Climate Related Natural Disasters and the Onset of Civil Conflict: 1970-2008

https://www.e-ir.info/2011/07/01/climate-related-natural-disasters-and-the-onset-of-civil-conflict-1970-2008-2/

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Since the end of the Cold War, research into the causes of civil conflict has intensified dramatically as scholars, policymakers, and NGOs have come to recognise the tremendous human toll they exact. As Fearon and Laitin observe, the second half of the 20th century witnessed approximately 127 major civil wars, as a direct result of which at least 16.2 million people are believed to have been killed across 73 states (2003). This is roughly five times the number of interstate wars that took place over the same period of time, and roughly five times the number of people that were killed. The switch in the focus of conflict research that accompanied this realisation has rapidly expanded our understanding of the factors that lead to civil conflict, and a degree of consensus has emerged over primary causes such as income, political instability, and opportunities for insurgency.[1]

However, almost completely absent from the civil war literature is the impact that natural disasters may have on the likelihood of conflict (Nordas & Gleditsch, 2007, Buhaug *et al,* 2008, Nel & Righarts, 2008). Within the environmental security literature, a number of studies have investigated the effect that environmental change could have on conflict, but these have focused largely on the impact of resource scarcity (e.g. Homer-Dixon, 1999, Kahl, 2006). While this is clearly a likely consequence that natural disasters may have, it is but one. Likewise, though a large body of literature is devoted to the effects of disasters in the fields of environmental science and geography, the focus is primarily on vulnerability, prevention, and reconstruction (e.g. Alexander, 1993, Cannon, 1994). This lack of specific research into the effect natural disasters have on conflict is surprising when, *prima facie,* natural disasters appear likely to increase the risk of conflict due to their often massive and unforeseen impact, as well as their effect on other predictors of conflict like income and political stability. It is also surprising considering the availability of anecdotal evidence to suggest that there may be a link between the two.

The impact of the 2004 Indian Ocean tsunami on Sri Lanka provides an example. Following 20 years of civil war between the Sri Lankan Government and the Tamil Tigers (LTTE), the two sides signed a peace agreement in 2002. After the tsunami however, control of foreign aid for rebuilding became a catalyst for a broader dispute over the way in which Sri Lanka should be governed (Uyangoda, 2005). Subsequently, conflict reignited, causing the annual death toll which had slowed to 14 by 2002 to reach over 4,000 by 2006 (Renner, 2007). Though a number of omissions from the peace agreement meant it was fragile in the first place, the tsunami is seen by many as a major contributing factor to its eventual break down (Uyangoda, 2005, Beardsley & McQuinn, 2009).

The need to better understand the relationship between natural disasters and civil conflict is more pertinent than ever in light of emerging evidence that suggests climate change is likely to increase the frequency of climate related natural disasters in coming years. In its 2007 report the International Panel on Climate Change (IPCC) states that expected changes in precipitation patterns and more pronounced weather extremes indicate that climate related disasters are likely to strike more often in most parts of the world. Though climate scientists are yet to link individual disasters to climate change, the trend at the aggregate level supports the IPCC's position (Dilley*et al,* 2005, Buhaug *et al,* 2008). Data compiled by the Centre for Research on the Epidemiology of Disasters (CRED) shows that the number of disasters increased substantially during in the latter half of the 20th century, with climate related disasters accounting almost entirely for this increase. On average, the number of annual climate related disasters is now twice the average throughout the 1980s (CRED, 2010). According to the World Bank, 82 percent of the global population now live in flood-prone areas, while 70 percent live in drought-prone areas (Dilley *et al,* 2005).

My research is designed to quantitatively analyse the effect of climate related natural disasters on the likelihood of civil conflict. To do this, I construct a dataset comprising all states in the international community from 1970 to 2008, with a population over 500,000 in 1990[2]. This gives a total of 5630 observations. I begin by reviewing the environmental security and civil conflict literature, outlining the range of causal pathways through which climate related natural disasters may lead to conflict. I hypothesise that both the frequency and intensity of climate related natural disasters will be positively related to the onset of violent civil conflict. Controlling for a range of other factors, I use logistic regression to test my hypotheses. Contrary to expectation, I find no statistically or substantively significant relationship between either the frequency or the intensity of disasters and the onset of civil conflict. On the other hand, income levels, inequality, regime type, population, and time dependence are all found to be statistically and substantively significant.

Literature Review

Political Instability

A review of the literature reveals a number of causal pathways through which natural disasters may increase the likelihood of civil conflict. Salient among these are the effect that natural disasters may have on the political stability of states (Barnett, & Adger, 2007, Buhaug *et al,* 2008). At an elementary level, the occurrence of a natural disaster is likely to impose a substantial financial burden on states as they attempt to clean up and rebuild. This subsequently weakens the state's capacity to provide the services necessary to maintain order and ensure economic stability (Buhaug *et al,* 2008, Hegre & Sambanis, 2006). At the same time, a natural disaster may damage government infrastructure, thereby affecting the state's ability to uphold local governance networks (Nel & Righarts, 2008). For groups in society that harbour grievances against the state, this may provide an ideal opportunity to contest the state's authority by force (Fearon & Laitin, 2003, Collier & Hoeffler, 2004).

In the case of states already poor or institutionally weak, governments may simply lack the resources or organisational capacity to respond to natural disasters in a manner that is acceptable to the population (Barnett & Adger, 2007). In such situations, popular support for the government is likely to decrease and the legitimacy of the government may be called into question. As a consequence, groups that seek to challenge the government's right to rule through undemocratic means may gain support (Buhaug *et al,* 2008). In states already characterised by a non-democratic system of government, regimes may simply lack the political will to respond to natural disasters with the degree of urgency necessary (Baechler, 1999). In democratic states, awareness of media scrutiny and the need to maintain popular support encourages regimes to ameliorate the effects of disasters as expediently as possible (Gurr, 2000). This helps to explain why, for example, democracies may sustain crippling droughts but never undergo famine (Sen, 1981). Non-democratic regimes lack such incentives to act. Subsequently, their response is likely to be slower, exacerbating grievances and lowering the perceived costs of joining rebel groups (Collier & Hoeffler, 2004).

Alternatively, states may foster political instability by attempting to use natural disasters for political gain (Raleigh & Urdal, 2007). For instance, regimes may seek to play social or ethnic groups off against each other to gain support or to divert attention away from their own failings (Kahl, 2006). This is exemplified by the situation in Kenya during the 1990s, in which increasing population density coupled with drought decreased the availability of arable land (Campbell *et al,* 2000). Rather than attempting to resolve the issue, the government of President Moi sought to incite violence between ethnic groups in an attempt to encourage voting along ethnic lines in the upcoming multiparty elections (Kahl, 2006). The result was five years of conflict characterised by fear and suspicion between ethnic groups that had previously coexisted peacefully.

Economic Instability and Poverty

Natural disasters may also increase the likelihood of civil conflict by increasing poverty and economic instability within states. For individuals, natural disasters such as floods and storms are expected to increase poverty by destroying homes, while droughts are expected to increase the costs of growing and procuring food (Buhaug*et al,* 2008). At the aggregate level, natural disasters are likely to affect economic stability by damaging the transport and communication networks essential for the economy to function efficiently (Barnett & Adger, 2007). Subsequently, opportunities for employment become increasingly scarce and the demand for goods and services declines.

