rebel	Communal
Positive Rainfall	0.185*** (0.0144)	0.0960*** (0.0101)	0.183*** (0.0144)	0.0972*** (0.0101)	0.184*** (0.0144)	0.0981*** (0.0101)
No Rainfall Change	0.0122 (0.0493)	-0.0442 (0.0642)	0.0135 (0.0493)	-0.0326 (0.0643)	0.0149 (0.0493)	-0.0338 (0.0643)
Distance Closest Aid	6.67e-05 (0.000510)	-0.00102 (0.000668)	-0.000308 (0.000532)	-0.00115* (0.000678)	-0.000538 (0.000536)	-0.000945 (0.000662)
\$ Closest Aid	-0.000473 (0.000633)	0.000699 (0.000449)	0.000242 (0.000634)	0.000871* (0.000476)	8.38e-05 (0.000660)	0.000759 (0.000493)
\$ Aid within radius	7.14e-06 (0.000259)	0.000473*** (0.000138)	-0.000137 (0.000128)	0.000122** (4.86e-05)	-9.40e-05 (5.81e-05)	8.05e-05*** (2.36e-05)
# Aid Projects within radius	-0.00739 (0.0121)	-0.0145* (0.00871)	-0.00659 (0.00487)	-0.00794** (0.00353)	-0.00416** (0.00195)	-0.00428*** (0.00152)
Local Population (2000)	0.0126 (0.0141)	0.000284 (0.0143)	0.0154 (0.0143)	0.00889 (0.0144)	0.0120 (0.0141)	0.00995 (0.0146)
Regional Poverty	0.000699 (0.00529)	0.0147*** (0.00542)	-0.000206 (0.00527)	0.00991* (0.00569)	0.00208 (0.00522)	0.0103** (0.00521)
Distance Nearest City	0.00676 (0.0169)	-0.0130 (0.0173)	0.00282 (0.0166)	-0.0315** (0.0159)	-0.00589 (0.0168)	-0.0297* (0.0156)
Distance Border	-0.0209 (0.0160)	0.0106 (0.0157)	-0.0160 (0.0164)	0.0111 (0.0157)	0.00252 (0.0173)	0.0140 (0.0157)
Conflict Previous Month	0.0109 (0.0491)	0.204*** (0.0645)	0.00579 (0.0492)	0.227*** (0.0639)	0.00183 (0.0494)	0.219*** (0.0638)
Conflict Same Period Previous Year	0.271 (0.303)	0.0815 (0.230)	0.281 (0.304)	0.0642 (0.230)	0.260 (0.304)	0.0689 (0.231)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.366* (0.210)	0.0946 (0.196)	0.309 (0.213)	0.0854 (0.195)	0.151 (0.218)	0.0478 (0.197)
Observations	2,021	1,312	2,021	1,312	2,021	1,312

Standard errors in parentheses

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

Discussion

The results in table 5 indicate that rainfall variation plays a small but significant role in explaining conflict. While interactive effects with aid project locations and values were not significant, aid does play a role in explaining the frequency of communal conflict events. The dollar value of aid projects located in close proximity to conflict sites is positively associated with an increase in the incidence of these conflicts.

Both rebel and communal violence increase in frequency with extreme changes in rainfall. For both groups livelihoods and tactical advantages are closely linked to the environment. Rainfall is a direct input agricultural production throughout East Africa, and therefore has an immediate and noticeable impact on resource availability. This finding lends support to the theory that conflict is driven by rent seeking behavior. Positive rainfall shocks and the location investment of

development assistance funding in a community drive the frequency of conflict events. In both cases existing instability is likely a prerequisite for conflict.

Given the sample used for this analysis, the findings may not be applicable outside of East Africa. However, it is clear from these results that policy makers and international donors should pay careful attention to both climate variability and aid project locations when examining the causes of conflict.

Conclusion

The role of climatic events as a motivator of conflict is contested by both policy makers and the existing literature. Given the inevitability of global climate change, it is important that we develop an accurate understanding of how climate affects conflict. In this paper I have tested two models of how climatic events affect conflict and have attempted to observe how development programs and humanitarian assistance influence any relationship that may exist between them.