Empirically, the relationship between poverty and the likelihood of civil conflict is strongly supported. For example, using logistic regression Collier and Hoeffler find that the power of income levels (defined by GDP per capita) to predict the onset of civil conflict is matched only by the size of population (2004). Similar empirical analyses by Fearon and Laitin (2003) and Hegre and Sambanis (2006) confirm these findings. A range of explanations for this relationship have been put forth.

At the individual level, poverty is argued to increase the likelihood of conflict by lowering the perceived costs of joining a rebel group (Berdal & Malone, 2000, Collier & Hoeffler, 2004). This is because high levels of poverty, characterised by low wages and high unemployment, limit the number of opportunities to earn a sufficient income by legal means (Ohlsson, 2003). Consequently, the expected economic gain from joining a rebel group increases relative to expected economic gain from remaining part of the conventional economy (Buhaug *et al,* 2008). Given this knowledge, rebel groups are able to specifically target areas with high levels of poverty to recruit new members (Hendrix & Glaser, 2007). Recruitment is expected to be particularly successful when rebel leaders are able to place the blame for poverty on other groups in society, whether based on ethnicity, class, or religion (Goodhand, 2003, Barnett & Adger, 2007).

At the national level, increased poverty and economic instability are likely to weaken state capacity by shrinking tax revenue. This reduces the ability of the government to effectively counter the threat posed by rebel groups because there are fewer resources that can be devoted towards policing, intelligence, and counterinsurgency (Fearon & Laitin, 2003). From this perspective, the increased likelihood of conflict in poor states is a product of the favourable conditions for insurgency they present (Collier & Hoeffler, 2004). Moreover, less income from taxation reduces the funds available to provide good and efficacious governance, thus feeding back into political instability. Statistically, poverty at the national level is strongly correlated with a lack of democratic governance, though the causal direction of this relationship is contested (Buhaug *et al,* 2008).

Inequality

Natural disasters are also argued to increase the likelihood of conflict by exacerbating inequality within states (Stewart, 2000, Ostby, 2008). This is primarily explained in terms of relative depravation, whereby sectors of the population that have been increasingly marginalised seek to challenge the status quo by force (Cramer, 2003). Inequality may be vertical or horizontal. Vertical inequality refers to the difference between the comparative positions of the best and worst off individuals in society (Stewart, 2000). Natural disasters are expected to increase vertical inequality in a number of ways. Firstly, wealthier individuals more likely to be able to relocate away from areas that are particularly disaster prone, thus leaving those less well of disproportionately at risk. This situation is exemplified by Hurricane Katrina in which those that could afford to leave the area did so, leaving mainly poorer citizens to rebuild (Burby, 2006). Secondly, the effect of natural disasters on national income outlined above means that the provision of social services by the state may be cut (Barnett & Adger, 2007). This is likely to increase vertical inequality because social services such as housing, welfare, and public transport are used disproportionately by poorer segments of society (Anand & Ravallion, 1993). Lastly, natural disasters are expected to impact most on the primary sector due to the close links between environmental conditions and productivity. This affects vertical inequality because the poor are disproportionately engaged in the primary sector in most countries, whether through subsistence farming or seasonal work (Ravallion & Datt, 1996).

Horizontal inequality refers to the systematic imbalance in the benefits and opportunities enjoyed by the different groups within a state (Buhaug *et al,* 2008). Natural disasters are expected to exacerbate horizontal inequality because some areas are intrinsically more at risk to natural disasters than others (IPCC, 2007). For instance, coastal areas are more likely to be affected by hurricanes than those inland, while low-lying areas are more likely to be affected by floods than those at altitude. Worsening horizontal inequality is particularly likely when group members are geographically concentrated, as is the case in the majority of developing states (Ostby, 2008).

Though still contested, case study research indicates that while both vertical and horizontal inequality can increase the likelihood of civil unrest, horizontal inequality is most likely to result in conflict (Murshed & Gates, 2005, Ostby, 2008). This is because horizontal inequality can increase cohesion within marginalized groups, thus providing better opportunities to mobilise against the state (Ostby, 2008).

Social Fragmentation

Related to the issue of worsening horizontal inequality is the effect that natural disasters may have on social fragmentation. This is defined in terms of how disasters can create or deepen ethnic divisions in society, primarily as a consequence of their discriminatory spatial impact (Buhaug *et al,* 2008). Notwithstanding, the specific conditions under which increased social fragmentation is likely to lead to conflict are contested. For instance, Gurr and Moore posit a direct positive relationship between ethnic heterogeneity and the likelihood of civil conflict. As the number of ethnic groups increases, so too does the risk of conflict, regardless of their size (1997). For most scholars however, it is the configuration of ethnic groups in society that matter. Some highlight the risk posed when one group is dominant (e.g. Collier & Hoeffler, 2004, Cederman & Girardin, 2007). For Collier and Hoeffler, dominance occurs when one group comprises more than 45 percent of the population. As a consequence, the dominant group are able to exclude minorities from power indefinitely. In such circumstances, minorities are likely to see violence as their only option in altering the status quo. Others argue that it is the degree of polarization between groups that is most important (e.g. Reynal-Querol, 2002, Esteban & Ray, 2008). However, rather than increasing the likelihood of the onset of conflict, polarization is argued to substantially increase the intensity of conflict once it has already broken out (Esteban & Ray, 2008).

Irrespective of whether ethnic heterogeneity is considered to be a cause of civil conflict, there is growing consensus that it can aid mobilisation once a conflict has become violent (Bachler, 1999, Kahl, 2006). This is essentially because shared identifiers such as religion, physical appearance, and language act as natural lines of demarcation between competing groups (Buhaug *et al,* 2008). 'Ethnic entrepreneurs' are then able to exploit these differences, real or imagined, to increase fear and hostility between groups (Lake & Rothchild, 1996). Consequently, ethnic heterogeneity is widely seen as a pivotal factor in building support and transforming grievances into opportunities for collective violence (Kahl, 2006). At this stage, the relationship between ethnicity and civil conflict can become mutually reinforcing. That is, ethnicity provides the initial mechanism through which conflicts are organised, while the onset of conflict severely magnifies pre-existing tensions (Gurr, 2000). Suliman contends that this has been the case in Sudan, in which ethnic boundaries have historically been weak, but have become increasingly pronounced as a result of ongoing conflict over resources (1997).

Migration

Natural disasters may also increase the likelihood of conflict by causing large scale migration within and between states. Slow onset disasters such as drought are expected to increase average migration levels over time, while rapid onset disasters such as tropical cyclones and floods are expected to increase the frequency of spikes in short term migration (Gleditsch *et al,* 2007, Reuveny, 2007). The extent to which migration is affected by natural disasters is heavily influenced by how dependent individuals and communities are on environment conditions for their economic livelihood. As a consequence, states with economies based primarily on agricultural output, such as those in Africa and South Asia, are likely to experience the greatest increase in disaster related migration (Reuveny, 2007). The degree of migration in response to natural disasters is further affected by the ability of states to mitigate their effects (Colomer, 2000). For instance, disasters are expected to result in less migration in developed countries as they are better equipped to minimise their the effects through technical innovation and economic support. Less developed countries lack such expertise and resources so disasters will likely lead to more migration (Reuveny, 2007).

There are four major pathways through which disaster related migration could lead to conflict in receiving areas. The first of these is by increasing competition for scarce resources (Gleditsch *et al,* 2007). As more migrants arrive, pressure on the resource base of the receiving area increases, thereby heightening competition between local and migrant groups (Reuveny, 2007). This is particularly likely to be problematic when resources are already stretched, or when norms of property rights are not well ingrained (Buhaug *et al,* 2008). Secondly, migration may lead to ethnic tension if local and migrant populations belong to different ethnic groups (Reuveny, 2007). This is most likely to be of concern when a rapid onset disaster has lead to a sudden influx of migrants. In such a situation, local groups may feel that their sense of identity is threatened and react violently. Thirdly, migration may create distrust and resentment between the migrants' place of origin and their destination (Reuveny, 2007). For example, the receiving authorities may feel that those sending the migrants are seeking to upset the ethnic balance of the region, while the sending authorities may resent the way that migrants are treated by those receiving them (Reuveny, 2007). Lastly, disaster related migration may deepen existing socioeconomic divisions in society. For instance, migrant pastoralists may become increasingly hostile towards large private landholders and vice versa (Buhaug *et al,* 2008). Similarly, migration from rural areas to cities may aggravate the urban poor as they are forced to compete for jobs with newcomers (Reuveny, 2007).

Empirical evidence suggests that there is a statistically significant positive relationship between increased migration and civil conflict (Salehyan, 2007, Buhaug & Gleditsch, 2008). However, this focuses primarily on increased migration as a result of conflict in the country of origin. As regional instability is widely considered to heighten the risk of conflict in individual states (Berdal, 2005, Cederman *et al,* 2008), it cannot be assumed that natural disaster related migration will have the same effect as migration stemming from conflict. Nevertheless, early exploratory research by Reuveny indicates that their may also be a significant relationship between environmental migration (including that caused by natural disasters) and conflict (2007). Investigating 38 cases of environmental migration, he finds that in fifty percent of all cases violent conflict occurred in the receiving state. In support of the theoretical model, in cases where the predominant ethnic group in the receiving area differed from that of the migrants, the percentage was substantially higher.

Research Questions and Hypotheses

Insights from the literature lead to two complimentary research questions and hypotheses for analysis:

R1: Does the number of climate related natural disasters affect the likelihood of violent civil conflict?

H1: The higher the number of climate related natural disasters per country-year, the greater the likelihood of violent civil conflict.

R2: Does the number of deaths from climate related natural disasters affect the likelihood of violent civil conflict?

H2: The higher the number of deaths from climate related natural disasters per country-year, the greater the likelihood of violent civil conflict.

Research Design

To test my hypotheses, I construct a dataset comprising all independent states with a population greater than 500,000 in 1990, for which data on both natural disasters and civil conflict are available. The dataset covers the period 1970 to 2008, with the country-year employed as the unit of analysis. Overall, there are 5630 observations derived from 131 independent states. Not all states are represented in each year of observation, as over time a number of states cease to exist, while others come into being. As a consequence of the increasing Balkanisation of the international state system since the end of the Cold War, there are more observations for later years than there are for earlier years. I do not attempt to address this because of the likelihood that Balkanisation is itself a product of civil conflict.

Dependent Variable: The Onset of Violent Civil Conflict

The dependent variable for this research is the onset of violent civil conflict. Conflict data is provided by the UCDP/PRIO Armed Conflict Dataset compiled by Uppsala University. I use the most recent version of the data; v4, completed in 2010. Using the definition given by the UCDP, violent civil conflict is conceptualised as ‘a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle related deaths in one calendar year’ (2008). In addition, only conflicts that are politically motivated are recorded. As a result, disputes primarily involving drug gangs or other organised crime outfits are excluded. The onset of violent civil conflict is recorded as a dichotomous variable; for each country-year observation, either conflict broke out, or it did not. Once a conflict has occurred between two or more belligerents, the onset of a new conflict is recorded only after there has been two years of inactivity. When coding, the date of the onset of civil conflict is the date of the first known battle-related death in episode, providing the threshold of at least 25 battle related deaths is subsequently met[3]. Due to uncertainty over the length of time expected to elapse between the incidence of a natural disaster and the onset of civil conflict, I observe the dependent variable at both t and t+1.

Though other sources of civil conflict data are available, the UCDP/PRIO dataset is preferred for two major reasons. Firstly, in comparison to its closest rival the Correlates of War (COW) dataset, UCDP/PRIO captures a significantly larger number of civil conflict onsets. This is essentially because the number of battle related deaths required before an onset is recorded is much lower for UCDP/PRIO; 25 compared to 1000 for COW. Capturing the largest number of civil conflict onsets is desirable because the research is concerned with what is termed ‘rare events’ (King & Zeng, 2001). That is, even in the UCDP/PRIO dataset, civil conflict onset occurs in less than 5 percent of all observations. Under such circumstances, the lower the number of onsets the higher the likelihood that the regression model will produce biased estimates (King & Zeng, 2001). Secondly, the UCDP/PRIO dataset is much more up to date than the COW dataset. While the UCDP/PRIO contains data on conflict up to and including 2009, COW has no new data after 1997. This is particularly pertinent because it is during this period that the incidence of climate related disasters has increased most rapidly (CRED, 2009). If this trend continues as the climate change literature suggests, it is observations from this period that are likely to provide the most accurate indication of future outcomes.

Nevertheless, though preferred to other datasets, the UCDP/PRIO dataset still has several limitations that impact upon what subsequent empirical analysis can achieve. Salient among these is the difficulty in obtaining accurate information on the number of battle related deaths. This can become particularly problematic when sides in a conflict have a strategic interest in misrepresenting the figures, for example, to downplay their own losses or to embellish the civilian toll of an enemy’s attack. Because the UCDP/PRIO dataset only includes figures that have been verified, there is a substantial risk that not all civil conflict onsets that should qualify for inclusion do so. Other limitations include the absence of information about conflict at the sub-national level, as well as the need to record conflict onset as a discrete event bound by the calendar year, irrespective of when in that year onset actually occurs.

Explanatory Variables: Disaster Variables

The explanatory variables of interest for this research are the number of climate related natural disasters, and the number of deaths from climate related disasters per country-year. Data on natural disasters is obtained from the Emergency Events Database (EM-DAT), compiled by the World Health Organisation (WHO) affiliated CRED. EM-DAT contains data on over 18,000 disasters that have occurred since 1900. CRED defines a natural disaster as ‘a sudden or unforeseen event that causes great damage, destruction, and human suffering, overwhelming local capacity, [and] necessitating a request to the national or international level for assistance’ (2007: 15). In addition, to be included in the database, a disaster must kill at least 10 people, affect at least 100 people, lead to a state of emergency being declared, or result in an appeal for international assistance (CRED, 2007). For the purpose of this research I consider only those disasters that are related to climate. These are referred to as hydro-meteorological in the climate science literature and include storms, floods, droughts, landslides, wildfires, heat waves, and cold snaps.[4] Geological disasters such as volcanic eruptions and earthquakes are not considered for analysis as they are largely unrelated to climate (IPCC, 2007). Disasters are recorded as a ratio variable. If a disaster spans multiple years, it is recorded only in the year in which it began. However, if a single disaster affects more than one country, as was the case with the Indian Ocean tsunami of 2004, it is recorded in each country for which all criteria for inclusion is met. Observations of the variable within the dataset range from 0 to 35 disasters per country year, with a mean of 1.25. Deaths from disasters is also recorded as a ratio variable, with observations ranging from 0 to 300,000 and having a mean of 273 deaths per country-year.