Using a cross country dataset including country-year observations in both the presence and absence of conflict or disaster incidence, I found no evidence that the incidence of natural disasters is a significant predictor of the risk of violent civil conflict. This finding of its self was not necessarily surprising since both disasters and conflicts are rare events. In cases such as Managua and Mexico City natural disasters are widely credited with being a direct influence of conflict and regime change. However, even if this relationship exists in other countries it is not unsurprising that the regression models tested here would fail to find a significant effect. What is interesting is the apparent link between humanitarian assistance after a natural disaster and a decrease in the likelihood of conflict. While the heterogeneity of the humanitarian assistance data in this model is suspect, this link deserves further study. Large disasters are becoming more common place, and climate change is expected to cause and increase in both the frequency and severity of disasters. Given concern that these disasters may provoke conflict, a thorough investigation the potential of humanitarian assistance to alleviate this relationship would be warranted.

Using a geocoded conflict dataset from East Africa comprised of subnational monthly observations of conflict incidence I found that extreme rainfall fluctuations lead to an increase in the number of conflict events in a given location. Extreme rainfall fluctuations are the primary cause of the most common natural disasters in East Africa, suggesting that country-year aggregation, using civil war incidence as a dependent variable, or the inclusion criteria from disasters may be hiding the link between climate and conflict. It is also possibly the inclusion of stable countries such as the United States who experience a large number of disasters but no civil conflict has further biased these results.

Overall, I find that a link between climate and conflict is plausible and deserving of additional study. It appears that foreign aid influences this relationship, at least when delivered as humanitarian assistance, and may also instigate rent-seeking behavior on in the absence of climate variability. Policy makers should carefully consider these implications when planning future projects.

Appendix 1: Additional East Africa Results

Table A1: East Africa Conflict Events, Negative Rainfall Shock Current Month

	(1)	(2)	(3)	(4)	(5)	(6)
	10 km		50 km		100 km	
	Rebel	Communal	Rebel	Communal	Rebel	Communal
Negative Rainfall	-0.132*** (0.0116)	-0.150*** (0.0152)	-0.130*** (0.0116)	-0.149*** (0.0153)	-0.129*** (0.0119)	-0.147*** (0.0154)
No Rainfall Change	0.0131 (0.0494)	-0.0594 (0.0651)	0.0135 (0.0494)	-0.0457 (0.0652)	0.0137 (0.0493)	-0.0454 (0.0651)
Distance Closest Aid	0.000320 (0.000505)	-0.000316 (0.000661)	-8.99e-05 (0.000528)	-0.000565 (0.000672)	-0.000328 (0.000519)	-0.000541 (0.000658)
\$ Closest Aid	-0.000502 (0.000640)	0.000379 (0.000454)	0.000196 (0.000640)	0.000812* (0.000481)	0.000787 (0.000661)	0.000876* (0.000497)
\$ Aid within radius	-6.55e-05 (0.000265)	0.000489*** (0.000138)	-0.000181 (0.000129)	0.000101** (4.91e-05)	-0.000142** (5.86e-05)	5.58e-05** (2.39e-05)
# Aid Projects within radius	0.00121 (0.0122)	-0.0136 (0.00870)	-0.00415 (0.00490)	-0.00796** (0.00354)	-0.00214 (0.00194)	-0.00390** (0.00153)
Local Population (2000)	0.0138 (0.0141)	-0.000297 (0.0142)	0.0163 (0.0143)	0.0104 (0.0143)	0.0171 (0.0142)	0.0120 (0.0145)
Regional Poverty	0.00107 (0.00531)	0.0138*** (0.00535)	-0.000375 (0.00529)	0.00725 (0.00558)	0.000632 (0.00523)	0.00788 (0.00511)
Distance Nearest City	0.0114 (0.0171)	-0.0161 (0.0172)	0.00564 (0.0168)	-0.0380** (0.0157)	0.000566 (0.0169)	-0.0360** (0.0154)
Distance Border	-0.00158 (0.0164)	0.0286* (0.0156)	0.00360 (0.0168)	0.0283* (0.0156)	0.00863 (0.0175)	0.0297* (0.0156)
Conflict Previous Month	0.0450 (0.0492)	0.141** (0.0653)	0.0390 (0.0492)	0.169*** (0.0648)	0.0278 (0.0494)	0.165** (0.0647)
Conflict Same Period Previous Year	0.293 (0.303)	0.0918 (0.230)	0.307 (0.304)	0.0660 (0.230)	0.310 (0.304)	0.0629 (0.230)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.162 (0.215)	-0.132 (0.197)	0.106 (0.218)	-0.135 (0.196)	0.0466 (0.222)	-0.154 (0.197)
Observations	2,021	1,312	2,021	1,312	2,021	1,312