For the purpose of large-N quantitative research, there are two main competitors to EM-DAT for data on disasters. These are NatCat, compiled by the Munich Reinsurance Company, and Sigma, compiled by the Swiss Reinsurance Company. EM-DAT is preferred to both of these alternatives for several reasons. Firstly, EM-DAT is the only one of the three developed specifically to provide data for scientific research; both NatCat and Sigma exist to provide private information to clients about the relative risk of investing in specific areas (Guha-Sapir & Below, 2002). As a consequence of this, EM-DAT codes according to much more rigorous methods and definitions, all of which are available to the researcher. This is not the case with the alternatives, which lack detailed recording procedures (Guha-Sapir & Below, 2002). Secondly, NatCat does not provide data on droughts. This is a significant problem as droughts affect more people than any other type of disaster except flooding, and are also a major focus of the theoretical literature in which I ground my research. Finally, a review of the literature indicates that EM-DAT has been used in almost all large-N quantitative analyses of natural disasters. Thus, employing EM-DAT is preferable because it improves the comparability of my research with that of others.

Nonetheless, though EM-DAT is the preferred source of disaster data, there are still a number of shortcomings that should be considered. Paramount among these is the dependence EM-DAT has on other sources to obtain information. These include UN agencies, national governments, news media, insurance companies, and NGOs (Guha-Sapir & Below, 2002, Jonkman, 2005). As a result of this dependence, the quality of data contained in EM-DAT is entirely dictated by the reliability of these sources. Most concerning from the perspective of statistical analysis is that because of fundamental differences in the degree of state reporting, media coverage, and NGO activity between states, it is probable that some states are systematically under-represented in the data, as disasters are not picked up (Jonkman, 2005). For the same reason, there is likely to be an underrepresentation of disasters in earlier years than in later years. Additional problems arise through the classification of disasters into mutually exclusive groups. This is an issue because the distinction between categories obfuscates the way disasters interact. For example, a disaster may be recorded as flooding (hydrological) when it has actually been caused by a tsunami (geological), while a landslide (hydrological) may have been caused by either flooding (hydrological) or an earthquake (geological). In the first example, the disaster will be included for analysis even though it is primarily geological, and therefore should have been excluded. The latter example will be included also, though whether correctly or not cannot be ascertained because EM-DAT gives only the final classification.

Control Variables: Income

In order to isolate the effect of climate related natural disasters on the likelihood of violent civil conflict, I include a number of control variables that the literature suggests are also related to conflict.[5] The first of these is income levels. As outlined in the literature review, a state's level of income is widely considered to be one of the most robust indicators of civil conflict, whether it is explained by greed (Collier & Hoeffler, 2004) or opportunity (Fearon & Laitin, 2003). I control for income using GDP per capita in thousands, measured in current US dollars, and weighted for purchasing power parity (PPP). This data is obtained from the UN Economic Statistics Division, which bases its figures on what states report to the UN through the annual National Accounts Questionnaire (UNSD, 2010). In addition to controlling for income, GDP per capita serves as a control for a range of other development indicators and is therefore included as a 'catch all' variable in most studies of civil conflict (Hegre & Sambanis, 2006, Nel & Righarts, 2008).

Inequality (Infant Mortality)

Because of the close correlation between GDP per capita and available measures of inequality, the former is sometimes employed as a proxy for the latter (Nel & Righarts, 2008). This is primarily because direct measures of inequality are difficult to observe (Knowles, 2005). Nevertheless, I follow Nel and Righarts by including a separate measure of inequality in my model. This is because in most studies, the relationship between GDP and the onset of conflict is linear, while theory indicates that the relationship between inequality and conflict is U shaped (Cramer, 2003, Ostby *et al,* 2006). This expected U shape reflects the notion that low levels of inequality reduce the likelihood of grievances arising in the first place; while high levels of inequality mean those at the bottom lack the resources to needed to mobilise. Subsequently, it is medium levels of inequality that are most likely to lead to conflict because both the grievances and resources necessary to encourage rebellion are present (Ostby *et al,* 2006). Due to the shortage of direct measures I proxy inequality with data on infant mortality rates. This is appropriate because of the very close correlation between infant mortality and available measures of inequality identified by Nel & Righarts (2008). Crucially, unlike GDP per capita, infant mortality rates follow the same U shape that is expected of the relationship between inequality and conflict. Data on infant mortality is obtained from the UN Department of Economic and Social Affairs.

Regime Type

Also controlled for in the model is the effect of political instability on the risk of civil conflict. This is done using data on regime type obtained from the Polity IV database developed by the Center for Systemic Peace (*sic).* Polity IV allocates states an annual score on a 21 point scale depending on the perceived level of governing authority. At one end, -10 denotes a 'fully institutionalised autocracy' and at the other, +10 denotes a 'fully institutionalised democracy'. In line with the theoretical literature, I expect the relationship between regime type and the risk of conflict to be U shaped (Hegre *et al,* 2001, Urdal, 2006). This is premised on the notion that fully democratic societies are able to reduce the risk of conflict by providing non-violent pathways through which grievances can be voiced, while fully autocratic societies are strongly positioned to suppress rebellion and dissent by force (Gates*et al,* 2006). Consequently, it is those regimes that are not fully autocratic or fully democratic that are most at risk of violent conflict because they are unable to effectively address grievances while simultaneously lacking the ability to prevent civil unrest (Merkel, 2005, Hegre & Sambanis, 2006). To control for this effect of regime type, I construct a dummy variable for anocracy, coding all observations between -5 (partial autocracy) and +5 (partial democracy) 1, with the remaining observations coded 0.

Population

Following most previous quantitative studies of civil conflict, I include the natural log of population as a control variable (Fearon & Laitin, 2003, Hegre & Sambanis, 2006). Controlling for population serves two main purposes. Firstly, population functions as a proxy for country size. *Ceteris paribus,* the larger a state's population is, the greater the likelihood of conflict occurring, because more people leads to more opportunities for grievances to arise (Nel & Righarts, 2008). Secondly, states with large populations are likely to have greater pressure placed on government capacity in the event of a disaster, and there is also likely to be a greater distance between the location of the disaster and that of the central government from which any response is coordinated. As a result, greater population is expected to correspond with greater opportunities for violent conflict. Data on population is obtained from the World Population Prospects Database compiled by the UN Department of Economic and Social Affairs.

Population Density

The model also controls for population density. This is measured in terms of the number of inhabitants per square kilometre (UN, 2009). Conflicting strands within the literature variously posit that the relationship between population density and the likelihood of violent civil conflict is positive (Hauge & Ellingsen, 1998), negative (Buhaug & Rod, 2006), or nonexistent (Collier & Hoeffler, 2004). Those that suggest a positive relationship contend that when population density is high, competition over scarce resources such as land and freshwater is likely to be at its fiercest, and therefore more likely to turn violent (Hauge & Ellingsen, 1998). On the other hand, those that posit a negative relationship argue that low population density is associated with less government control and less infrastructure, as is the case in the tribal regions of North-West Pakistan for instance. Subsequently, areas with low population density provide better conditions for rebellion (Buhaug & Rod, 2006). Data on population density is also obtained from the World Population Prospects Database.