Standard errors in parentheses

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

Table A2: East Africa Conflict Events, Positive Rainfall Shock Lagged

	(1)	(2)	(3)	(4)	(5)	(6)
	10 km		50 km		100 km	
	Rebel	Communal	Rebel	Communal	Rebel	Communal
Positive Rainfall	0.111*** (0.0160)	0.0499*** (0.0119)	0.110*** (0.0160)	0.0511*** (0.0120)	0.111*** (0.0161)	0.0522*** (0.0120)
Positive Rainfall 1 month prior	0.0759*** (0.00965)	0.0985*** (0.0114)	0.0751*** (0.00963)	0.0980*** (0.0115)	0.0735*** (0.00962)	0.0976*** (0.0115)
Positive Rainfall 2 months prior	0.111*** (0.0112)	0.0163 (0.0123)	0.111*** (0.0112)	0.0178 (0.0123)	0.109*** (0.0112)	0.0181 (0.0123)
No Rainfall Change	0.00284 (0.0491)	-0.0274 (0.0635)	0.00343 (0.0492)	-0.0117 (0.0636)	0.00349 (0.0491)	-0.0115 (0.0636)
Distance Closest Aid	0.000130 (0.000519)	-0.000864 (0.000659)	-0.000205 (0.000542)	-0.000872 (0.000669)	-0.000445 (0.000541)	-0.000620 (0.000656)
\$ Closest Aid	-0.000450 (0.000637)	0.000918** (0.000446)	4.97e-05 (0.000637)	0.00106** (0.000474)	0.000121 (0.000663)	0.000967** (0.000492)
\$ Aid within radius	-4.57e-05 (0.000257)	0.000456*** (0.000137)	-0.000143 (0.000127)	0.000121** (4.82e-05)	-9.68e-05* (5.77e-05)	7.63e-05*** (2.35e-05)
# Aid Projects within radius	0.00284 (0.0120)	-0.0119 (0.00866)	-0.00248 (0.00485)	-0.00622* (0.00350)	-0.00246 (0.00196)	-0.00326** (0.00151)
Local Population (2000)	0.00541 (0.0141)	0.00694 (0.0143)	0.00652 (0.0142)	0.0136 (0.0144)	0.00524 (0.0141)	0.0141 (0.0146)
Regional Poverty	0.000312 (0.00531)	0.0150*** (0.00546)	-0.000901 (0.00528)	0.0113** (0.00573)	0.000623 (0.00524)	0.0109** (0.00523)
Distance Nearest City	0.0180 (0.0170)	0.00203 (0.0174)	0.0130 (0.0168)	-0.0169 (0.0161)	0.00612 (0.0170)	-0.0171 (0.0157)
Distance Border	-0.0204 (0.0162)	0.0116 (0.0157)	-0.0159 (0.0165)	0.0125 (0.0157)	-0.00290 (0.0174)	0.0149 (0.0158)
Conflict Previous Month	0.00579 (0.0492)	0.229*** (0.0642)	0.00265 (0.0493)	0.250*** (0.0637)	-0.000974 (0.0495)	0.244*** (0.0635)
Conflict Same Period Previous Year	0.221 (0.303)	0.103 (0.229)	0.230 (0.304)	0.0901 (0.230)	0.212 (0.304)	0.103 (0.230)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.303 (0.213)	-0.00554 (0.198)	0.263 (0.215)	-0.0294 (0.197)	0.147 (0.220)	-0.0706 (0.199)
Observations	2,021	1,312	2,021	1,312	2,021	1,312