Time dependence

Lastly, in line with previous studies utilising the UCDP/PRIO dataset, I include a variable to control for the likelihood of time dependence in the onset of violent civil conflict (Hegre *et al,* 2001, Urdal, 2006, Nel & Righarts, 2008). Time dependence is expected to be an issue in studies of civil conflict because states that undergo conflict in a given year have an increased probability of undergoing conflict in the years immediately following. Likewise, states characterised by the absence of conflict in a given year have an increased probability of remaining conflict free in the following years (Nel & Righarts, 2008). I control for the effects of time dependence using a formula developed by Urdal. This is defined as *exp((-years in peace)/4)*. The formula assumes that the effect of a previous conflict on the likelihood of conflict onset declines geometrically, at a rate which halves the risk approximately every three years (Urdal, 2006).[6]

Results

Table 1: Logistic Analyses of Number of Climate Related Natural Disasters and the Onset of Violent Civil Conflict

	(1) Conflict Onset (t)	(2) Conflict Onset (t+1)	(3) Conflict Onset (t)	(4) Conflict Onset (t+1)
Number of Disasters	-0.026 (0.044)	-0.040 (0.048)	0.000 (0.041)	-0.013 (0.045)
GDP Per Capita (000s)	-0.246*** (0.076)	-0.242*** (0.077)		
Infant Mortality Rate			0.015*** (0.002)	0.017*** (0.002)
Regime Type	0.448* (0.234)	0.278 (0.247)	0.652*** (0.235)	0.515** (0.249)
LN Population	0.366*** (0.087)	0.357*** (0.089)	0.409*** (0.088)	0.416*** (0.091)
Population Density	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Brevity of Peace	1.143** (0.504)	1.282** (0.505)	0.901* (0.517)	1.001* (0.520)
Constant	-7.231*** (0.823)	-7.129*** (0.836)	-9.337*** (0.876)	-9.553*** (0.910)
N	5630	5630	5630	5630

Logistic regression coefficients with standard errors in parentheses.
* p < 0.1; ** p < 0.05; *** p < 0.01.
Estimates obtained using PASW Statistics 18.

Table 1 shows the results of logistic analyses run using the complete dataset of violent civil conflict onset with the number of disasters per country-year as the independent variable of interest. Model 1 and 2 include all control variables measured at times t and t+1 respectively, except for inequality (infant mortality rate). Inequality is excluded due to collinearity with GDP per capita.[7]

Contrary to expectations, the results from model 1 indicate that the number of disasters is neither statistically or substantively significant in predicting the onset of violent civil conflict. If anything, the results from model 1 suggest that the occurrence of a natural disaster slightly decreases the likelihood of conflict, though the coefficient is far from reaching statistical significance ($p = 0.563$). The results at t+1 (Model 2) also indicate that there is no statistically significant relationship between the occurrence of natural disasters and the onset of violent civil conflict. As in Model 1, the coefficient is negative but not close to the first critical p value of 0.1.

As expected, the results of models 1 and 2 indicate that GDP per capita is both a statistically and substantively significant predictor of the onset of violent civil conflict. At time t, for a one unit increase in GDP per capita (000s), there is a 0.442 decrease in the log of the odds of violent conflict onset, controlling for all other variables ($p = 0.001$). In percentage terms, this means that on average, an increase of US$1000 in per capita GDP decreases the odds of civil conflict onset by 22 percent, controlling for all other variables. The results at t+1 are very similar, with an increase of US$1000 in per capita GDP also corresponding to a 22 percent decrease in the odds of civil conflict, on average ($p = 0.002$). I confirm the robustness of these results by removing the states with the highest (Luxembourg) and lowest (Ethiopia) average GDP per capita and re-running the regression.[8]

The results from Model 1 also suggest that regime type is a statistically and substantively significant predictor of the onset of civil conflict. On average, there is a 0.448 increase in the log of the odds of conflict onset for anocracies compared to democracies or autocracies, controlling for all other variables ($p = 0.056$). More intuitively, the odds of conflict onset are on average 57 percent higher for states governed by anocracies when compared with any other form of government. Surprisingly however, Model 2 shows that the effect of regime type loses statistical significance at t+1 (p = 0.260).

In line with expectation, the effect of population size on the likelihood of conflict onset is both statistically and substantively significant. Model 1 indicates that a one unit increase in the natural log of population increases the log of the odds of conflict onset by 0.366 (p = 0.000). On the other hand, population density is not statistically significant in either Model 1 or Model 2. Though the coefficient in both models is positive, it does not come close to reaching statistical significance at either t (p = 0.434) or t+1 (p = 0.407).

Lastly, the measure of time dependence is both statistically and substantively significant. Model 1 indicates that on average, the odds of conflict onset in states that have experienced conflict in the previous year are three times the odds of conflict onset in states with no history of conflict in the previous twenty years, controlling for all other variables (p = 0.023). The effect of time dependence is just as significant whether observed at t or t+1 (Model 2).

For Models 3 and 4, GDP per capita is replaced by infant mortality rate. All other variables in the regression remain the same. Once again the effect of natural disasters on the likelihood of civil conflict onset is neither statistically or substantively significant. At time t (Model 3), the coefficient is 0.000 indicating that natural disasters have no predictive capability in the equation (p = 0.992). At t+1 (Model 4), the coefficient is slightly negative though far from statistically significant (p = 0.778). In order to assess whether any effect of natural disasters on the onset of civil conflict is mediated by income levels, I split the dataset into two equal subsets according to GDP per capita. Neither the high or low income subsets came close to indicated a statistically significant relationship; either positive or negative. Taken together, the results of models 1 to 4 provide no evidence in support of hypothesis 1. Consequently, I reject the research hypothesis in favour of the null hypothesis of no relationship.

In contrast, the results of both Models 3 and 4 indicate that infant mortality rate is both a statistically and substantively significant predictor of the onset of civil conflict. On average, a one unit increase in infant mortality increases the log of the odds of conflict onset by 0.015 at time t, controlling for all other variables (p = 0.000). In percentage terms, an increase of 10 infant deaths per 1000 increases the odds of conflict onset by 15 percent, on average. This effect is even more pronounced at time t+1 (Model 4) where an increase of 10 infant deaths per 1000 increases the odds of conflict onset by 17 percent, on average (p = 0.000). These results are robust when states with the highest (Afghanistan) and lowest (Finland) average infant mortality rates are removed from the regression.

The effect of regime type on the likelihood of civil conflict onset becomes more significant in Models 3 and 4 when compared with Models 1 and 2. At time t (Model 3), the odds of conflict onset are on average 92 percent higher for anocracies than for either democracies or autocracies (p = 0.006). At time t+1 the odds are 67 percent higher (p = 0.039). Overall then, the results for regime type across models 1 to 4 appear to support the contention that the relationship between regime type and the likelihood of conflict is U shaped, with mixed regimes most at risk. The relatively weaker results in Models 1 and 2 may suggest that the full effect of regime type is obscured by income levels, implying that mixed regimes perform worse than either democracies or autocracies economically. This is supported by the statistically significant negative correlation between the two variables.[9]

The effect of population size is again both statistically and substantively significant in Models 3 and 4. At time t (Model 3), a one unit increase in the natural log of population increases the log of the odds of conflict onset by .409 (p = 0.000), while a one unit increase at time t+1 increases the log of the odds of conflict onset by 0.416 (p = 0.000). Population density remains statistically insignificant at both t (Model 3) and t+1 (Model 4). This indication of no relationship between population density and the onset of civil conflict appears to support the earlier findings of Collier & Hoeffler (2004). Alternatively, it may be the case that measuring population density at state level provides insufficient data, but that regions of particularly high or low population density within states are still more likely to foster rebellion (Hauge & Ellingsen, 1998, Buhaug & Rod, 2006).

The effect of time dependence on the likelihood of the onset of civil conflict is slightly weaker in Models 3 and 4 when compared with Models 1 and 2. However, it still reaches a degree of statistical significance at both t (p = 0.081) and t+1 (p = 0.054). Overall, models 1 to 4 support the notion that states with a recent history of conflict have a higher likelihood of conflict in subsequent years, while states characterised by a recent history absent of conflict have a higher likelihood of remaining peaceful.

On the whole, the results show that the models based around inequality (3 and 4) provide a better fit for predicting the onset of civil conflict than the models based around income (1 and 2). The Nagelkerke R square values for both inequality models (Model 3 = 0.102, Model 4 = 0.110) are notably higher than either of the Nagelkerke R square values for the income models (Model 1 = 0.089, Model 2 = 0.085). This implies that the inequality models are able to explain more of the pseudo variance in the onset of violent conflict than the income models. Subsequently, these findings provide some support for theoretical explanations of civil conflict that prioritise the effects of grievances over greed in increasing the risk of outbreak.

Table 2 (overleaf) shows the results of logistic analyses run using the complete dataset of violent civil conflict onset with the number of deaths from disasters per country-year as the independent variable of interest. Following the same pattern as Models 1 to 4, Models 5 and 6 include all control variables except inequality (infant mortality), and are based on measures of the dependent variable at times t and t+1 respectively.

Contrary to hypothesis 2, the results from Model 5 indicate that there is no statistically significant relationship between the number of deaths from climate related natural disasters and the onset of violent civil conflict at time t. Though the sign of the coefficient is positive, its size relative to the standard error is negligible. This is confirmed by the large p value (0.761).

Table 2: Logistic Analyses of Number of Deaths from Climate Related Natural Disasters and the Onset of Violent Civil Conflict

	(5) Conflict Onset (t)	(6) Conflict Onset (t+1)	(7) Conflict Onset (t)	(8) Conflict Onset (t+1)
Number of Deaths	-0.001 (0.003)	0.001 (0.001)	-0.001 (0.003)	0.001 (0.001)
GDP Per Capita (000s)	-0.251*** (0.077)	-0.244*** (0.077)		
Infant Mortality Rate			0.015*** (0.002)	0.017*** (0.002)
Regime Type	0.453* (0.234)	0.294 (0.247)	0.651*** (0.235)	0.526** (0.034)
LN Population	0.339*** (0.071)	0.311*** (0.073)	0.413*** (0.075)	0.401*** (0.078)
Population Density	0.000 (0.001	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Brevity of Peace	1.146** (0.503)	1.288** (0.506)	0.900* (0.516)	1.004* (0.521)
Constant	-7.000*** (0.696)	-6.741*** (0.706)	-9.385*** (0.806)	-9.434*** (0.836
N	5630	5630	5630	5630

Logistic regression coefficients with standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Estimates obtained using PASW Statistics 18.

The results of Model 6 also show that the number of deaths from disasters per country-year has no predictive capability in the equation at time t+1. Though the sign of the coefficient is again positive, its size relative to the standard error is insignificant ($p = 0.173$).

Confirming the relationship uncovered in Models 1 and 2, low GDP per capita remains a statistically and substantively significant indicator of the likelihood of civil conflict onset, as are regime type, population, and time dependence. Population density remains statistically and substantively insignificant.

For Models 7 and 8 I replace GDP per capita with infant mortality rate (inequality). At both time t (Model 7) and t+1 (Model 8) the results show that the effect of the number of deaths from climate-related natural disasters remains statistically and substantively insignificant. The coefficients in both models are very similar to those observed in Models 5 and 6, as are the p values (Model 7 = 0.708, Model 8 = 0.305). On the whole, the results from Models 5 to 8 provide no empirical evidence for Hypothesis 2. As a consequence, I reject the research hypothesis in favour of the null hypothesis of no relationship.

In line with the results of Models 3 and 4, higher infant mortality rates are both statistically and substantively significant in increasing the odds of the onset of civil conflict. All other control variables retain their relationships with the onset of conflict already outlined. Overall, the models based on inequality explain more of the pseudo variance in the onset of civil conflict than those based on income. The Nagelkerke R square values for models 7 and 8 are 0.103 and 0.112 respectively, compared to 0.090 and 0.086 for Models 5 and 6.

Discussion

Overall then, the empirical findings of the analysis fail to link either the frequency or the intensity of climate related natural disasters to the onset of violent civil conflict. As a consequence, my research is unable to add statistical support to the theoretical literature which presents a strong case for how and why the occurrence of natural disasters should be associated with a higher likelihood of conflict onset. Nevertheless, a number of instances in which a climate related natural disaster has appeared to play a crucial role in bringing about conflict can be discerned. How is this support at the individual case level able to be reconciled with the absence of support at the aggregate level? In this section I explore several possible explanations.

As discussed in the literature review, there are a variety of possible causal pathways through which a natural disaster may lead to conflict. Which pathway a state is most likely to follow, if it follows any at all, is influenced firstly by the individual characteristics of that state, and secondly, by the type of disaster that occurs. This is problematic because the time that different pathways take to result in the outbreak of conflict varies widely. This can be illustrated by comparing the case of Sudan in the 1980s with that of Eastern Pakistan in 1970. In 1982 a drought began in Sudan that is widely considered to be a major contributing factor to the onset of renewed civil conflict that subsequently occurred (Suliman, 1999, Salih, 2005). The drought gradually reduced the availability of arable land in the north, increasing competition for food, and pushing up prices. Skirmishes broke out between the newly formed People's Liberation Army from the south and the Islamic government in the north as the latter sought greater control of southern land. As the severity of the drought increased, the intensity of fighting escalated, resulting in a full scale civil war by 1985 (Suliman, 1999, 2005). Though the war was the consequence of a number of interacting factors, my point is that it was three years between the beginning of the drought and the onset of full civil conflict. This is essentially because droughts are, by definition, slow onset disasters.

This contrasts with the experience of the then called Eastern Pakistan in 1970 when a cyclone devastated the province of East Bengal. Decades of dissatisfaction with the central government over economic and cultural issues had already led to the formation of a movement for autonomy in the region when the cyclone hit. Though political developments in 1971 had made conflict more likely, it was widespread anger at the poor response of the national government to the disaster that created the impetus for civil war and the subsequent formation of Bangladesh (van der Hoorn, 1996). In large part due to the rapid onset of the cyclone, the timeframe of the chain of events from disaster to conflict is much shorter. In this case the amount of time that passed between disaster and conflict onset was only one year. This variation in the time that different pathways take to lead to conflict presents a major obstacle to conducting quantitative analysis because the measurement of the dependent variable cannot change depending on each country-year observation. Consequently, many instances in which there is a strong case for the effect of natural disasters on conflict onset, such as the example of Sudan outlined above, will not be picked up in the analysis.

Another factor which may contribute to the lack of empirical evidence for the effect of natural disasters on civil conflict is the possibility that different types of disasters increase the risk of onset while others actually reduce it. For instance, rapid onset disasters such as floods and storms may increase the risk of conflict as hypothesised, but slow onset disasters like droughts could decrease the risk of conflict, particularly if they can foster cooperation between affected groups (Wolf, 1998, Gleditsch *et al,* 2006). The likelihood of cooperation is more likely with slow onset disasters because they allow time to find negotiated solutions before the effects of the disaster become too severe. This argument has been proffered in research focusing on the effect of water-scarcity on the likelihood of inter-state conflict, but has not previously been made in the civil conflict literature. For example, analysing all interstate water disputes in the fifty years to 2006, Wolf finds that those resulting in cooperation outnumber those that resulted in conflict by two to one. States may cooperate even when there relations with each other have traditionally been hostile. This was the case when Cambodia, Thailand, Vietnam and Laos formed The Mekong Committee in 1957 to agree rights to river access. Though the states were at times on opposing sides during the Vietnam War, they continued to participate in the Committee (Wolf, 2007).