Standard errors in parentheses

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

Table A3: East Africa Conflict Events, Positive Rainfall Shock Lagged

	(1)	(2)	(3)	(4)	(5)	(6)
	10 km		50 km		100 km	
	Rebel	Communal	Rebel	Communal	Rebel	Communal
Negative Rainfall	-0.0919*** (0.0136)	-0.0733*** (0.0163)	-0.0909*** (0.0136)	-0.0711*** (0.0164)	-0.0937*** (0.0136)	-0.0700*** (0.0165)
Negative Rainfall 1 month prior	-0.0744*** (0.0182)	-0.0514*** (0.0185)	-0.0748*** (0.0182)	-0.0523*** (0.0186)	-0.0782*** (0.0183)	-0.0529*** (0.0187)
Negative Rainfall 2 months prior	-0.113*** (0.0163)	-0.160*** (0.0147)	-0.113*** (0.0163)	-0.164*** (0.0148)	-0.120*** (0.0165)	-0.162*** (0.0148)
No Rainfall Change	0.0449 (0.0488)	-0.0540 (0.0618)	0.0432 (0.0489)	-0.0433 (0.0619)	0.0458 (0.0487)	-0.0418 (0.0618)
cp_km_to_smallaid_id	0.000429 (0.000500)	-0.000125 (0.000622)	3.12e-05 (0.000524)	-0.000548 (0.000640)	-0.000205 (0.000507)	-0.000524 (0.000626)
\$ Closest Aid	-0.000148 (0.000640)	0.000295 (0.000432)	0.000534 (0.000634)	0.000921** (0.000456)	0.00142** (0.000657)	0.000957** (0.000478)
\$ Aid within radius	-9.91e-05 (0.000264)	0.000441*** (0.000135)	-0.000197 (0.000128)	8.27e-05* (4.80e-05)	-0.000154*** (5.69e-05)	4.22e-05* (2.30e-05)
# Aid Projects within radius	0.00367 (0.0120)	-0.0148* (0.00844)	-0.00230 (0.00480)	-0.00720** (0.00339)	-0.000281 (0.00191)	-0.00309** (0.00144)
Regional Poverty	0.00306 (0.00524)	0.0110** (0.00511)	0.00192 (0.00523)	0.00497 (0.00538)	0.00156 (0.00515)	0.00607 (0.00492)
Distance Nearest City	0.00375 (0.0140)	-0.0311* (0.0160)	-0.00388 (0.0139)	-0.0525*** (0.0143)	-0.00606 (0.0139)	-0.0503*** (0.0139)
Distance Border	0.00808 (0.0164)	0.0106 (0.0150)	0.0102 (0.0168)	0.00908 (0.0150)	0.00498 (0.0174)	0.0100 (0.0151)
Conflict Previous Month	0.0515 (0.0489)	0.166*** (0.0620)	0.0450 (0.0490)	0.188*** (0.0618)	0.0315 (0.0492)	0.184*** (0.0617)
Conflict Same Period Previous Year	0.175 (0.304)	0.127 (0.216)	0.194 (0.304)	0.103 (0.217)	0.204 (0.304)	0.101 (0.217)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.00892 (0.211)	-0.0460 (0.172)	-0.00960 (0.213)	-0.00345 (0.174)	0.0162 (0.216)	-0.0160 (0.176)
Observations	2,058	1,389	2,058	1,389	2,058	1,389