Lastly, the lack of quantitative evidence linking natural disasters to conflict may result from the level of conflict measured being too large. As in almost all quantitative analyses of civil conflict, I rely on a definition of conflict which requires that the state be part of the dispute. However, this excludes a number of lower intensity or regionalised forms of violence that may take place following a disaster. This group includes non-state violence between different ethnicities, social classes, or sub-national political entities, as well as one-sided violence against non-organised groups. The effect of natural disasters on these forms of conflict cannot be measured quantitatively because there is insufficient data to analyse. Yet there is emerging evidence to suggest that it is precisely these forms of conflict that may be most likely in the aftermath of a disaster (Suliman, 1999, Buhaug *et al,* 2008). This is primarily because in most cases, disasters strike specific regions of states, rather than states as a whole. Though not a climate related disaster, the Indian Ocean tsunami that struck Aceh province in Indonesia illustrates this point. While it was estimated that Aceh province lost up to 97 percent of its annual income, the total effect on the Indonesian economy on a whole was less than 2 percent of GDP (Buhaug *et al,* 2008). In situations where the impact of a disaster is localised, using data measured at the national level creates a real risk of committing an ecological fallacy. Nevertheless, until conflict data is available at the sub-state level, it is not possible to quantitatively analyse the effect of climate related natural disasters regionally.

Conclusion

To conclude, this paper has sought to quantitatively analyse the relationship between climate related natural disasters and the onset of violent civil conflict. Though the causes of civil conflict have been the focus of much attention in recent decades, little research has explored the role that natural disasters may play in such events. Nevertheless, anecdotal evidence suggests that natural disasters have contributed to the onset of civil conflict on several occasions, as the examples of Sri Lanka, Kenya, Sudan, and Bangladesh illustrate.

Insights from the theoretical literature suggest a number of causal pathways through which natural disasters may increase the risk of conflict. For instance, disasters may destroy infrastructure, thereby weakening the state and making it more susceptible to undemocratic challengers. Likewise, disasters may exacerbate poverty and economic instability by destroying homes and affecting agricultural productivity. Because of their uneven geographical distribution, disasters may also increase inequality and social fragmentation, or create migration flows that increase competition over scarce resources.

To quantitatively assess the relationship between climate related natural disasters and civil conflict I used logistic regression to analyse a dataset comprising all states with a population over 500,000 in 1990, between 1970 and 2008. Contrary to expectation, I found no statistically or substantively significant relationship between either the frequency or the intensity of natural disasters and the onset of violent civil conflict. This result was consistent across all eight regression models, irrespective of the control variables included or whether conflict onset was observed in the year of disaster observation or the year following. In contrast, income levels, high inequality, anocratic regimes, population size, and time dependence were all found to increase the likelihood of civil conflict onset to a degree that is both statistically and substantively significant. Population density was found to be insignificant.

The failure to obtain quantitative support for the hypothesised effect of climate related natural disasters on civil war onset was then explored. I identified three possible explanations for the discrepancy between the relationship indicated at the individual level and the results obtained at the aggregate level. The first of these is the variation in the length of time that different causal pathways from disaster to conflict take to run their course. Because the time at which the dependent variable is observed must be consistent within each model, a number of conflict onsets that may be related to a previous disaster will not be connected in the regression analysis. In order to overcome this problem, I suggest that future research in this area will need to distinguish between different categories of disasters depending on the causal pathway each is most likely to take. For instance, slow onset disasters such as droughts that are likely to take until the medium term to increase the risk of conflict, if they do at all, will need to be treated in a different way to rapid onset disasters such as storms and floods.

The second explanation offered was that slow onset disasters may affect disasters in a fundamentally different way to rapid onset disasters. An argument borrowed from research on interstate conflict, I propose that slow onset disasters may actually decrease the likelihood of conflict by fostering cooperation between affected groups, while rapid onset disasters increase the likelihood of conflict as hypothesised. To test for this possibility, future research will be required to differentiate between disasters on the basis of how quickly they impact on a population

Lastly, I posited that the failure to obtain results for the hypothesised relationship may indicate that the level of measurement of the dependent variable is too large. Using sub-national data on conflict may be preferable because disasters more often affect particular regions, as opposed to states as a whole. To overcome this problem, new data is needed on conflict taking place below state level. Fortunately, such data is already being compiled by the UCDP, with the first instalment covering 1989 to 2001 set to be released in November 2010.

By quantitatively analysing the effects of climate related natural disasters on conflict this paper has sought to contribute to the literature on the effects of environmental change on the peace and stability of states in the international system. Though the results observed do not provide empirical support for the theoretical literature, it is hoped that the findings and subsequent analysis provide some direction for further research in an area still relatively inchoate. As evidence begins to emerge that climate change is likely to increase the frequency of climate related disasters by changing precipitation patterns and exacerbating weather extremes, greater understanding of the way they affect state security is imperative.

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Appendix 1: Table of Climate Related Natural Disaster Classification

Category of Natural Disaster	Type of Natural Disaster	Sub-Type of Natural Disaster
Hydrological	Flood	General River Flood Flash Flood Storm Surge Coastal Flood
	Slide	Avalanche Landslide Mudflow Rock Fall
	Wave / Surge	Tsunami Tidal Wave
Meteorological	Extreme Temperature	Heat Wave Cold Wave
	Storm	Cyclone Hurricane Tropical Storm Storm Tornado Typhoon Winter Storm
	Drought	Drought
	Wildfire	Forest Peat Steppe Scrub

Source: Adapted from EM-DAT list of natural disaster types and sub-types. Available at http://www.emdat.be/classification

Appendix 2: Summary of Descriptive Statistics for Variables Used in Models 1-8

Variable	*N*	Mean	Std. Dev.	Min	Max
Dependent Variables					
Violent Civil Conflict Onset (t)	5630	0.020	0.125	0	1
Violent Civil Conflict Onset (t+1)	5630	0.020	0.125	0	1
Independent Variables					
Number of Climate Related Natural Disasters	5630	1.250	2.686	0	35
Number of Deaths from Climate Related Natural Disasters	5630	273.230	5587.610	0	300000
GDP Per Capita (000s)	5630	5.000	9.563	0.035	129.222
Infant Mortality Rate	5630	59.35	46.522	3	263
Regime Type	5630	0.190	.395	0	1
LN Population	5630	9.034	1.550	4.710	14.120
Population Density	5630	120.610	407.531	1	7082
Time Dependence	5630	0.0511	0.141	0	0.779

Appendix 3: Robustness Checks

	Conflict Onset (t) without Luxembourg and Ethiopia	Conflict Onset (t) without Afghanistan and Finland	Conflict Onset (t) Low Income States	Conflict Onset (t) High Income States
Number of Disaster	-0.019 (0.044)	0.003 (0.933)	0.018 (0.051)	-0.277 (0.151)
GDP Per Capita (000s)	-0.245*** (0.076)		-0.958** (0.378)	-0.112 (0.077)
Infant Mortality Rate		0.016*** (0.002)		
Regime Type	0.517** (0.237)	0.625*** (0.236)	0.279 (0.280)	1.037** (0.480)
LN Population	0.368*** (0.088)	0.410*** (0.87)	0.293*** (0.099)	0.532*** (0.207)
Population Density	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.004 (0.004)
Time Dependence	0.816 (0.135)	0.900* (0.519)	0.807 (0.580)	1.992* (1.086)
Constant	-7.264*** (0.832)	-9.400*** (0.875)	-6.173*** (0.960)	-9.250*** (1.51)
N	5446	5446	2815	2815

Logistic Regression Coefficients with standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Estimates obtained using PASW Statistics 18.