Standard errors in parentheses

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

Works Cited

- Anderson, T. P. (1988). Politics in Central America: Guatemala, El Salvador, Honduras, and Nicaragua, Praeger Publishers.
- Azam, J. P. (1995). "How to pay for the peace? A theoretical framework with references to African countries." Public Choice **83**(1): 173-184.
- Bahar, D. (2009). "Aid and Fertility." CID Graduate Student Working Paper Series No. 38 Center for International Development at Havard University. Available at <http://www.cid.harvard.edu/cidwp/grad/038.html>.
- Berrebi, C. and J. Ostwald (2011). "Earthquakes, hurricanes, and terrorism: do natural disasters incite terror?" Public Choice **149**(3): 383-403.
- Brancati, D. (2007). "Political Aftershocks: The Impact of Earthquakes on Intrastate Conflict." Journal of Conflict Resolution **51**(5): 715-743.
- Brezina, T. and J. M. Kaufman (2008). "What Really Happened in New Orleans? Estimating the Threat of Violence During the Hurricane Katrina Disaster*." Justice Quarterly **25**(4): 701-722.
- Bueno de Mesquita, B. (2011). The dictator's handbook [electronic resource] : why bad behavior is almost always good politics. New York, PublicAffairs.
- Bulir, A. and A. J. Hamann (2008). "Volatility of development aid: From the frying pan into the fire?" World Development **36**(10): 2048-2066.
- Cavallo, E. and I. Noy (2009). The Economics of Natural Disasters: A Survey, Inter-American Development Bank, Research Department.
- CIESIN, I. "WRI, 2000. Gridded Population of the World (GPW), version 2." Center for International Earth Science Information Network (CIESIN) Columbia University, International Food Policy Research Institute (IFPRI) and World Resources Institute (WRI), Palisades, NY.
- Collier, P., A. Hoeffler, et al. (2009). "Beyond greed and grievance: feasibility and civil war." Oxford Economic Papers **61**(1): 1.
- Crandall, R. (2004). "Mexico's Domestic Economy." Crandall, R; Paz, G; Roett, R, Mexico's Democracy at Work: Political and Economic Dynamics, Lynne Reiner Publishers, ISBN: 10-1588263002.
- Cruz, C. (2005). Political culture and institutional development in Costa Rica and Nicaragua: world-making in the tropics, Cambridge Univ Press.
- de Ree, J. and E. Nillesen (2009). "Aiding violence or peace? The impact of foreign aid on the risk of civil conflict in sub-Saharan Africa." Journal of Development Economics **88**(2): 301-313.
- Disaster Research Group (1961). Field Studies of Disaster Behavior: An Inventory, National Academy of Sciences. National Research Council.
- Drury, A. C. and R. S. Olson (1998). "Disasters and Political Unrest: An Empirical Investigation." Journal of Contingencies and Crisis Management **6**(3): 153-161.
- Durkheim, E. (1897). Le Suicide. Paris. Translated 1952 as Suicide: a study in sociology by JA Spaulding and C. Simpson, London: Routledge and Kegan Paul.
- Eifert, B. and A. Gelb (2005). "Improving the dynamics of aid: towards more predictable budget support." World Bank Policy Research Working Paper No. 3732.
- Fearon, J. D. and D. D. Laitin (2003). "Ethnicity, insurgency, and civil war." American Political Science Review **97**(1): 75-90.
- Fritz, C. E. (1961). Disaster, Institute for Defense Analyses, Weapons Systems Evaluation Division.
- GLEDITSCH, N. P., P. WALLENSTEEN, et al. (2002). "Armed Conflict 1946-2001: A New Dataset." Journal of Peace Research **39**(5): 615-637.
- Grossman, H. I. (1991). "A general equilibrium model of insurrections." The American Economic Review: 912-921.
- Homer-Dixon, T. F. (1999). Environment, scarcity, and violence, Princeton Univ Pr.
- Jenkins, J. C. and D. Bond (2001). "Conflict-carrying capacity, political crisis, and reconstruction." Journal of Conflict Resolution **45**(1): 3-31.

- Knabb, R. D., J. R. Rhome, et al. (2005). Tropical cyclone report: Hurricane Katrina, 23-30 August 2005, National Hurricane Center.
- Miguel, E., S. Satyanath, et al. (2004). "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." Journal of Political Economy **112**(4): 725-753.
- Nel, P. and M. Righarts (2008). "Natural Disasters and the Risk of Violent Civil Conflict." International Studies Quarterly **52**(1): 159-185.
- Nielsen, R. A., M. G. Findley, et al. (2011). "Foreign Aid Shocks as a Cause of Violent Armed Conflict." American Journal of Political Science **55**(2): 219-232.
- Olson, R. S. and V. T. Gawronski (2003). "Disasters as Critical Junctures? Managua, Nicaragua 1972 and Mexico City 1985." International Journal of Mass Emergencies and Disasters **21**(1): 5-36.
- Polman, L. (2010). The crisis caravan : what's wrong with humanitarian aid? New York, Metropolitan Books.
- Prince, S. H. (1920). Catastrophe and social change: based upon a sociological study of the Halifax disaster, Columbia university.
- Raleigh, C. and D. Kniveton (2012). "Come rain or shine: An analysis of conflict and climate variability in East Africa." Journal of Peace Research **49**(1): 51-64.
- Settles, T. and B. R. Lindsay (2011). "Crime in post-Katrina Houston: the effects of moral panic on emergency planning." Disasters **35**(1): 200-219.
- Slettebak, R. T. (2012). "Don't blame the weather! Climate-related natural disasters and civil conflict." Journal of Peace Research **49**(1): 163-176.
- Solnit, R. (2009). A paradise built in hell: The extraordinary communities that arise in disaster, Viking Pr.
- Uvin, P. (1999). "Development Aid and Structural Violence: The case of Rwanda." Development **42**(3): 49-56.
- Varano, S. P., J. A. Schafer, et al. (2010). "A tale of three cities: Crime and displacement after Hurricane Katrina." Journal of Criminal Justice **38**(1): 42-50.
- Walker, T. W. (2000). "Nicaragua: Transition through revolution." Repression, resistance and democratic transition in Central America: 67-88.
- Woodward Jr, R. L. and D. E. Worcester (1976). "Central America: A nation divided." History: Reviews of New Books **4**(7): 148-148.