Appendix 4: Correlation Matrix for Independent Variables
(Pearson's r, two-tailed)

	Number of Disasters	Number of Disaster Deaths	GDP Per Capita	Regime Type	Infant Mortality Rate	LN Population	Population Density
Number of Disaster Deaths	0.045*						
GDP Per Capita	0.102*	-0.015					
Regime Type	-0.044*	-0.007	-0.170*				
Infant Mortality Rate	-0.155*	0.039*	-0.489*	0.098*			
LN Population	0.514*	0.058*	-0.020	0.016	-0.087*		
Population Density	0.013	0.007	0.145*	0.145*	-0.163*	-0.007	
Time Dependence	0.023	0.021	-0.148*	0.065*	0.216*	0.138*	-0.041*

Denotes correlation is significant at 0.01

Appendix 5: Conflict Onsets

Year of Onset	Side A	Side B
1970	Philippines	MNLF, ASG, MIM
1970	United Kingdom	PIRA
1970	Uruguay	MLN/Tupamaros
1971	Sudan	SPLM, Sudanese Communist Party, Islamic Charter Front
1971	Madagascar	Monima
1971	Morocco	Military Faction
1971	Pakistan	Mukti Bahini
1971	Sri Lanka (Ceylon)	JVP
1971	Uganda	Military Faction, Kikosi Maalum, LRA, UPA
1972	El Salvador	Military Faction, ERP, FPL, FMLN
1972	Iran	MEK, PJAK
1973	Pakistan	Baluchi Insugents, BLA, BRA
1973	Chile	Military Faction
1974	Ethiopia	OLF
1974	Nicaragua	FSLN, Contras/FDN
1975	Bangladesh	JSS/SB
1975	Ethiopia	ALF, ARDUF
1975	Sri Lanka (Ceylon)	LTTE, TELO, EPRLF
1975	Morocco	POLISARIO
1975	Angola	FNLA, UNITA, Military Faction
1975	Indonesia	Fretlin
1975	Mauritania	POLISARIO
1976	South Africa	ANC
1976	Ethiopia	ONLF
1977	Mozambique	Renamo
1978	India	TNV, ATTF, NLFT
1978	Somalia	Military Faction, SSDF, SNM, Al-Shabaab, ARS/UIC
1978	Afghanistan	UIFSA, Taleban, Hizb-i Islami-yi Afghanistan
1979	India	PLA, UNLF, KNF, KCP, PREPAK
1979	Equatorial Guinea	Military Faction
1979	Iran	APCO
1979	Saudi Arabia	JSM
1980	Tunisia	Résistance Armée Tunisienne
1980	Liberia	Military Faction, NPLF, INPLF, LURD, MODEL
1981	Gambia	NRC
1981	India	Sikh Insurgents
1981	Egypt	Al Gama'a al-Islamiyya
1981	Venezuela	Bandera Roja
1982	Kenya	Military Faction

ISSN 2053-8626

Appendix 5: Conflict Onsets (Continued)

Year of Onset	Side A	Side B
1983	India	ULFA
1983	Turkey	PKK
1984	India	Kashmir Insurgents
1986	Togo	MTD, Military Faction
1987	Turkey	Devrimci Sol, MKP
1988	Burkina Faso	Popular Front
1988	Senegal	MFDC
1989	India	ABSU, NDFB
1989	Haiti	Military Faction, FLRN, OP Lavalas
1989	Indonesia	GAM
1989	Panama	Military faction
1989	Papua New Guinea	BRA
1989	Romania	NSF
1990	Russia (Soviet Union)	APF
1990	Pakistan	MQM, TNSM, TTP
1990	Mali	MPA, FIAA, ATNMC
1990	Trinidad and Tobago	Jamaat-al-Muslimeen
1990	Rwanda	FPR, FDLR
1991	Angola	FLEC-R, FLEC-FAC
1991	Sierra Leone	RUF, AFRC, Kamajors, WSB
1991	Algeria	Takfir wa'l Hijra, AIS, GIA, AQIM
1991	Georgia	Anti-government alliance, Zviadists
1991	Niger	FLAA, UFRA, MNJ
1991	Djibouti	FRUD
1991	Moldova	Dniestr Republic
1991	Georgia	Republic of South Ossetia
1991	Azerbaijan	Republic of Nagorno-Karabakh
1992	Bosnia and Herzegovina	Serbian irregulars, Serbian Republic
1992	Croatia	Serbian irregulars, Serbian Republic of Krajina
1992	Tajikistan	UTO, Movement for Peace in Tajikistan
1992	Georgia	Republic of Abkhazia
1993	Azerbaijan	Military Faction, OPON
1993	Russia	Parliamentary forces
1993	Bosnia and Herzegovina	Autonomous Province of Western Bosnia
1993	Congo	Cobras, Ninjas, Cocoyes, Ntsiloulous
1993	Eritrea	EIJM-AS
1993	Niger	CRA
1994	Mexico	EZLN, EPR
1994	Yemen	Democratic Republic of Yemen

Appendix 5: Conflict Onsets (Continued)

Year of Onset	Side A	Side B
1994	Russia	Chechen Republic of Ichkeria
1995	Niger	FDR, FARS
1995	Ethiopia	al-Itahad al-Islami
1996	Central African Republic	Military Faction, Forces of Francois Bozize, UFDR
1996	Serbia	UCK
1997	Myanmar	UWSA
1998	Guinea-Bissau	Military Junta for the Consolidation of Democracy, Peace, and Justice
1998	Democratic Republic of Congo	BDK
1998	Lesotho	Military Faction
1999	Uzbekistan	IMU, JIG
1999	Russia	Wahhabi Movement of the Buinaksk district
2000	Macedonia	UCK
2000	Guinea	RFDG
2002	Cote D'Ivoire	MJP, MPCI, MPIGO, FN
2004	Nigeria	NDPVF, Ahlul Sunnah Jamaa
2004	India	PULF, DHD-BW
2007	Russia	Forces of the Caucasus Emirate

Source: Adapted from UCDP/PRIO Armed Conflict Dataset v.4-2010. Available at http://www.pcr.uu.se/research/UCDP/data_and_publications/datasets.htm

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[1] For a full overview of the causes of civil conflict that are robust to sensitivity checks see Hegre & Sambanis (2006).

[2] The minimum population requirement reflects the unavailability of data on regime type below this threshold.

[3] A complete list of conflict onsets is provided in Appendix 5.

[4] A complete list of hydro-meteorological natural disaster types and subtypes is given in Appendix 1.

[5] A summary of descriptive statistics for all dependent and independent variables can be found in Appendix 2.

[6] The formula gives a value of 0.79 in the first year following conflict termination, decreasing to 0 over time.

[7] Two-tailed Pearson's r coefficient is -0.49 and is statistically significant to 0.01. A full matrix of two-tailed correlation coefficients is provided in Appendix 4.

[8] The results of all robustness checks are given in Appendix 3. States with highest and lowest GDP are found by summing GDP data for each year of the dataset and dividing by years of observation.

[9] Two-tailed Pearson's r is -0.170, the correlation is significant to 0.01.

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